



OPTIMISING THE SUSTAINABILITY OF BLOCKCHAIN-BASED SYSTEMS:

Balancing Environmental Sustainability, Decentralisation and Trustworthiness

by

AKRAM MOHAMMEDALI ALOFI

A thesis submitted to the University of Birmingham for the degree of
DOCTOR OF PHILOSOPHY

School of Computer Science
College of Engineering and Physical Sciences
University of Birmingham
April 2023

UNIVERSITY OF
BIRMINGHAM

University of Birmingham Research Archive

e-theses repository

This unpublished thesis/dissertation is copyright of the author and/or third parties. The intellectual property rights of the author or third parties in respect of this work are as defined by The Copyright Designs and Patents Act 1988 or as modified by any successor legislation.

Any use made of information contained in this thesis/dissertation must be in accordance with that legislation and must be properly acknowledged. Further distribution or reproduction in any format is prohibited without the permission of the copyright holder.

ABSTRACT

Blockchain technology is an emerging technology revolutionising information technology and represents a change in how information is shared. It has captured the interest of several disciplines because it promises to provide security, anonymity and data integrity without any third-party control. Although blockchain technology has great potential for the construction of the future of the digital world, it is facing a number of technical challenges. A most critical concern is related to its environmental sustainability. It has been acknowledged that blockchain-based systems' energy consumption and carbon emissions are massive and can affect their sustainability. Therefore, optimising the environmental sustainability of these systems is necessary. Several studies have been proposed to mitigate this issue. However, the literature needs to include models for optimising the environmental sustainability of blockchain-based systems without compromising the fundamental properties inherent in blockchain technology. In this context, this thesis aims to optimise the environmental sustainability of blockchain-based systems by balancing different conflicting objectives without compromising the decentralisation and trustworthiness of the systems. First of all, we reformulate the problem of the environmental sustainability of the systems as a search-based software engineering problem. We represent the problem as a subset selection problem that selects an optimal set of miners for mining blocks in terms of four conflicting objectives: energy consumption, carbon emissions, decentralisation and trustworthiness. Secondly, we propose a reputation model to determine reputable miners based on their behaviour in a blockchain-based system. The reputation model can support the enhancement of the environmental sustainability of the system. Moreover, it can improve the system's trustworthiness when the number of miners is reduced to minimise energy consumption and carbon emissions. Thirdly, we propose a self-adaptive model that optimises the environmental sustainability of blockchain-based systems taking into account environmental changes and decision-makers' requirements. We have conducted a series of experiments to evaluate the applicability and effectiveness of the proposed models. Finally, the results demonstrate that our models can enhance the environmental sustainability of blockchain-based systems without compromising the core properties of blockchain technology.

ACKNOWLEDGEMENTS

First of all, I would like to express my deepest and most sincere appreciation to my supervisors: Dr Rami Bahsoon and Dr Robert Hendley, for their endless support and dedication, motivation and patience throughout the last several years, especially during the COVID-19 pandemic. I cannot envisage completing this complex journey without their inspiration, encouragement and profound knowledge. They were always available for discussions, suggestions and advice that guided me to conduct high-quality research in my field. I have learned a lot from them. Our meetings were cherished moments because they were as meeting friends rather than meeting supervisors.

Secondly, I wish to offer special thanks to the thesis group members: Prof David Oswald, Dr Miqing Li and Dr Sandy Gould (Cardiff University), for their time in providing guidance, insightful comments and valuable feedback. I also wish to thank all the administrative and academic staff of the School of Computer Science for creating the friendliest environment and for their great support, kindness and welcome.

I would like to express my cordial gratitude to Dr Mahmoud Bokhari for his ideas and collaborations throughout the PhD journey. Also, a special thanks to Dr Ayman Albassam for his valuable time in providing helpful and insightful comments. I am also pleased to say thanks to all my friends, especially Dr Abdullah Alharbi, Dr Abdulla Aldoseri, Hassan Labani, Abdullah Alsalmi and my close friend Ayman Albenyan for their continuous support that made the PhD journey an enjoyable journey.

I would like to acknowledge Umm Alqura University in the Kingdom of Saudi Arabia for funding and supporting me financially during my studies.

Last and most importantly, I would like to express my extreme gratitude to my beloved parents, sisters and brothers. My family was always beside me, providing endless support, guidance and love. Also, I would like to express my heartfelt gratitude to my loved nephews and nieces for their support. This complex journey could not be possible without my family, their encouragement and continuous prayers.

CONTENTS

	Page
1 INTRODUCTION	1
1.1 Introduction	1
1.2 Problem Statement	3
1.3 Research Questions	8
1.4 Research Methodology	8
1.5 Thesis Contributions	10
1.5.1 Summary of Contributions	11
1.5.2 Publications	12
1.6 Thesis Roadmap	13
2 BACKGROUND	15
2.1 Introduction	15
2.2 Blockchain Overview	15
2.2.1 Blockchain Architecture	16
2.2.2 Blockchain System Types	17
2.2.3 Blockchain Characteristics	18
2.3 Sustainability Overview	19
2.3.1 Definition of Sustainability	20
2.3.2 Dimensions of Sustainability	20
2.3.3 Sustainability in Computer Science	21
2.3.4 Sustainability in Blockchain Technology	22
2.3.4.1 Environmental Sustainability of Blockchain Technology	22

2.3.4.2	Social Sustainability of Blockchain Technology	23
2.3.4.3	Economic Sustainability of Blockchain Technology	23
2.4	Trust and Reputation Overview	24
2.4.1	Definition of Trust and Reputation	24
2.4.2	Trust Provision within Blockchain-based Systems	25
2.4.3	Blockchain-based Systems as Trust Machines	27
2.4.4	Trust and Reputation for Environmentally Sustainable Blockchain-based Systems	27
2.5	Decentralisation Overview	28
2.5.1	Benefits of Decentralisation	29
2.5.2	Requirements of Blockchain Decentralisation	30
2.5.3	Taxonomy of Blockchain Decentralisation	30
2.5.3.1	Consensus Decentralisation	30
2.5.3.2	Network Decentralisation	31
2.5.3.3	Wealth Decentralisation	32
2.5.3.4	Governance Decentralisation	32
2.5.4	Blockchain Decentralisation and Environmental Sustainability	32
2.6	Conclusion	34
3	BLOCKCHAIN-BASED SYSTEMS DESIGN AND ITS ENVIRONMENTAL SUSTAINABILITY: A SYSTEMATIC LITERATURE REVIEW	35
3.1	Introduction	37
3.2	Systematic Literature Review Methods	39
3.3	Related Work	40
3.4	Factors Affecting the Environmental Sustainability of Blockchain	41
3.4.1	Architectural Factors	42
3.4.2	Technological Factors	43
3.4.3	Deployment Factors	43
3.4.4	Humanity Factors	43

3.4.5	Economy Factors	44
3.4.6	Policy Factors	44
3.5	Existing Methods for Improving the Environmental Sustainability of Blockchain	46
3.5.1	Blockchain Consensus Algorithms	46
3.5.1.1	Proof-based Consensus Algorithms	47
3.5.1.2	Vote-based Consensus Algorithms	58
3.5.2	Blockchain Structure	60
3.5.2.1	Directed Acyclic Graph	60
3.5.3	Decision Making	61
3.5.3.1	Decision Models	61
3.5.4	Adaptive Techniques	62
3.5.5	Extra Block Structure	64
3.5.6	Blockchain Hash Algorithm	64
3.5.7	Assist Methods	65
3.5.7.1	Renewable Energy	65
3.5.7.2	Regulations and Fiscal Policies	66
3.5.7.3	Mining Devices	66
3.5.8	Characterisation of Methods for an Environmentally Sustainable Blockchain	67
3.6	Existing Measurement Tools for the Environmental Sustainability of Blockchain	69
3.6.1	Measuring Energy Consumption	69
3.6.2	Measuring Carbon Emission	71
3.6.3	Measuring Electronic Waste	72
3.6.4	Environmental Sustainability Assessment Systems	72
3.6.5	Predicting Effects on Environmental Sustainability	74
3.7	Discussion	74
3.7.1	Principal Findings	74
3.7.1.1	RQ1.1	74

3.7.1.2	RQ1.2, RQ1.3 and RQ1.4	75
3.7.1.3	RQ1.5	76
3.7.1.4	RQ1.6	76
3.7.2	Implications of the Review on Research	76
3.8	Future Research Directions for more Environmentally Blockchains	77
3.8.1	Factors Related to Blockchain Sustainability	77
3.8.2	Methods for Developing Blockchain Sustainability	77
3.8.2.1	Consensus Algorithms	77
3.8.2.2	Sharding	78
3.8.2.3	Many/Multi-Objective Optimisation	79
3.8.2.4	Adaptive Blockchain	79
3.8.2.5	Renewable Energy	80
3.8.2.6	Regulations	81
3.8.2.7	Mining Techniques	81
3.8.3	Measuring Blockchain Sustainability	82
3.9	Conclusion	82

4 A NEW PROBLEM FORMULATION FOR OPTIMISING THE ENVIRONMENTAL SUSTAINABILITY OF BLOCKCHAIN-BASED SYSTEMS 85

4.1	Introduction	87
4.2	Optimisation Overview	88
4.2.1	Optimisation Using Meta-heuristic Algorithms	89
4.2.1.1	Selected Evolutionary Algorithms	89
4.2.2	Search-Based Software Engineering	91
4.2.2.1	Blockchain and Search-based Software Engineering	92
4.3	Related Work	93
4.4	Optimisation Problem Formulation for Blockchain-based Systems	95
4.4.1	Solution Representation	96
4.4.2	Optimisation Model for Blockchain-based Systems	97

4.4.2.1	Energy Consumption Objective	97
4.4.2.2	Carbon Emission Objective	98
4.4.2.3	Decentralisation Objective	99
4.4.2.4	Trustworthiness Objective	100
4.4.2.5	Fitness Functions Constraints	101
4.5	Experiment Design	102
4.5.1	Research Questions	102
4.5.2	Evaluation Procedure	103
4.5.2.1	Evaluating the Effectiveness of the model	103
4.5.2.2	Performance Metrics	103
4.5.3	Implementation Details	105
4.5.3.1	Experiment Settings	106
4.5.3.2	Bitcoin Simulator Settings	106
4.5.3.3	MOO Model Assumptions	108
4.6	Results and Discussion	109
4.6.1	Objectives Space Results	109
4.6.1.1	Energy Consumption and Trustworthiness Objective Space	109
4.6.1.2	Energy Consumption, Carbon Emissions, and Trustworthiness Objective Space	110
4.6.1.3	Energy Consumption, Decentralisation, and Trustworthiness Objective Space	111
4.6.1.4	Energy Consumption, Carbon Emissions, Decentralisation, and Trustworthiness Objective Space	112
4.6.2	Research Questions Answers	113
4.6.2.1	Improvement in Energy Consumption and Carbon Emission	113
4.6.2.2	Performance Analysis	115
4.7	Conclusion	117

5 A REPUTATION MODEL FOR MINERS IN BLOCKCHAIN NETWORKS 119

- 5.1 Introduction 121
- 5.2 Related Work 123
 - 5.2.1 Trust-based Consensus Algorithms 123
 - 5.2.2 Reputation-based Consensus Algorithms 124
- 5.3 Reputation Model for Miners within Blockchain-based Systems 125
 - 5.3.1 Reputation Model Properties 126
 - 5.3.2 Reputation Derivation 128
 - 5.3.3 Reputation Quantification 129
 - 5.3.4 Reputation Computation 130
 - 5.3.4.1 Mining Time 131
 - 5.3.4.2 Propagation Time 133
 - 5.3.4.3 Final Reputation Value 134
- 5.4 Evaluation 135
 - 5.4.1 Analytical Approaches 135
 - 5.4.1.1 Criteria Framework-based Analytical Evaluation 135
 - 5.4.1.2 Threat-based Analysis 137
 - 5.4.2 Experimental Approaches 139
 - 5.4.2.1 Blockchain Simulator 139
 - 5.4.2.2 Miners Reputation Values Variations 140
 - 5.4.2.3 Malicious Miner Detection 140
 - 5.4.2.4 Model Accuracy 141
 - 5.4.2.5 Energy Saving and Carbon Emissions 142
- 5.5 Conclusion 145

**6 SELF-OPTIMISING THE ENVIRONMENTAL SUSTAINABILITY OF
BLOCKCHAIN-BASED SYSTEMS 147**

- 6.1 Introduction 149
- 6.2 Self-adaptation Overview 151
 - 6.2.1 Self-adaptive Definition 151

6.2.2	Adaptation Loop	151
6.2.3	Self-adaptive Properties	152
6.2.4	Blockchain and Self-adaptive	152
6.3	Related Work	153
6.3.1	Blockchain and Self-Adaptive Models	153
6.3.2	Blockchain and MOO Models	155
6.4	Self-optimising Model for Blockchain-based systems	155
6.4.1	Knowledge Component	156
6.4.1.1	General System Knowledge	157
6.4.1.2	System Environment Knowledge	157
6.4.1.3	System Concern Knowledge	158
6.4.1.4	Historical Adaptation Knowledge	158
6.4.2	Monitoring Component	158
6.4.3	Analysis Component	158
6.4.3.1	Carbon Emission Analyser	159
6.4.4	Planning Component	160
6.4.4.1	MOOM for self-adaptive blockchain-based systems	160
6.4.4.2	Adaptation Plan	163
6.4.5	Execution Component	164
6.4.5.1	Pre-Execution Phase	164
6.4.5.2	Plan Execution Phase	164
6.5	Experiment Design	164
6.5.1	Research questions	165
6.5.2	Evaluation Procedure	165
6.5.3	MOOM Settings	167
6.5.4	Implementation Details	167
6.5.4.1	Experimental Settings	167
6.5.4.2	Self-Optimising Model Assumptions	168

6.6	Results and Discussion	169
6.6.1	Improvement in Energy Consumption and Carbon Emission (RQ4.1)	170
6.6.2	Reduction in Decentralisation and Trustworthiness (RQ4.2)	170
6.6.3	Self-optimising Model Versus Similar Studies (RQ4.3)	173
6.6.4	The Relationships Between Objectives (RQ4.4)	173
6.7	Conclusion	176
7	CONCLUSION	179
7.1	Introduction	179
7.2	Addressing the Research Questions	179
7.2.1	Research Question 1	179
7.2.2	Research Question 2	180
7.2.3	Research Question 3	181
7.2.4	Research Question 4	182
7.3	Summary of Contributions and Findings	182
7.4	Threats to Validity	184
7.4.1	Threats to Validity Related to the Literature Review	184
7.4.2	Threats to Validity Related to Proposed Approaches	185
7.4.3	Threats to Validity Related to Evaluation	185
7.5	Future Directions	186
7.5.1	Optimising Blockchain-based Systems Using their Different Decentrali- sation Types	187
7.5.2	Optimising Blockchain-based Systems Using Renewable Energy	187
7.5.3	Integrating Machine Learning Approaches with Blockchain-based Systems	187
7.5.4	Multi-Criteria Decision Making for Optimising Blockchain-based Systems	188
7.6	Closing Remarks	188
A	Systematic Literature Review Methods	191
A.1	Goal and Research Questions	191

A.2	Search Strategy	192
A.2.1	Data Sources	192
A.2.2	Search Terms	192
A.3	Selection of Primary Studies	193
A.4	Search Execution	193

References **195**

LIST OF FIGURES

2.1	An example of a blockchain-based system	17
3.1	Ishikawa Diagram of the Impact Factors on Blockchain Sustainability	46
3.2	Thematic Analysis of Methods for Developing Blockchain Environmental Sustainability	68
4.1	The results of trading-off energy consumption with trustworthiness using five algorithms. The Pareto front is shown in black.	111
4.2	The results of trading-off energy consumption with carbon emissions and trustworthiness using five algorithms. The dot markers show the Pareto front.	112
4.3	The results of trading-off energy consumption with decentralisation and trustworthiness using five algorithms. The Pareto front is shown using the dot marker.	113
4.4	The results of trading-off energy consumption with carbon emissions, decentralisation, and trustworthiness using five algorithms. The Pareto front is shown using the dot marker.	114
4.5	Algorithms effect sizes and P-values. The letter S indicates significant differences, and the letter I denotes insignificant differences.	117
5.1	The variation of reputation values for honest and malicious miners	141
5.2	The fluctuation of miners' reputation during mining of blocks	142
5.3	The accuracy rate of detecting honest and malicious miners with different intervals	143
6.1	A self-adaptive model for blockchain-based systems.	157
6.2	The energy consumption (A) and carbon emission (B) percentages of the ten experiments for one decade.	171

6.3	The decentralisation (A) and trustworthiness (B) percentages of the ten experiments for one decade.	172
6.4	The Kendall rank correlation coefficient heatmap for every two objectives and for each objective with the number of miners.	175
6.5	The energy consumption, carbon emissions and the number of miners (A) and the decentralisation, trust and the number of miners for one experiment (B) for one experiment.	176
A.1	SLR Processes	191

LIST OF TABLES

2.1	Comparisons among Private, Consortium and Public Blockchain-based Systems	18
3.1	Factors Affecting the Environmental Sustainability of Blockchain-based Systems	45
4.1	Examples of Blockchain Objectives for Optimisation Models	93
4.2	A Summary of Related Work	95
4.3	A List of Notations	97
4.4	Implementation Details	105
4.5	A List of Notations for Evolutionary Algorithms Parameters	106
4.6	The values of the Parameters for the Used Algorithms	107
4.7	The Distribution of Miners' Locations and their Hashrates Percentages.	108
5.1	Properties for Trust and Reputation Models	128
5.2	Evaluation of Trust and Reputation Models for Miners within Blockchain-based Systems	136
5.3	Experimental parameters	139
5.4	The energy consumption of a blockchain-based system using MinerRepu	144
6.1	Experiments Parameters	168
6.2	Summary of the final improvement of the environmental sustainability of blockchain-based systems and its reductions on decentralisation and trustwor- thiness using Self-optimising Model, Static Model and Green-PoW model.	174
A.1	Selection Criteria of Primary Studies	194
A.2	Number of Related Papers Collected for the Study	194

Chapter One

INTRODUCTION

1.1 Introduction

Blockchain technology has emerged to change the mechanism of transactions between parties, which is usually performed in a centralised manner and requires the engagement of a trusted third party. It is arguably one of the most significant technological breakthroughs since the invention of the internet [1]. Blockchain technology is for storing data, performing functions, executing transactions and establishing trust within an open environment, without relying on a central party.

Blockchain refers to a data structure that facilitates transactional and decentralised data sharing among a group of participants that are not necessarily trusted. Software architectures induced by blockchain technology can promote new design modalities where users can agree on a shared state in the absence of a central trusted integration point. A blockchain, as a data structure, is composed of a list of ordered blocks, each of which contains a list of transactions. In a way, it is considered to be the same as a traditional public ledger [2]. Each new block in a blockchain-based system is linked to the previous block by a hash that represents the previous block. As a result, the existing transactions within a blockchain-based system cannot be changed or removed without invalidating the hash chain. In practice, when merged with computational restrictions and the incentive arrangements pertaining to the creation of blocks, this can prevent people from interfering with the data that are stored in the blockchain.

Nodes are an integral component of blockchain systems as they link with their peers (i.e., other nodes) to form the Peer-to-Peer (P2P) network on which a blockchain-based sys-

tem operates. The function of a node lies in creating new transactions and facilitating the transmission of the transactions across a blockchain network. They uphold the state of a blockchain-based system by confirming transactions that have not yet been confirmed. Nodes also collect transactions for verification in the form of blocks and then add new blocks to the blockchain ledger. This type of confirmation is called mining, and nodes are called miners. Miners are generally offered incentives that motivate their honest behaviour. Miners can be operated by an individual or a company.

Although Bitcoin, which was proposed by Satoshi Nakamoto in 2008 [3], is the best-known cryptocurrency and application using blockchain technology, this technology is not restricted to cryptocurrencies. It has promise as a technique in a very large number of application domains. Recently, both researchers and practitioners have shown a growing interest in blockchain technology. Indeed, it has attracted extensive interest from energy supply companies, financial firms, emerging businesses, national governments, technology developers and the academic community [4]. This technology is expected to underlie many current and future technologies. In many fields, blockchain technology can help to enhance security, transparency, trust, reliability and decentralised control over data.

Presently, although blockchain technology can benefit many areas, there are debates in regard to its environmental sustainability. Therefore, researchers attempt to develop sustainable blockchain-based systems. Designing sustainable systems is considered one of the most significant challenges of the 21st century as we seek digital transformation, where using blockchain technology can be one target. It is difficult to scientifically evaluate the sustainability of a technique or its advantages for enhancing the sustainability of systems.

In 1987, the United Nations Brundtland Commission defined sustainability as “meeting the needs of the present without compromising the ability of future generations to meet their own needs”. Sustainability covers five dimensions: environmental, social, economic, technological and individual [5]. Although these dimensions have been seen as one because they are connected, each dimension has its own objectives and merits. Historically, sustainability was thought to involve environmental sustainability primarily. Environmental sustainability

has gradually been understood and becomes commonly established [6]. Recently, the term “environmental sustainability” has attracted a lot of attention from academics and practitioners aiming to solve environmental issues related to new technologies, such as blockchain technology and cloud computing.

1.2 Problem Statement

Despite the huge potential of blockchain technology, including its contribution to creating a more sustainable world, there has been considerable criticism about the environmental sustainability of this technology. Blockchain-based systems have been designed in a way that involves a resource-intensive design for trust provision. In particular, the Proof of Work (PoW) consensus protocol has been designed to be a computationally expensive design for the process of verifying transactions. PoW has been criticised because of the large amount of energy consumed and carbon emissions produced by miners for mining blocks within blockchain-based systems [7]–[9]. According to [10], one Bitcoin transaction uses approximately the same amount of energy as that consumed by the average British household in eight weeks. Moreover, as of 31 March 2023, Cambridge Bitcoin Electricity Consumption Index (CBECI) estimated that the Bitcoin network consumed 142.25 *TWh* (Terawatt-hours) of electricity per year [11], producing Greenhouse Gas (GHG) emissions of 72.08 *MtCO₂e* (Million-tonnes carbon dioxide equivalents).

The current debate concerning environmental sustainability and global warming could constrain or limit the global adoption of blockchain technology at scale [9]. Therefore, the question of optimising and finding solutions for this issue is currently receiving much attention, particularly in proposing lighter mechanisms for trust provision within blockchain-based systems that use PoW without compromising the fundamental nature of this technology.

Lighter mechanisms that optimise energy and carbon emissions may improve the viability and long-term sustainability of the technology; such optimisation may render a cost-effective, dependable and climate-friendly solution. Since blockchain technology has become an integral part of many systems, improving the environmental sustainability of this technol-

ogy is a serious and essential part of achieving the United Nations' Sustainable Development Goals. Therefore, a more critical perspective is necessary on developing the efficiency of energy and carbon use of blockchain-based systems while ensuring the decentralisation and trustworthiness of these systems. Researchers have proposed more sustainable and energy-efficient mechanisms for blockchain technology. Solutions include new consensus algorithms, regulatory mechanisms, and fiscal policies, as well as limiting the use of these systems. However, more studies are needed to enhance the environmental sustainability of blockchain-based systems without compromising the inherent features of blockchain technology, such as its decentralisation and trustworthiness.

Whereas environmental sustainability issues are now an element of the discussion regarding blockchain processes, there is a need for an approach that improves the sustainability of blockchain-based systems by providing trade-offs between conflicting objectives taking into account environmental changes and decision-makers requirements. In particular, there is limited literature on formulating the environmental sustainability of blockchain-based systems as an optimisation problem and solving it using evolutionary algorithms (EAs). If this formulation is introduced, the fundamental premise is that it may enhance blockchain technology's environmental sustainability without compromising its features. In other words, the formulation may help balance conflicting objectives, such as energy consumption, carbon emissions, decentralisation and trustworthiness of blockchain-based systems. Further, this optimisation model can be integrated with trust and reputation models for blockchain-based systems, which may prevent compromising the core properties of blockchain technology in delivering trust. In addition, the optimisation model can react to environmental changes and benefit from self-adaptive techniques to optimise these systems' sustainability and dynamically balance conflicting objectives.

This thesis aims to address these gaps by suggesting lighter mechanisms for mining blocks of a blockchain-based system that enhance its environmental sustainability without compromising the inherent features of blockchain technology. The lighter mechanisms can balance the inherent decentralisation and trustworthiness of the technology and its environ-

mental sustainability in terms of energy consumption and carbon emissions. We envision that this balancing can contribute to the Sustainable Development Agenda. Specifically, we can accomplish this by addressing the following open problems:

- **Problem 1. Investigation for systematic synthesis and compilation of methods, techniques, and design decisions on the environmental sustainability of blockchain-based systems, as a pre-requisite for informing the design of more environmentally sustainable solutions for this category of systems:** To integrate a synthesis of current scientific studies for research questions on a specific topic, a Systematic Literature Review (SLR) is among the commonly used approaches. Since the environmental sustainability of blockchain technology is considered critical, several studies have proposed solutions for this issue. However, there is a lack of knowledge that brings together advances in state-of-the-art practices, techniques, methods and metrics that consider the environmental sustainability of blockchain-based systems. To address this gap, an SLR on the topic can provide a better understanding of the existing studies, covering their fundamentals, strengths and limitations, and advance a road-map for designing and proposing environmentally sustainable blockchain-based systems.
- **Problem 2. Enhancing the environmental sustainability of blockchain-based systems without compromising the underlying properties and benefits of blockchain technology, including the provision of trust and decentralisation:** Blockchain technology design provides an expensive trust mechanism that affects its environmental sustainability. Blockchain-based systems that use the PoW consensus algorithm require miners to invest their resources to mine new blocks. Consequently, the systems consume massive energy and produce considerable carbon emissions. Blockchain-based systems are like many computing systems, where improving one objective can affect other conflicting objectives and may compromise the core features of blockchain technology. Thus, trade-offs between enhancing the environmental sustainability of these systems and other conflicting objectives, such as decentralisation and trustworthiness, are required to improve the efficiency of blockchain-based systems. From another point

of view, the systems provide a high level of decentralisation and trust, but they fail to save wasted energy and carbon emissions when these systems do not need that level of decentralisation and trust. Therefore, when requested, the systems should be designed to balance energy consumption and carbon emissions with decentralisation and trustworthiness. Some studies attempt to improve the environmental sustainability of blockchain-based systems by reducing the number of miners within these systems to minimise energy consumption. However, they need to focus on the effects of reducing miners on other conflicting objectives, taking into account decision-makers' preferences. To this end, there is a need to formulate the problem of selecting miners for mining blocks in a blockchain-based system as a Search-Based Software Engineering (SBSE) problem. It can be represented as a subset selection problem that balances conflicting objectives, such as energy consumption, carbon emissions, decentralisation and trustworthiness. In addition, the formulation can consider decision-makers' preferences in balancing the conflicting objectives. Such a formulation can optimise the environmental sustainability of blockchain technology without compromising its fundamental properties.

- **Problem 3. Evaluating the miners' reputation within a blockchain-based system, considering the dynamic of their behaviours to support the design of more environmentally sustainable blockchain-based systems:** The high number of miners within blockchain-based systems has crucial effects on environmental sustainability. Accordingly, reducing the number of miners within blockchain networks is essential to obtain better efficiency for mining blocks. However, lowering miners within a blockchain-based system can affect the system's trustworthiness. In other words, it can successfully minimise energy consumption and carbon emissions but also compromise the system's trustworthiness. However, restricting mining new blocks to reputable miners can shorten this compromise. Nevertheless, selecting reputable miners, among others, is still challenging because the architecture of blockchain technology provides an open and unrestricted environment for miners to participate in mining new blocks. Miners are neither fixed nor authorised, and there is no prior knowledge of their behaviour in

mining blocks. Since blockchain networks are P2P networks, there are several trust and reputation models for P2P networks in the literature that can be used to select reputable miners. However, these models have limitations for their application to blockchain networks. Hence, there is a need for trust or reputation models that can dynamically define reputable miners within a blockchain-based system based on their behaviour and then enhance trust provision. Such a model can support fewer miners within a blockchain network and improve its trustworthiness. Also, it can boost the trustworthiness of these systems while balancing conflicting objectives.

- **Problem 4. Optimising blockchain-based systems' environmental sustainability dynamically, taking into account conflicting objectives, environmental changes and decision-makers' requirements:** As we have mentioned, selecting a set of reputable miners can balance the environmental sustainability and the trustworthiness of blockchain-based systems. However, this may only sometimes be the case because of dynamic changes in the environment associated with the systems. Blockchain-based systems operate in dynamic and non-stationary environments, including environmental changes for miners' locations. Therefore, the environmental sustainability of a blockchain-based system can change over time because of changes in the environmental conditions of miners within the system's network. In addition, blockchain-based systems need to respond to decision-makers' requirements during run-time, which may include optimising the systems' efficiency, performance or security. For example, decision-makers may seek to increase the efficiency of a blockchain-based system in terms of energy consumption and carbon emissions, which requires the system to adapt in response to these requirements. Therefore, blockchain-based systems need to adapt themselves to operate in dynamic environments, taking into consideration decision-makers' requirements. There are existing works that employ self-adaptive concepts for blockchain-based systems. However, there is a lack of a self-adaptive model for blockchain-based systems that integrates self-adaptive techniques with optimisation models to optimise these systems. Such a model could be utilised to enhance blockchain-based systems' environmental

sustainability without compromising the inherent objectives of blockchain technology, considering environmental changes and decision-makers' preferences.

1.3 Research Questions

In this thesis, we address the following research questions:

RQ1: What is the state of the art in optimising the environmental sustainability of blockchain technology and its design?

RQ2: How can the environmental sustainability of a blockchain-based system be optimised without compromising its inherent properties, such as decentralisation and trustworthiness?

RQ3: How can we evaluate the reputation of miners within blockchain-based systems, considering the dynamic of miners' behaviours, to support the environmental sustainability of these systems?

RQ4: How can we dynamically enhance the environmental sustainability of blockchain-based systems while maintaining their decentralisation and trustworthiness, taking into account environmental changes and decision-makers' requirements?

1.4 Research Methodology

In this thesis, we address the above research questions by adopting the classical research methodology presented in [12] to develop the study. The methodology is carried out to lead our research through six steps as follows:

- **Identifying the thesis problem.** The initial step is to gain insights into blockchain technology and its environmental sustainability. Therefore, we have conducted an SLR that helps our understanding of the field and allows us to investigate progress of research and identify open problems and gaps in the current state of the art. The review covers the state-of-the-art methods and techniques for developing the environmental sustainability of blockchain design. Also, it identifies the factors that affect its environmental

sustainability. Based on the key findings, we identify the problem of this thesis and formulate it in the form of research questions.

- **Identifying the thesis objective.** Motivated by the identified problems from the previous step, the next step is to define the objectives of their solutions. In this thesis, we focus our efforts on optimising the environmental sustainability of blockchain-based systems. The main objective of this thesis is to formulate the problem of blockchain-based systems' sustainability as an optimisation problem and design environmentally sustainable blockchain-based systems without compromising the fundamental properties of blockchain technology. We have formulated this objective as our contributions in Section 1.5.
- **Designing and developing the thesis contributions.** We conduct an SLR for blockchain technology and the environmental sustainability of its design with a particular focus on methods and techniques that attempt to enhance the environmental sustainability of this emerging technology. The results obtained from our review present some inadequacies of research in optimising the sustainability of blockchain-based systems as an optimising problem. In this regard, we reformulate the problem of minimising the energy consumption and carbon emissions of blockchain-based systems as an SBSE problem and solve the problem using EAs. Moreover, this thesis designs a reputation model for miners within blockchain-based systems that can also support the environmental sustainability of the systems. This reputation model can offset the trustworthiness problem that may occur as a result of reducing the number of miners to minimise the energy consumption and carbon emissions of these systems. Finally, this thesis leverages self-adaptive techniques to dynamically optimise the environmental sustainability of blockchain-based systems.
- **Demonstrating the thesis contributions.** In this thesis, we have carefully designed our experiments to simulate a real-world scenario of blockchain-based systems. We have used a blockchain simulator, Bitcoin-Simulator [13], a well-known simulator for

the blockchain environment. Our use of simulation is consistent with scientific work on blockchain as it is widely acknowledged that it is not feasible and is expensive to undertake experimentation within large-scale blockchain networks. Simulation can serve to evaluate scale and non-typical what-if scenarios that are difficult to cater for and reconfigure in blockchain-based systems. We use information retrieved from well-known resources to simulate a real-world scenario of a blockchain-based system.

- **Evaluating the thesis contributions.** We conduct a set of experiments to evaluate each of the proposed contributions. In particular, we evaluate the proposed approaches using a quantitative experimental evaluation. We compare the performance of the approaches with other state-of-the-art approaches, using appropriate comparison measurements for each contribution in this thesis. These comparisons include the energy consumption, carbon emissions and trustworthiness of blockchain-based systems over time. In addition, we evaluate our reputation model using an analytical framework to evaluate and compare our model with existing trust and reputation models for miners in blockchain networks.
- **Communicating the thesis contributions.** We communicate the problem, its importance, novelty and utility to researchers and relevant audiences. We have communicated the proposed approaches in this thesis through papers that have either already been published in high-quality and reputable scholarly conferences and journals or are currently on their way toward scholarly publications.

1.5 Thesis Contributions

The thesis presents several novel contributions to complement the working of trustworthy blockchain technology and its design. It significantly contributes to the area of computational sustainability, an emerging field that aims to apply methods from applied mathematics, statistics, operations research, information science and computer science for sustainable development [14].

The study contributes to improving the environmental sustainability of blockchain-based systems that are involved in green computing. Also, it contributes to enhancing the trustworthiness of these systems when the number of miners within their networks is reduced to minimise energy consumption and carbon emissions. In this section, we outline the study's contributions and publications.

1.5.1 Summary of Contributions

In this thesis, we make the following contributions:

1. **An SLR on the environmental sustainability of blockchain technology and its design.** We conduct an SLR that covers the state of the art of methods and techniques attempting to improve the environmental sustainability of blockchain-based systems. We also provide a classification of factors that affect the environmental sustainability of these systems. We present the assessment and measurement tools for the environmental sustainability of blockchain-based systems. Based on the SLR findings, several prospective directions and studies for designing environmentally sustainable blockchain-based systems are identified. These research gaps allow us to design our novel contributions that are presented in research question form.
2. **A multi-objective optimisation model for blockchain-based systems.** We reformulate the environmental sustainability problem of blockchain-based systems as an SBSE problem. In particular, we reformulate the problem of selecting a subset of miners in blockchain-based systems as an optimisation problem and design a Multi-objective Optimisation Model (MOOM). The model optimises the environmental sustainability of these systems in terms of energy consumption and carbon emissions, using EAs, while maximising conflicting objectives, such as the decentralisation and trustworthiness of the systems.
3. **A reputation model for miners in blockchain-based systems.** We propose a novel model for calculating the reputation of miners within a blockchain-based system.

The model dynamically calculates and evaluates the reputation of miners within the system by computing the situational reputation of each miner based on the satisfaction that is gained through the contributions to mining blocks. This reputation model can enhance the trustworthiness of blockchain-based systems by selecting reputable miners to mine new blocks. Moreover, it can enhance the environmental sustainability of these systems. The model can also be integrated with other models, such as multi-objective optimisation models.

4. **A self-adaptive model for blockchain-based systems.** We develop a novel self-adaptive model to optimise the environmental sustainability of blockchain-based systems. The self-optimising model integrates self-adaptive architectures and multi-objective optimisation models. The model dynamically uses an EA to maintain the decentralisation and trustworthiness of blockchain-based systems, while reducing energy consumption and carbon emissions and considering the environmental conditions and users' requirements. The self-adaptive model uses our reputation model to counteract the reduction of trustworthiness that may occur due to minimising the number of miners.

1.5.2 Publications

The work described in this thesis has supported publication in key conferences and journals related to the subject of its investigation. This thesis is considered as an updated reference for the following published and under-review works:

- Akram Alofi, Rami Bahsoon and Robert Hendley. 2023. A Systematic Review on Blockchain-based Systems Design and its Environmental Sustainability. ACM Computing Surveys. (*Review Cycle*).
- Akram Alofi, Mahmoud A. Bokhari, Robert Hendley, and Rami Bahsoon. 2021. Selecting Miners within Blockchain-based Systems Using Evolutionary Algorithms for Energy Optimisation. In Proceedings of the Genetic and Evolutionary Computation Conference Companion (GECCO '21).

- Akram Alofi, Mahmoud A. Bokhari, Rami Bahsoon and Robert Hendley. 2022. Optimising the Energy Consumption of Blockchain-based Systems Using Evolutionary Algorithms: A New Problem Formulation. *IEEE Transactions on Sustainable Computing*.
- Akram Alofi, Rami Bahsoon and Robert Hendley. 2021. MinerRepu: A Reputation Model for Miners in Blockchain Networks. In the Proceeding of IEEE International Conference on Web Services (ICWS).
- Akram Alofi, Mahmoud A. Bokhari, Rami Bahsoon and Robert Hendley. 2023. Self-Optimising the Sustainability of Blockchain-based Systems. *IEEE Transactions on Sustainable Computing*. (*Second Review Cycle*).

1.6 Thesis Roadmap

In this section, we illustrate the structure of the remaining chapters of the thesis. The structure is presented as follows:

- **Chapter 2:** In this chapter, background information is presented that is related to the basis of this work and facilitates the reading of this thesis. It introduces an overview of blockchain technology and the concept of sustainability. It also discusses trust and reputation definitions and their integration with blockchain-based systems. Finally, an overview of blockchain technology decentralisation is provided.
- **Chapter 3:** In this chapter, an SLR on the environmental sustainability of blockchain technology is conducted. It surveys the state-of-the-art techniques and methods attempted to enhance the environmental sustainability of its blockchain design. Also, it classifies factors that play a role in affecting the environmental sustainability of blockchain-based systems. Finally, this chapter indicates research gaps in the literature that motivated the need for the proposed approaches of this thesis.
- **Chapter 4:** In this chapter, we propose a multi-objective optimisation model that improves the environmental sustainability of blockchain-based systems by minimising en-

ergy consumption and carbon emissions without compromising the fundamental properties of blockchain technology, such as decentralisation and trustworthiness. The chapter discusses results from a set of experiments to show the effectiveness and applicability of the model in reducing energy consumption and carbon emissions of blockchain-based systems. We have derived this chapter from our published works presented in [15] and [16].

- **Chapter 5:** In this chapter, we introduce a dynamic reputation model for miners within a blockchain-based system. The chapter presents an analytical approach to evaluate and compare the model against similar existing works. It also conducts a series of experiments to demonstrate the effectiveness of the reputation model. We have derived this chapter from our published work presented in [17].
- **Chapter 6:** In this chapter, we develop a self-adaptive model to optimise the environmental sustainability of blockchain-based systems at run-time. The chapter conducts a set of experiments to evaluate the proposed model. It also shows how the model balances energy consumption and carbon emissions with conflicting objectives under different operating conditions.
- **Chapter 7:** In this chapter, we perform a reflective evaluation of our research contributions. Furthermore, the chapter suggests future research directions and summarises the main contributions of this thesis.

Chapter Two

BACKGROUND

2.1 Introduction

In this thesis, we research ways to enhance the sustainability of blockchain-based systems without compromising the fundamental properties of blockchain technology. Therefore, this chapter gives an overview of blockchain technology and sustainability that provides the basis for this work in Sections 2.2 and 2.3. In addition, we present a brief overview of trust and reputation since the trustworthiness of blockchain-based systems is one core property that should not be compromised. Therefore, we discuss these terms in Section 2.4. Moreover, this chapter explains the concept of decentralisation for blockchain-based systems in Section 2.5 because the thesis also aims not to affect this essential property of the technology. Finally, we conclude the chapter in Section 2.6.

2.2 Blockchain Overview

Blockchain technology can be considered one of the most important technological breakthroughs in recent years. Blockchain technology is an emerging technology that has attracted close attention from academic communities, technology developers, energy supply companies, emerging businesses, national governments and financial firms. According to many studies from these fields, such as [18], [19], blockchain technology has significant potential to benefit the world. The blockchain concept was initially outlined in a paper by Satoshi Nakamoto (2008), entitled: “Bitcoin: A peer-to-peer electronic cash system” [3]. Bitcoin, the first known cryptocurrency using blockchain technology, was implemented in 2009 following

the public release of Nakamoto’s paper [20]. Bitcoin has initiated a range of new potential options for blockchain-based applications for maintaining financial transactions. Blockchain can also be applied in many other fields, including security services [4], public services [21], smart contracts [22], reputation systems [23] and the Internet of Things (IoT) [24]. The innovation of blockchains has entirely changed the structure of technologies, industries and businesses [25]–[27] through its combination of key features, including decentralisation, distribution, consensus mechanism, persistency and auditability [28].

2.2.1 Blockchain Architecture

The Blockchain is a series of blocks that contain lists of transaction records. It is regarded as similar to a traditional public ledger [2]. Every block is connected to a parent block (i.e., a previous block) by a hash value reference. The initial chunk of a blockchain is called a “genesis block” and does not connect to a previous block because it is the first block in the blockchain. A block contains two entities: the header and the block’s body. The header contains the block version, the parent block hash, the timestamp, the Merkle tree root hash, the nBits and the nonce. The block’s body comprises lists of transactions and transaction counters (see Figure 2.1). All nodes in a blockchain network have their public keys and private keys. The private key is utilised for signing transactions. These digitally-signed transactions are extended through the entire system and will be recognisable to every node of the network through the public key [8].

Blockchain is developed for particular networks of untrusted and, possibly, compromised participants. Such participants can establish agreements on shared information safely and securely. In addition, these agreements do not need any central points of control, authority or regulatory administration. Blockchain ensures that the element of trust among unidentified, corresponding items in decentralised systems do not require central administrator authorities to verify the accuracy of ledger records [8].

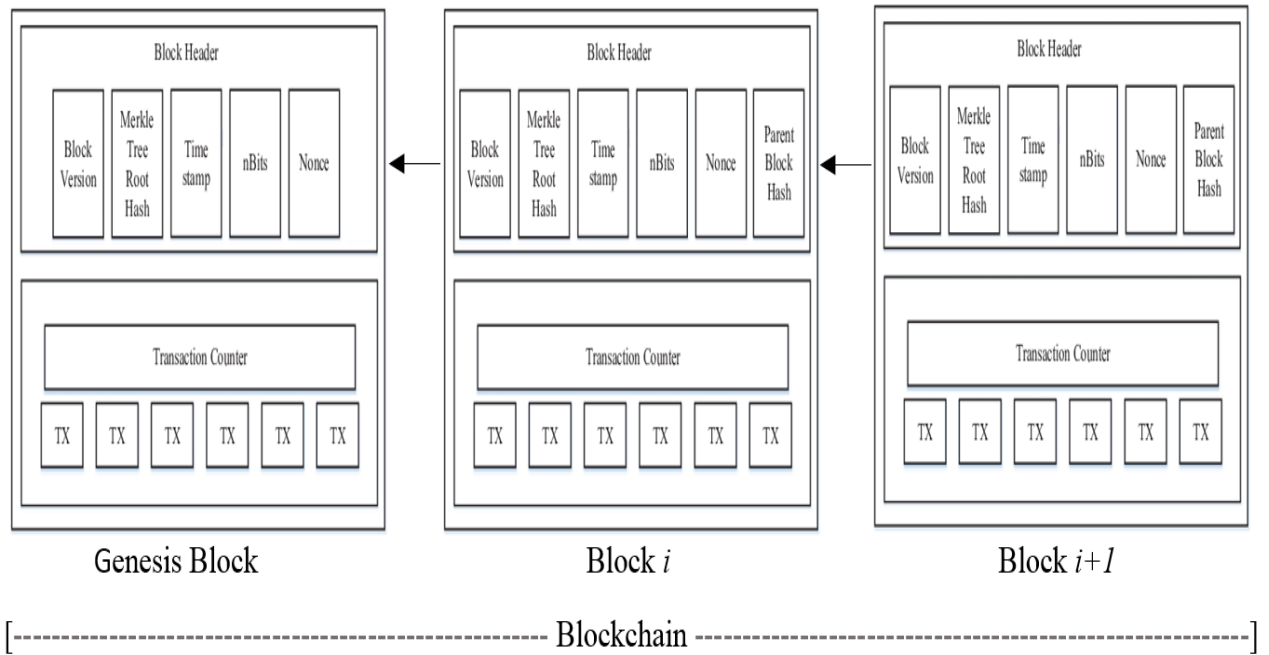


Figure 2.1: An example of a blockchain-based system

2.2.2 Blockchain System Types

Blockchain-based systems can follow diverse architectures and rules, according to the particular use case and desired operation. The systems are characteristically composed of network validators and users. A transaction can be initiated or received by user nodes in a blockchain network, and a copy of the network's ledgers can also be held by users. Validators have read access privileges and are responsible for approving alterations to ledgers. Also, they are highly accountable for reaching a consensus throughout the entire network. Depending on the system's configuration, private, partial or public access and validation privileges may apply. There are diverse blockchain-based systems that can be classified as private or public and permissioned or permissionless. It is essential to point out that some researchers have used the terms "private/permissioned" and "public/permissionless" as synonyms. These synonyms can be coherent with cryptocurrencies; however, this is not the case for all blockchain applications. Therefore, it is important to differentiate between authentication and authorisation. Authentication can identify who has permission to access blockchain ledgers, whether private or public. By contrast, authorisation is related to who can do tasks, either permissioned or

Table 2.1: Comparisons among Private, Consortium and Public Blockchain-based Systems

Property	Private	Consortium	Public
Read permission	Restricted or Public	Restricted or Public	Public
Tampering immutability	Possible	Possible	Almost impossible
Efficiency	High	High	Low
Centralisation	Yes	Partial	No
Consensus process	Permissioned	Permissioned	Permissionless
Consensus determination	One organisation	Pre-defined set of nodes	All miners

permissionless [29].

Different researchers have given various definitions of blockchain-based systems, depending on their research works and the resulting consequences. This means that these definitions are still debated; therefore, the following descriptions may differ from those presented by other researchers. Current blockchain-based systems can be classified into three categories: public, consortium and private [30]. In a public blockchain, public users can reach all records, and any individual entity can participate in the agreement procedure, which makes this a highly decentralised type. In contrast, only certain selected nodes would contribute to the consensus procedures within a consortium blockchain; thus, it is partially decentralised. In a private blockchain, only particular nodes that originate from a single and particular organisation are allowed to connect to the mutual consensus process. Consequently, these private blockchains are highly centralised [31]. It does not matter what types of blockchain-based systems are used, because they all have advantages and disadvantages. Sometimes, a public system is required, while private systems are mandatory at other times. We can determine which system is necessary depending on the situation and the requirements. The evaluation and comparison of these three categories of blockchains are discussed in [8] and are listed in Table 2.1.

2.2.3 Blockchain Characteristics

Blockchain technologies are composed of four key characterises:

1. **Decentralisation.** Blockchain-based systems are decentralised, so they do not have

to rely on a single entity as a centralised node. Instead, data is recorded, stored, and updated on multiple distributed systems.

2. **Transparency.** Nodes within blockchain-based systems may see the history of the data because the systems are transparent. Also, they can update data, making it trustworthy and transparent.
3. **Autonomy.** Nodes have the autonomy to update or transfer data safely without intervention due to the use of consensus algorithms.
4. **Anonymity.** Blockchain-based systems establish trust between nodes with secrecy technologies to solve the necessity for privacy and anonymity.

2.3 Sustainability Overview

The concept of sustainability has been given substantial attention in academic, social, legal and political contexts in recent years. A marked change in attitudes towards sustainability has been observed over the last ten years. At one point, the environmental impacts of human activity were perceived to be a distant problem that did not impact people's current lives. However, these impacts are now acknowledged as a humanitarian crisis that requires urgent attention. As a result, more attention has been invested in developing sustainable technologies that can halt humanity's journey to destruction [32]. Many scholars have dedicated their research to examining people's perceptions of sustainability and identifying associated actions. In 2015, the 2030 Agenda for Sustainable Development was adopted by each United Nations Member State. This agenda provides a shared vision for the planet and people to live in peace and prosperity between 2015 and 2030. It comprises 17 Sustainable Development Goals (SDGs) and 169 targets that address sustainability dimensions [33].

2.3.1 Definition of Sustainability

Although the term “sustainability” is in everyday use, people attach different meanings to it and have different perceptions. The German word for sustainability, “*Nachhaltigkeit*”, was first used in 1713 within the forestry context, to describe a situation in which people were harvesting more than the forest could replenish [34]. In [35], the authors adopt a different perspective of sustainability, describing it as representing the “capacity of a system to endure”. Most definitions of sustainability rely on the Brundtland report’s definition of sustainable development [36], which defines it as “meeting the needs and aspirations of the present generation without compromising the ability of future generations to meet their need” [37]. According to [38], sustainability is underpinned by two key pillars: “the ability of some things to last a long period” and “the resources used”. Therefore, in our context, sustainable blockchain-based systems can be defined as the systems’ ability to persist for a long time while using only the resources that are strictly required.

2.3.2 Dimensions of Sustainability

According to [35] and [39], there are five dimensions of sustainability:

1. **Environmental.** The environmental aspect of sustainability is concerned with the long-term implications that the actions of humans have on the environment. It spans multiple dimensions, including raw resources, waste, water, pollution, climate change, food production and ecosystems.
2. **Social.** The social aspect of sustainability is concerned with the role that social communities, such as organisations and groups of people, have in the degradation of trust within a given society. This aspect spans multiple dimensions, including employment, justice, democracy and social equity.
3. **Economic.** The economic aspect of sustainability is concerned with added value, capital and assets. It spans multiple dimensions, including prosperity, wealth creation, income and profitability.

4. **Technical.** The technical aspect of sustainability is concerned with the lifespan of systems, information technologies, infrastructure, and the evolution of technologies in line with changes in external conditions. It includes the dimensions of data integrity, innovation, maintenance and obsolescence.
5. **Individual.** The individual aspect of sustainability is concerned with the well-being of people. Its dimensions include education, training, health, mobility and self-respect.

The five dimensions are interdependent, and the cumulative effects of one dimension can impact another. For example, technological changes can enhance people's well-being but can negatively affect the world climate. Despite their interrelated nature, the dimensions represent a meaningful tool for disaggregating and assessing issues of relevance to sustainability.

2.3.3 Sustainability in Computer Science

Sustainability in computer science is a vast field that aims to optimise economic, social and environmental resources through computer technology. There are many initiatives and programmes, such as the International Science Council (ISC), the World Climate Research Programme (WCRP) and the United Nations Environment Programme (UNEP), that support research for environmental sustainability. These initiatives enable educators and researchers to follow and observe research programmes, bringing society benefits. In addition, there are widespread uses and applications of sustainability in computer science. For instance, energy production has been dramatically revamped through smart grids; these grids incorporate renewable energy resources and capacities for storage that can effectively control the expenditure and production of energy [40].

In the software engineering (SE) context, sustainability considerations can be found as far back as 1968, when software evolution and maintenance concepts were considered during the NATO SE conference [35]. Currently, some SE structures are not designed to maintain sustainable development, although computers and their associated software systems impact people's lives in numerous areas and disciplines [41]. Therefore, SE architectures and develop-

ers utilising SE to make natural resources sustainable and the planet greener have enormous scope and potential.

2.3.4 Sustainability in Blockchain Technology

Blockchain technology is already acknowledged as significantly impacting innovations. Consequently, the link between blockchain and sustainability is worth further analysis. Recently, a range of debates has been initiated related to the sustainability of blockchain-based systems and their environmental, social and economic impacts on the world.

2.3.4.1 Environmental Sustainability of Blockchain Technology

Some scholars have argued that blockchain-based systems reduce humanity's environmental impact and motivate people to behave more sustainably [42]. These authors discuss the various methods for achieving global sustainable development targets, such as using blockchain-based systems in supply chains to make supply chain networks more sustainable [43]. However, other scholars argue the opposite.

From another perspective, some researchers claim that the way blockchain technology has been purposefully computationally designed (i.e., energy-intensive) can represent a serious threat to the global commitment to reduce Greenhouse Gas (GHG) emissions following the Paris Agreement [9]. In addition, these scholars point out that the electricity expended in mining is extremely heavy [44]. Different surveys, such as [45]–[47], have studied the electricity consumption of blockchain-based systems. They have shown different results because they have used other estimation methods with different methods to identify the geographic location of miners. However, they have reached the same conclusions that indicate the high levels of energy consumed by miners. Moreover, they have shown that this consumption has been on a rising trend.

The vast energy consumption of miners for adding blocks can result in massive carbon emissions. As of 31 March 2023, CBECI [11] estimated that the Bitcoin network, which is the most common cryptocurrency using PoW, consumed 142.25 *TWh* of electricity per

year, which is more than the energy consumption of Finland. This amount of energy can produce GHG emissions of 572.08 $MtCO_2e$. In [45], the authors show that Bitcoin can consume energy up to 45.8 TWh per year, which can lead to carbon emissions between 22.0 to 22.9 $MtCO_2e$. According to [47], the carbon emissions resulting from Bitcoin will push global warming over 2°C.

To solve this issue, researchers have focused on enhancing the environmental sustainability of blockchain-based systems. Therefore, they have proposed potential solutions in the literature that include new consensus algorithms, regulatory mechanisms and fiscal policies, as well as restrictions on the usage of these systems. More details are discussed in Chapter 3.

2.3.4.2 Social Sustainability of Blockchain Technology

Blockchain technology has become a part of the United Nations discussions related to this technology's sustainability and how it can contribute to implementing sustainable development. It views this technology as a crucial tool for achieving social sustainability by developing export applications for poor farmers that can improve the lives of those farmers and their families. In [48], an analysis of the possible social sustainability of using blockchain technology in the supply chain is given.

In contrast, there are concerns about the social sustainability of blockchain technology. For example, Bitcoin, an application of blockchain technology, can affect society because criminal organisations can use it for illegal trade, such as weapons, drugs, or other fraudulent activities [49].

2.3.4.3 Economic Sustainability of Blockchain Technology

Blockchain technology has created a digital economy that is democratic, open, and scalable, which makes every transaction between two or more economic units traceable. These developments open new and challenging opportunities for economic sustainability. Therefore, banking and financial systems have become interested in applying this technology and studying its impacts on their economic systems [49].

2.4 Trust and Reputation Overview

Trust and reputation have existed since human beings have lived and have significant roles in our lives. The goal of scientific research in the field of computational mechanisms that focuses on trust and reputation for virtual communities is to improve the performance and dependability of online communities. In computer science, the idea of isolated machines has been replaced by networks and distributed systems. Therefore, interest in trust and reputation mechanisms applied to this paradigm has increased. Reputation and trust management can establish a greater prior knowledge among participants and users within a network that, in turn, might assist in collaborating efficiently and healthily. The research field of trust and reputation management is multidisciplinary and includes researchers from several areas, such as communication, service computing, data management and networking [50].

2.4.1 Definition of Trust and Reputation

Daily, we use and make decisions based on the trust and reputation of others. Nevertheless, it is challenging to define trust and reputation precisely and clearly. Trust and reputation are strongly related but differ in how they are developed [51], [52].

According to [53], trust is derived from an entity's reputation. The authors state that an entity receives a certain level of trust based on its reputation that has been gained over time. Therefore, building a reputation depends on the history of the entity's behaviour that reflects its negative and positive aspects.

In [54], trust is defined following a definition stated by Gambetta [55]. This definition is a well-agreed definition, used by many works on trust. The study defines trust as “a particular level of the subjective probability with which an agent will perform a particular action, both before [we] can monitor such action (or independently of his capacity of ever to be able to monitor it) and in a context in which it affects [our] own action”. In contrast, the study defines reputation as “an expectation about an agent's behaviour based on information about its past behaviour”.

Regarding trust and reputation models, the study [51] states that trust models often use

subjective measurements as inputs for measuring the trust of entities. In contrast, reputation models accept ratings or information regarding certain occurrences, such as transactions.

These definitions present a relation between the concept of trust and reputation, which is one consideration of this thesis. In this thesis, we use these definitions to adapt the definition of trust and reputation in the context of blockchain-based systems. Thus, we can define trust as strong confidence in an entity's ability (i.e., a blockchain-based system) to act as expected in a given situation with a sense of relative security, despite the possibility of negative consequences. In addition, reputation is defined as the expectation of an entity's behaviour (e.g., a miner's behaviour) relying on information related to its previous behaviour within a specific context (e.g., within a blockchain-based system) at a given time.

In blockchain-based systems, we expect miners to build their reputations based on previous behaviours that reflect their honesty by submitting trusted blocks. This means each miner has a reputation value gained based on its previous behaviour. Also, the high reputation values of participating miners within a blockchain network make the blockchain-based system more trustworthy.

2.4.2 Trust Provision within Blockchain-based Systems

The methods of reaching consensus amongst untrustworthy nodes in decentralised systems is a way of solving the Byzantine Generals (BG) Problem [56]. Blockchain-based systems are one of these systems, where there is no middle or hub node to ensure the correctness of the ledgers on distributed nodes. Also, nodes do not need to trust other nodes. In a blockchain-based system, when nodes start to share and exchange data, there is no central party for the regulation and resolution of disputes or to protect against breaches of security. Instead, one ledger copy is available in synchronisation with all involved parties. Blockchain-based systems allow information to be shared and exchanged between nodes via a P2P network. To avoid any fraud and conflict and establish trust in such a network, a mechanism is needed [8]. Blockchain-based systems rely on three built-in mechanisms: transaction verification, consensus algorithms and block validation.

In transaction verification, every transaction should be broadcast across a complete network to be verified. Every node in a blockchain-based system should verify the transaction before re-broadcasting it to others. First, verifier nodes must verify the sender node's identity, ensuring that the sender node and no other entity has asked for the interaction between it and the receiver node. They could do this by checking the public and private keys used to sign the transaction. This sign is known as a digital signature. Second, the verifier nodes must ascertain whether the sender has provided a valid transaction. In Bitcoin, for example, a transaction is only valid if the sender has sufficient funds to furnish the recipient. The validation can be achieved by scrutinising past ledgers containing data regarding all previous successful transactions [31].

When a trusted party is not present, there should not be simply an acceptance of blocks as an element of the blockchain unless a majority of other nodes give their agreement. A consensus system will be in place as to how nodes can provide confirmation of or dismiss blocks to ensure that conflict does not arise later in the process. This is referred to as a consensus algorithm that allows for the creation of blocks and their addition to the extant ledger to be employed in future. In Bitcoin, the consensus is reached via PoW, which offers proof of the quantity of work that has been used to solve a cryptographic puzzle and validate a block. The subsequent secure update for the shared status is solely based on these consensus algorithms. This makes blockchain-based systems more immutable and irreversible [31].

The independent validation by all nodes within a blockchain network for each new block means that miners cannot cheat. Every time a node is sent a new block, validation will occur by making checks through a set of criteria; if the block fails any of these checks, it is rejected. First, every transaction that the current block contains must be verified. Next, the previous block's hash that is contained within the new block must be shown to exist and have validity. Usually, this is checked from the first block, the genesis block. Finally, the timestamp's accuracy also undergoes verification. When all of these have been completed, validation of the new block's proof of work is possible [57].

2.4.3 Blockchain-based Systems as Trust Machines

Blockchain technology is widely regarded as a powerful technology, a trust machine. In the last decade, the use of blockchain-based systems as trust machines has become more interesting for researchers because of its promises. Data integrity and non-repudiation are the major advantages of adopting these systems. Moreover, they provide secure access and identity management possibilities. Also, blockchain-based systems are recognised to be very beneficial for trust and reputation systems.

There are two main ideas behind utilising blockchain-based systems. First, some studies, such as [58], [59], propose solutions to solve some issues in their existing systems, including privacy, trust and security issues. Second, some other studies, such as [60], [61], present ideas for using blockchain-based systems to design trust and reputation models. They use these systems to store transactions and calculate trust or reputation values, since managing trust and reputation values in a decentralised community is challenging. These proposed ideas are applied in various fields, such as crowdsourcing, IoT and edge computing [62].

2.4.4 Trust and Reputation for Environmentally Sustainable Blockchain-based Systems

As we have discussed earlier, blockchain technology does not rely on trusted parties. Therefore, it uses consensus algorithms to reach agreements among untrusted entities for confirming or dismissing blocks. However, the most common consensus algorithm, PoW, is considered a threat to our world's environmental sustainability due to its energy consumption and carbon emissions.

Many researchers have attempted to enhance the environmental sustainability of this technology by proposing new consensus algorithms. One kind of these consensus algorithms relies on trust or reputation models. Trust and reputation models have been used to identify trustworthy miners that are going to participate in blockchain-based systems. This means that mining new blocks will be restricted to trustworthy miners. Consequently, the number

of miners of a blockchain-based system will be reduced, lowering its energy consumption and carbon emissions.

The trust and reputation models used with these consensus algorithms are limited. More details about these consensus algorithms are discussed in Chapters 3 and 5.

2.5 Decentralisation Overview

The idea of decentralisation has been used for years in various fields, such as strategy, management, and governance. Decentralisation involves distributing control and authority to several entities instead of having one central authority completely controlling an organisation. This can lead to benefits, such as improved efficiency, faster decision-making, higher motivation, and less strain on top management. Additionally, stronger decentralisation can increase resistance to censorship and tampering [63].

Decentralisation has taken on renewed importance in the world of blockchain technology. It is a fundamental concept and benefit of the technology, allowing for the democratisation of trust. This is particularly relevant when it comes to the decentralisation of system nodes. For example, a more decentralised network of miners can create more robust resistance to censorship of individual transactions and elevate trust in the system [64].

Blockchain-based systems, by design, are an ideal platform for eliminating intermediaries and allowing consensus, with many different leaders chosen via consensus mechanisms. In this context, “consensus” refers to the process by which multiple nodes in a blockchain network use to agree on the network’s conditions and the transactions’ validity. The most widely used consensus mechanism is PoW, which involves solving complex computational problems in order to validate blocks and add them to the blockchain [63].

Decentralisation can take on various levels of intensity depending on requirements and circumstances. For example, a blockchain network can be semi-decentralised, with some central authority overseeing certain network aspects. On the other hand, it can be fully decentralised, with no control at all. From a blockchain perspective, decentralisation is a mechanism that allows the redesigning of existing applications and paradigms or the building of new ap-

plications that give complete control to users [63].

2.5.1 Benefits of Decentralisation

Centralised systems are based on the absence of mutual trust among nodes or users, so a trusted intermediary is needed to facilitate cooperation. However, this lack of transparency can lead to single points of failure, censorship and abuses of power. Decentralised systems address these issues while providing added benefits [64]:

- **Trust.** Users do not need to trust a central authority to cooperate with each other. Instead, they can trust each other directly. Hence, any modification to data in the context of blockchain technology can be seen by all participants. This creates a high level of accountability, where users believe that no “trusted” group can exert control, seize assets or impose changes without consent.
- **Immutability.** Blockchain systems allow for the permanent storage of data. Once data has been added to the blockchain, it cannot be modified (i.e., changed or deleted).
- **Robustness.** The decentralised nature of blockchain technology provides a high level of resilience. Since data is distributed across multiple nodes in the network, the failure of a single node does not affect the availability of data on other nodes. For example, the data remains accessible on other nodes, even if many nodes fail or are hacked by attackers.
- **Attack resistance.** Decentralised systems are more resistant to attack, destruction, or manipulation because they do not have weak central points that can be easily compromised.
- **Collusion resistance.** Nodes in a decentralised system have more difficulty conspiring in ways that help a group of nodes and harm others.
- **Central censorship free.** Decentralisation makes censorship difficult because it requires the cooperation of multiple nodes in a network, and it is difficult to identify

where traffic is coming from and where it is going. A single party would find it highly challenging to censor such network traffic.

2.5.2 Requirements of Blockchain Decentralisation

A blockchain-based system should meet several requirements to be considered decentralised:

- It does not rely on a trusted third party.
- It allows any node to submit transactions to the system.
- It allows any node to validate transactions.
- It distributes mining power evenly among miners. In other words, no single miner or group of miners (i.e., pool mining) should have more control over mining and adding new blocks.
- It implements a fair incentive system. Otherwise, a coalition of miners may occur, leading to a concentration of mining power and a reduction in the number of independent miners.

2.5.3 Taxonomy of Blockchain Decentralisation

The existing research on decentralisation in blockchain technology focuses on how decentralisation affects blockchain layers. Classifications of decentralisation can incorporate four categories: consensus, network, wealth and governance. Consensus and network decentralisation relate to the infrastructure layer, while wealth is connected to the incentive layer. Finally, governance decentralisation is associated with the application layer.

2.5.3.1 Consensus Decentralisation

Consensus decentralisation can be linked to the consensus algorithms of blockchain-based systems. As we have discussed previously in this chapter, consensus determination can be limited to one organisation or a selected set of nodes or open to any nodes. Also, consensus

decentralisation is associated with consensus processes that can be described as permissioned or permissionless. One way to measure consensus decentralisation is by looking at consensus determination that is related to the number of miners participating in the mining process and adding new blocks [64].

It is noteworthy that the high number of miners within a blockchain-based system only sometimes indicates that the system is highly decentralised. For example, a blockchain-based system can be centralised if only a few miners add new blocks even though it has a large number of miners in its network. Therefore, consensus decentralisation can be described as the decentralisation of miners' participation in consensus processes. It ensures mining power is distributed evenly so that no single miner can have too much control over mining new blocks [65]. In particular, decentralisation can be measured using miners' relative power measured by their hashrate. A miner's hashrate is its ability to compute the hash of new blocks and add them over time. Consensus decentralisation is essential to a blockchain system's security [66].

In this thesis, we focus on this type of decentralisation, and we have considered this as an objective of blockchain-based systems that should not be compromised. In particular, we measure the decentralisation of blockchain-based systems using the decentralisation of miners' participation in consensus processes. As we have shown earlier in this section, this type of decentralisation is connected to consensus algorithms, including their mining processes and their participating miners, one of the main factors related to the environmental sustainability of blockchain-based systems [18]. Moreover, the absence of this decentralisation can be responsible for well-known attacks, such as the 51 % attack and the Selfish Mining attack [8], [67].

2.5.3.2 Network Decentralisation

The concept of network decentralisation refers to blockchain technology's underlying peer-to-peer network infrastructure. Network decentralisation is related to how nodes interact on a blockchain network and how they are connected. It measures a node's influence, importance,

or power in the network and is often used to perform analytics on social networks [64].

2.5.3.3 Wealth Decentralisation

Wealth decentralisation can be described as the evenness of distribution of wealth among miners [65]. In other words, it refers to the distribution of monetary assets (i.e., tokens and native cryptocurrencies) across miners of a blockchain-based system. The blockchain-based system can be considered to be wealth-centralised when only a few miners gain many tokens.

2.5.3.4 Governance Decentralisation

Governance is used to define the systems and processes by which decisions are made, and actions may be taken. This may include formal groups or organisations, such as governments, markets or networks. It may also be applied to informal territories, families, or tribes. Governance may be exercised through language, norms, laws, or power. Governance decentralisation is the degree to which owners and users share authority over a blockchain-based system. In other words, it determines blockchain technology's operations and how users engage with it. Blockchain governance applies to direction, control, coordination, or decision-making [68]. In decentralised governance, the goal is to prevent the concentration of power while ensuring the system operates in the best interest of all stakeholders and participants.

2.5.4 Blockchain Decentralisation and Environmental Sustainability

In the previous section, we described four types of decentralisation of blockchain technology. Each type of decentralisation can have implications for energy consumption and carbon emissions and, henceforth, the sustainability of blockchain-based systems. Below, we discuss the potential relationships.

In consensus decentralisation, the consensus process can be permissioned or permissionless: the choice can have implications for the environmental sustainability of the system. A permissioned consensus process limits the number of participating miners, while a permissionless consensus process lets any node join mining processes. Consequently, the latter can

include many miners, which may result in high energy consumption and carbon emissions, depending on different factors, such as the type of energy source and location.

From another perspective, it can be argued that blockchain-based systems with high decentralisation can negatively affect their environmental sustainability. This effect can be linked to the number of miners participating in mining blocks (i.e., consensus determination), relying on the argument that a greater number of participating miners leads to high decentralisation. However, we have mentioned that a higher number of miners only sometimes leads to high decentralisation in blockchain-based systems. Thus, high decentralisation that results from measuring the consensus decentralisation only sometimes means high energy consumption and carbon emissions.

Let us assume there are two blockchain-based systems. The first system has 1000 miners, of which a few have high hashrates while others have low hashrates. The second system has 50 miners, with a slight difference between each miner's hashrate. The first system is more centralised than the second. In the first system, mining blocks are practically limited to a few miners because of their high hashrate among other miners.

Network decentralisation can be connected to the environmental sustainability of blockchain-based systems. Blockchain networks are P2P, and nodes that hold blockchain are distributed. The nodes within a blockchain-based network must stay online and connected to the network for a long time to receive and validate new blocks. Also, data transmission (i.e., the transmission of new blocks in this thesis) to all nodes can be affected by several network properties, such as bandwidth, throughput and the number of nodes. In addition, it can be affected by the centrality of the network, including betweenness centrality, degree centrality, and closeness centrality. Thus, all of these can affect the sustainability of these systems through the energy consumed by nodes and their carbon emissions [69], [70].

Wealth decentralisation can be one factor related to blockchain-based systems' environmental sustainability. A blockchain-based system that is wealth-decentralised can be seen as distributing the wealth between many miners. As a result, it can be argued that this system is likely to consume more energy and produce more carbon emissions than blockchain-based sys-

tems that are wealth-centralised. However, this is only sometimes the situation. Since wealth decentralisation is related to miners' hashrates, the impact on environmental sustainability may be similar to the case of consensus decentralisation. For example, a blockchain-based system with 1000 miners can be wealth-centralised when only a few miners mine blocks and gain rewards and fees. However, the system can consume more energy and produce more carbon emissions than other systems with fewer miners and more decentralisation in rewards and fees among all miners.

Governance decentralisation may implicitly affect the environmental sustainability of blockchain-based systems. Several factors can play roles in the environmental sustainability of the systems, such as the governance models, the number of governance entities, the resources needed for authorising and decision-making, and energy sources.

2.6 Conclusion

In this chapter, we have introduced substantial background information related to this thesis. First, the background covers essentials related to blockchain technology and sustainability. In addition, the chapter provides a general background to a deeper understanding of the contributions of this study by giving overviews of the trustworthiness and decentralisation of blockchain-based systems.

Chapter Three

BLOCKCHAIN-BASED SYSTEMS DESIGN AND ITS ENVIRONMENTAL SUSTAINABILITY: A SYSTEMATIC LITERATURE REVIEW

Context. Blockchain design has become a threat to our environment because of its very high energy usage. Due to the growing attention paid to applying blockchain technology in many fields, numerous studies have focused on proposing methods to improve the environmental sustainability of this technology.

Objective. This chapter provides a comprehensive and systematic review of the state-of-the-art efforts related to blockchain-based systems' environmental sustainability.

Method. It systematically reviews 104 related research papers published from 2008 to December 2022. The chapter discusses the notion of environmental sustainability in computing and how it can be contextualised in blockchain technology. The specific aims of the review are to 1) discuss the factors affecting the environmental sustainability of blockchain technology, 2) to review the current state of the art of methods and techniques for developing more environmentally sustainable systems enabled by blockchain, and 3) to review tools for the assessment and measurement of the environmental sustainability of blockchain-based systems.

Results. The results of the SLR show that most methods for enhancing the environmental sustainability of blockchain-based systems focus on reducing the systems' energy consumption. In particular, several methods propose alternative consensus algorithms to PoW. However, there is a need for optimisation models that enhance the environmental sustainability of blockchain-based systems without compromising the core properties of blockchain technology.

Conclusion. The review suggests future research directions for environmentally-aware and energy-efficient blockchain-based systems.

Contribution to Literature. This chapter will contribute to the research literature through our full paper "*A Systematic Review on Blockchain-Based Systems Design and its Environmental Sustainability*", which is under review.

3.1 Introduction

Blockchains have been recognised as a notable step forward for securing data in large-scale software systems. However, the significant amount of energy consumed by the miners within blockchain-based systems has received much criticism. Solving the challenge of energy-inefficient blockchain-based systems is an important prerequisite for the sustainability and longevity of the systems. Therefore, many researchers have proposed alternative solutions to decrease the energy consumed by this technology and develop its environmental sustainability. Research regarding these new technologies has generally discussed the energy consumption problem related to blockchain design. Researchers have proposed new methods to save energy by presenting other consensus algorithms or using renewable energy for the mining processes.

Given that environmental issues are now an element in the discussion of blockchain processes, we argue that a comprehensive review to identify the current research related to the environmental sustainability of blockchains and systematically map out and analyse all the relevant studies is necessary. We need to build a better understanding of factors, current practices, methods and mechanisms, and their fit and inadequacies in optimising for environmental concerns and targets. This can subsequently accelerate the adoption and sustainability of the use of this technology. A systematic understanding of the environmental sustainability of blockchain-based systems through comprehensively reviewing state of art is essential. Additionally, a better understanding of these factors can inform the engineering of environmentally-aware and more sustainable blockchain-based frameworks, methods, mechanisms, as well as metrics for blockchain-based systems.

Though significant studies have been devoted to understanding and optimising the energy consumption of these systems, there is still a general lack of a unified consensus about the factors and dimensions that need to be considered. A systematic review exploring the environmental sustainability of blockchain-based systems has the promise to provide a unified consensus of the factors and dimensions critical for these systems' sustainability. Most reviews of recent blockchain research have focused on blockchain applications and existing consensus algorithms [4], [71]–[74]. Also, other reviews focus on integrating blockchain in other fields,

such as cloud computing [75] and healthcare [76]. However, a comprehensive review for understanding the current state of the art and its progress, covering approaches and methods for environmental awareness and sustainability in relation to energy consumption and efficiency, has generally been missing. This chapter provides a Systematic Literature Review (SLR) that comprehensively reviews and discusses the developments in the literature regarding environmental sustainability within blockchain design. It advances our understanding of the topic and provides the following contributions for those concerned with improving the environmental sustainability of blockchain design. In particular:

- An overview and analysis of blockchain technology and sustainability are presented.
- The factors affecting the environmental sustainability of blockchain technology are identified.
- We classify the state-of-the-art methods for developing the environmental sustainability of blockchain design.
- Existing methods are analysed, and their weaknesses are discussed.
- Frameworks for measuring blockchain environmental sustainability are explored.
- We provide a roadmap for potential research directions.

The rest of this chapter is organised as follows: Section 3.2 describes the methodology of the SLR. Section 3.3 briefly analyses the existing related reviews. Section 3.4 identifies the factors affecting blockchain-based systems' environmental sustainability. Section 3.5 presents a comprehensive taxonomy of the current research regarding the improvement of these systems' environmental sustainability, and it analyses the challenges and drawbacks of these methods. Measurement techniques for the environmental sustainability of blockchain are explored in Section 3.6. Discussions and guidelines to support further work in this area are provided in Section 3.7. Finally, Section 3.9 concludes the chapter.

3.2 Systematic Literature Review Methods

The purpose of this chapter is to conduct a review of the environmental sustainability of blockchain-based systems. Our systematic literature review focuses on analysing the existing methods proposed as a way to promote the environmental sustainability of blockchain-based systems. In this chapter, we answer the first question of the thesis introduced in Chapter 1:

RQ1: What is the state of the art in optimising the environmental sustainability of blockchain technology and its design?

The review is focused on answering the following sub-questions:

- **RQ1.1:** What are the factors that need to be considered when systematically evaluating the environmental sustainability of blockchain-based systems?
- **RQ1.2:** What are the state-of-the-art methods and techniques for developing a more environmentally sustainable blockchain technology?
- **RQ1.3:** How can the current methods for improving the environmental sustainability of blockchain-based systems be categorised?
- **RQ1.4:** What are the challenges and weaknesses of these methods?
- **RQ1.5:** How is the environmental sustainability of blockchain technology measured?
- **RQ1.6:** What are the gaps in the current research regarding the development of environmentally sustainable blockchain designs?

The procedures of SLR in this research follow the guidelines for undertaking SLRs proposed by Brereton, Kitchenham, Budgen, *et al.* [77] and Kitchenham and Charters [78]. In more detail, we perform six main stages in the current SLR: 1) defining the purpose of the SLR, 2) identifying the SLR questions, 3) search strategy, 4) selection of primary studies, 5) search execution, 6) report the results. Each of the six main steps is described in further detail in Appendix A. In addition, we identify and analyse related studies (i.e., other systematic reviews, surveys, or mapping studies) that cover the topic of the environmental sustainability of blockchain-based systems. Finally, we report and discuss the outcome of the study.

3.3 Related Work

Several surveys related to blockchain exist in the literature, but most of them survey blockchain applications that are proposed across multiple domains [4] or for a specific field, such as IoT [79], cloud storage [80], supply chain [81], healthcare [82], e-government [83], business [84], cities [85] and agriculture [86]. Although blockchain faces environmental sustainability challenges, few related reviews discuss the environmental consequences of blockchains. Also, the literature has not presented a systematic literature review of blockchain-based system design and its environmental sustainability.

The review of [87], which consists of a systematic mapping study, aims to bring together the research addressing the relationship between blockchain technology and sustainability, as defined by the UN's goals. The authors also discuss the possible use of blockchain in developing sustainable technology, specifically for cases involving smart grids and supply chains.

The study [88] provides a systematic overview of extant consensus algorithms employed with public blockchains described in scientific papers and also practical blockchain applications. Additionally, this paper provides a contemporary assessment of the most common consensus algorithm used in public blockchains. It also assesses the consensus algorithms described in terms of their sustainability.

In [46], the author provides an overview and synthesis of the literature published on the environmental and economic sustainability of Bitcoin. The author summarises the developments in hardware used by miners for Bitcoin mining, addressing the environmental impact of this process. He debates Bitcoin's sustainability, given the energy consumption used in mining, which has also been addressed by multiple scholars in recent years. The study argues that the energy consumption of blockchain-based systems is not a major concern. This viewpoint is the opposite to the view of many studies, such as [44], [89].

In [90], the authors present a literature review that aims to explore the current research trends on the sustainability concepts of Bitcoin regarding its environmental, economic and societal impacts.

The authors of [91] first describe recent trends in blockchain applications on the cryp-

tocurrencies market and, second, new projects designed to address the various elements of sustainability; these elements include environmental questions, including energy consumption and materials depletion, as well as social impacts. Moreover, they discuss how blockchain has the potential to reduce bureaucracy, enable faster administrative processes and to incentivise environmentally responsible behaviour.

In [92], the author offers another overview of the current trends concerning the development of the PoW consensus algorithm, which is the main component of the well-known blockchain application, Bitcoin. The author divides his review into three parts to reflect the ugly, the bad and the good regarding the potential of using blockchain. ‘Good blockchain’ gives a positive view by summarising the ways in which it can be harnessed to improve society. ‘Bad blockchain’ tempers this with a summary of how some mining activities have the potential to generate substantial levels of pollution. Finally, Ugly blockchain’ examines the risk that the use of blockchain could become overconcentrated in the mining industry, posing an existential threat to the technology.

The study [93] scrutinises the concept of cryptocurrencies and how sustainable they are within a digital economy. The mining details are investigated from a number of perspectives: theoretical economics, contemporary costing, and technical demands. The paper details the environmental and economic impacts of cryptocurrency mining and suggests a number of solutions to the problems caused by cryptocurrency mining and the currencies’ instability: this includes smart electricity monitors incorporated into the Internet of Things (IoT) alongside smart energy grids, integrating the mining of cryptocurrencies into smart city infrastructure, and heat monitoring powered by GIS.

3.4 Factors Affecting the Environmental Sustainability of Blockchain

The environmental sustainability of blockchain-based systems can be affected by several factors. According to many studies on blockchain energy consumption, there are different main

parameters, from the developer’s behaviours to the technologies used in blockchain. After reviewing the existing consensus algorithms that aim to improve the environmental sustainability of blockchain and reduce energy consumption and reviewing papers discussing the environmental sustainability of blockchain and energy consumption factors for blockchain, we distinguish twenty-eight main factors affecting environmental sustainability and classify them into six groups, as shown in Figure 3.1. The results of answering RQ1 are presented in Table 3.1. Specifically, for each blockchain component, we report the reference to the paper in the bibliography that considers the component as a factor affecting the environmental sustainability of blockchain technology.

3.4.1 Architectural Factors

Blockchain architectural design has a significant influence on energy expenditure. Blockchain architectural design factors include the consensus algorithm, blockchain type, difficulty (parameters) of the algorithm and the hashing mechanism. There are various types of consensus algorithms that are determined by computational effort (energy consumption), such as Proof of Work. Also, there are consensus algorithms that do not rely on mining to reach a consensus, so they save a great amount of energy, such as Proof of Stake (PoS) and Practical Byzantine Fault Tolerance (PBFT) [9]. The number of nodes (miners—validators) is associated with the type of blockchain (public—consortium—private). The amount of energy consumed in a blockchain is affected by the number of nodes [9]. The difficulty of mining is also related to the number of miners. The study [94] shows that the reason behind the increase in difficulty is the growing amount of resources devoted to calculating hashes within blockchain-based systems. Consequently, the increase in difficulty and the number of miners impacts energy consumption. In addition, the paper [95] shows that mining efficiency is mainly determined by the hashing algorithm. According to [96], privacy, throughput, scalability and block verification can affect the total energy consumption by reducing the degree of redundancy. Peer-to-Peer (P2P) communication can also be considered a factor affecting energy consumption [29]. In [97], the block size is identified as the primary effector for E-waste and energy consumption.

3.4.2 Technological Factors

Mining hardware is one of the most important components of blockchain-based systems, and its technology has a significant effect on the level of system sustainability. The technological factors associated with this include two components. First, the hardware's energy efficiency, which is measured by computing the number of hashes per Joule (hash/J). The second component is the hashrate, which is generally measured as the number of hashes per second or mega-hashes per second (Mhash/s) [46], [94]. These factors further determine the amount and cost of energy consumption. Other auxiliary components include cooling systems [98], using renewable energy [20], [90] and the data storage devices, all of which relate to mining hardware, also influence energy consumption [99].

3.4.3 Deployment Factors

The deployment factors involve location and the climate zone. Both the mining hardware and its components' efficiency are affected by the weather and the climate of the locations where the mining devices are [9], [92], [99]. Cold climates obviously offer an advantage in decreasing cooling requirements [100]. The use of cooling systems is connected to the ambient temperature and humidity. Other influencing factors can be season characteristics, the length of day hours and air density which are affected by the location of miners.

3.4.4 Humanity Factors

Miners (as people) and developers play a crucial role in any blockchain-based system, so their behaviour affects environmental sustainability. Miners can be categorised by their consciousness of the environmental effect of their activities. According to [101], large miners are concerned about the environmental impact of PoW mining. However, small miners believe that the negative environmental effects of mining are not an important issue. Moreover, motivating developers to be concerned about the environmental effects could change their behaviour to modify the existing models and build future systems that are less polluting. Also,

this could help them find transaction verification models that are more sustainable. It could encourage manufacturers of mining devices to produce devices that consume a low amount of energy. End-users and organisations using blockchain-based systems can play a positive role by demanding more efficient technology for blockchain-based systems [9].

3.4.5 Economy Factors

The consumption of energy could be affected by rewards, fees, cryptocurrency price, cryptocurrency demand and the cost of electricity. To maintain profitable mining revenue (block rewards and transaction fees), miners switch to less energy-demanding hardware. They also consider the costs of electricity, which vary depending on the country of operation [90], [102]. Most mining activity is reported to take place in countries offering cheaper energy costs, such as China [9]. In addition, the demand for cryptocurrencies due to their price changes in financial markets can affect the environment. Therefore, people may invest more in cryptocurrencies when their prices increase, which may lead to more mining devices, energy consumption, and carbon emissions [103].

3.4.6 Policy Factors

In [9], the author claims that law and policy choices and government regulation could reduce the energy consumption of blockchain technology, such as a surcharge on profits declared by miners and charging a customs duty or excise tax based on the energy consumption for imported devices.

Table 3.1: Factors Affecting the Environmental Sustainability of Blockchain-based Systems

Blockchain Components	References	
Architectural	Consensus Algorithm	[104] [4] [29] [105] [9] [15] [106] [107]
	Blockchain Type	[4] [108] [109] [15]
	Number of Nodes	[17] [94] [96] [9] [15]
	Hashing Algorithm	[29] [95] [110]
	Hashrate	[97]
	Mining Difficulty	[99] [94]
	Block Size	[97]
	New Block's Verification	[96] [107]
	Privacy	[96]
	Throughput	[96]
	Scalability	[96]
P2P communication	[29] [110] [107]	
Technological	Mining Device	[99] [94] [9] [15] [111] [97] [107]
	Cooling System	[98] [99] [112] [95] [9] [107]
	Renewable Energy	[20] [4] [90] [113] [9] [114]
	Data Storage	[99] [107]
Deployment	Location	[99] [92] [45] [9] [111] [106] [115]
	Climate Zone	[100] [9] [115]
Humanity	Miner	[4] [101] [45] [9]
	Developer	[92] [9] [116]
	End-user	[9]
	Organisation	[117] [9]
Economy	Fee	[118] [113] [102] [97] [119]
	Reward	[118] [113] [102] [120] [119]
	Cryptocurrency Price	[111] [114]
	Cryptocurrency Demand	[103]
	Electricity Cost	[112] [90] [113] [102] [9] [111]
Policy	Government Regulations	[112] [45] [9] [111] [116] [106] [97]

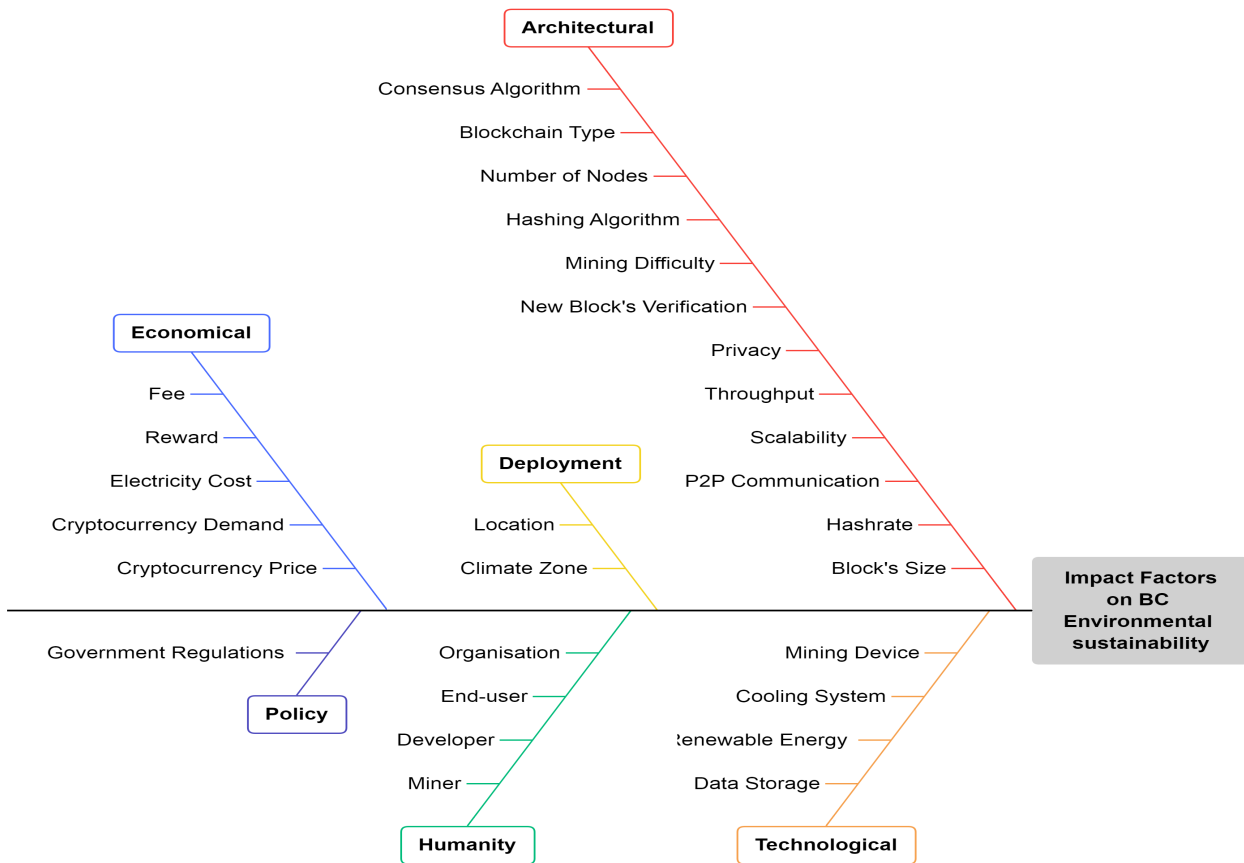


Figure 3.1: Ishikawa Diagram of the Impact Factors on Blockchain Sustainability

3.5 Existing Methods for Improving the Environmental Sustainability of Blockchain

3.5.1 Blockchain Consensus Algorithms

A significant variety of alternative consensus techniques have been proposed to address the problems of Proof of Work energy consumption. In the current paper, we focus on algorithms that consider energy consumption as a problem to be solved so as to develop an environmentally sustainable blockchain-based systems design. We categorise these consensus algorithms into two main categories: proof-based consensus algorithms and vote-based consensus algorithms.

3.5.1.1 Proof-based Consensus Algorithms

In these algorithms, miners need to prove that they are more eligible than others miners to participate in the verification processes and append new blocks to the chain.

Stake. One frequently proposed alternative to PoW is Proof of Stake [121]. PoS represents a consensus mechanism requiring fewer computer resources than PoW, so it has lower levels of energy consumption. The assumption with a PoS-based blockchain is that miners with higher levels of network participation are those who have low levels of motivation for launching an attack. Thus, miners have to show proof at set intervals that a particular proportion of network participation is attributable to them (e.g., by showing currency). There is an inherent unfairness in this plan because those with the greatest wealth will have the greatest control, so variations have been suggested. One example is Ppcoin's consensus algorithm that incorporates the coin's age; miners holding the largest and earliest coin sets would be those most likely to mine a new block. Because of PoS's benefits, certain blockchains, such as Ethereum [122], have plans to shift from PoW to PoS. However, PoS is facing some serious problems, such as the rich getting richer and nothing-at-stake attacks [123].

In [124], the author suggests a new extended PoS consensus protocol (e-PoS), which deals with the constraints of PoW and PoS and allows blockchain systems to become less energy-hungry and to implement fair mining practices. The abstract implementation of e-PoS incorporates a collection of miners that execute invisible smart contracts implementing PoS auction rules. This mechanism has some drawbacks regarding its security. Blockchain application software clients have a vulnerability to being attacked. While software client security is extremely important in e-PoS, the study does not cover this element. It should be noted that e-PoS has a lower fault tolerance than other cryptocurrencies based on PoW and PoS.

Variations of PoS exist, such as delegated Proof of Stake (DPoS) [125] and Proof of Stake Velocity (PoSV) [126], but these are only intended to address particular issues without holistic solutions. Other issues remain open and may cause new constraints or security prob-

lems [127]. Proof of Activity (PoA) [128] combines PoW and PoS, in which useless nonces are regarded as wasting computer power.

Proof of Importance (PoI) was designed by NEM [129]. PoI represents a consensus algorithm created for determining those participants in the network who have eligibility for adding blocks. An evaluation of every account will be undertaken and rated for importance. Importance is dependent upon a vested stake, transaction amounts and a number of transaction partners. A high importance score would mean that the participant is rewarded and has no need to commit any computer resources, earning rewards even if offline. In this algorithm, the richest participants benefit in that, the greater the value of coins held, the more blocks can be mined.

Recently, interest has grown in the employment of blockchain consensus protocols for P2P energy transactions. The primary target is to create self-sufficient Local Energy Markets (LEM) by offering incentives for consumers to have Renewable Energy Sources (RES) installed and used.

In [130], the authors further suggest a new Proof of Energy (PoE) function for the initiation of the P2P exchange of energy on the basis of blockchain within LEM contexts. The PoE concept is suggested to modify the PoS protocol for increasing prosumer self-consumption ratios leading to further cuts in power loss. The prosumer who produces energy from a renewable energy source equal to the energy consumed has a high chance of being chosen to add new blocks. This is a means of promoting social behaviours centred on sustainability and a circular economy.

Similarly, the work in [131] proposes two blockchain-based LEM systems assisting prosumers (users with a RES that produces or absorbs energy) and consumers in securely trading energy, balancing demand and supply using a decentralised system, with any surplus energy being sold to the main grid. The researchers suggest Proof of Energy Generation (PoEG) for increasing the energy output of RESs by providing rewards for prosumers as miners for adding blocks to the blockchain-based system. Prosumers that generate more RES than they consume will most likely be invited to be miners. This paper also suggests an alternative con-

sensus algorithm, Proof of Energy Consumption (PoEC), for incentivising users to consume less energy at peak times. Prosumers using higher levels of energy will have fewer chances of adding blocks to the chain.

A new consensus algorithm is proposed in [132]. This consensus algorithm calls for prosumers to use some form of an energy management system to track Percentage Power Change (PPC) on an hour-by-hour basis. The PPC is employed as a criterion for choosing blockchain validators, and the weighted average consensus is used to certify the validator. The prosumers share the computed PPC values among each other. The blockchain's validator, which will create the subsequent block within the blockchain, is chosen as the prosumer with the lowest PPC value. This paper refers to this consensus algorithm as (PoPPC).

Proof of Supply Chain Share (PoSCS) [133], similarly to PoS, is suggested as a means of adding blocks employing validators as an alternative to miners. This algorithm uses the stakeholders within the supply chain as validators. The creators of new blocks are decided by aggregating the responsibilities and shares of the supply chain into a normalised supply-chain share.

In [134], the paper suggests a consensus algorithm centred on PoW, called Proof of Participation and Fees (PoPF), offering savings of computational power that have improved the efficiency of transaction handling for JCLedger. This system only allows mining from selected candidates, with selection based on the fees paid by a participant and the number of times they have acted as an accountant. Each miner is presented with a range of difficulty levels for solving the PoW, making mining easier for those with a higher rank.

As blockchain technology has continually developed and matured over the last few years, cloud manufacturers have become increasingly interested in its potential. However, because of its energy consumption, blockchain technology is not suited to the specialised requirements of cloud manufacturing, with considerable quantities of large deals. In [135], a novel blockchain consensus protocol is proposed to be applied in cloud manufacturing environments, Proof of Service Power (PoSP). PoSP employs historical transaction volumes and total transaction amounts gained by member nodes within the cloud manufacturing system's

service chain. Service power is represented by the sum of the product of the time factor and historical transaction volumes for every member node. one drawback of using this consensus algorithm is that the degree of decentralisation will be negatively affected.

A new blockchain ledger approach, "Meshwork ledger", and an associated consensus algorithm are explored in [136]. Client and validator nodes of the blockchain-based system actively participate in the consensus algorithm. The aggregate multi-signatures provide the foundation of the consensus algorithm. A joint aggregate signature is created for a series of transactions in a block based on the signatures gathered from the mesh client nodes in a multi-signature system. If a client node's signature is present on the block, the block is treated as approved. The main goal of the consensus is to attach a block to the blockchain by gathering the most signatures (approvals) from mesh clients possible. The competition for the most approvals from the mesh clients is between specific nodes called validator nodes in the consensus process. Clients that take part in the winner validator node-organized aggregate signature are rewarded with a tiny portion of the transaction fee.

Physical Resource: Unlike PoS, which has the intention to reduce the computational demands of PoW systems, Proof of Elapsed Time (PoET) [137] has been proposed. PoET employs a model based on a random leader election or a lottery-based election using a specific Intel device (Intel Software Guard Extensions (SGX)), in which the protocol randomly selects a new leader for the finalisation of a block. Every validating or mining node must use Intel SGX for the execution of the Trusted Execution Environment (TEE). All validators request a waiting time from the code that runs within the TEE. The validator awarded the briefest waiting time is the winner of the lottery and, thus, may assume leadership. PoET needs specific hardware, which places limitations on decentralisation and the number of participants. It is also vulnerable to security threats via the employment of a partially decentralised (Intel as authority) PoET model that can command an idle elapsed time before block signing.

In [138], the authors discuss an approach similar to PoET. They propose a type of consensus called Proof of Luck (PoL). PoL is TEE with SGX. For execution, after all blocks are synchronised in the blockchain, all miners will create a new block to add to their chain.

Then, each new block will be assigned a value from zero to one at random; this may be seen as a lucky value. Every node would have to agree that the chain holding the highest combined lucky value would be the main chain. The authors claim that PoL is equitable for every miner. Additionally, carrying out attacks, such as double spending attacks, would be extremely difficult because the attacker would have to rely on extremely high levels of luck to be successful. However, the participants within this consensus algorithm must have central processing units (CPUs) that implement a suitable TEE, such as Intel SGX. This means that PoL relies on the ownership of particular physical resources.

Proof of Space (PoSpace) [139] has also been proposed as an alternative. A miner must use a particular quantity of memory for computational proofs. The probability of successfully mining a block increases by dedicating more disk space. A related concept to PoSpace is proof of Space Time (PoST), which requires miners to prove that they have kept data for a specific period [140]. Permacoin [141] asks miners to make an investment in system memory and storage via Proof of Retrievability (PoRs) [142]. Although these algorithms demand less energy over time, as claimed by authors, they rely on expensive physical resources.

Useful Work: Again focusing on reducing wasted energy, proof of eXercise (PoX) [105] has been presented, which is a solution that channels computer power into real-world scientific challenges. Under this system, miners are presented with matrix-based problems offered by ‘employers’ inside the system. There are two reasons for employing matrices: a) they can be composed, which allows network difficulty to be tuned more easily, and b) they are a major source of abstraction for numerous computational scientific challenges. Although the work done by the miners will be useful, the energy consumption of solving real-world matrix-based scientific problems in this algorithm remains questionable.

Other alternative consensus algorithms have attempted to simply replace the puzzle with real-world problems of greater use, as with PoX. Nevertheless, the proposed replacements do not offer a broad array of genuinely interesting challenges. One example is PrimeCoin [143], which proposed the discovery of prime numbers rather than a random and pointless nonce, while PieceWork [144] attempted the outsourcing of tasks, such as Denial of Service (DoS)

defence and spam deterrence. Proofs of Useful Work (uPoW) [104] extend PoW, requiring miners to solve meaningful problems, such as all-pairs shortest path, 3SUM and orthogonal vectors.

WekaCoin is a design in [145] that employs Proof of Learning (PoLearning), a new form of a distributed consensus protocol that reduces the amount of computing power required to solve a hash-based puzzle. PoLearning accomplishes validation by using energy in solving tasks in machine learning models. In other words, machine learning puzzles are employed for the validation of blockchain transactions. Nevertheless, it remains a challenge to ensure that the three central actors (suppliers, trainers and validators) in the network who use this consensus algorithm do not collude with each other. WekaCoin has no real built-in defence against attackers who take an honest miner's submitted pre-trained model, steal it, improve it and then submit the enhanced model prior to confirmation of the block.

The Proof of Deep Learning (PoDL) protocol has been suggested in [146] for the maintenance of blockchains using Deep Learning (DL) training rather than artificial hash calculations. The PoDL protocol is an improvement on the PoW consensus mechanism and uses the DL power of legitimate miners to improve security. The generated valid proof for a new block comes only upon producing a genuine DL model. This optimises the employment of nodes' energy and computing resources to facilitate and maintain blockchains. Nevertheless, it is possible for multiple malicious actors to generalise the model requester in collusion with miners. We can also not overlook the block generation's latency as it will take a substantial time to train the DL model. Additionally, more research is required using realistic block submission patterns and a wider range of DL models and data sets [147].

In [148], the authors present a comprehensive proof of federated learning (PoFL) consensus framework that repurposes the computational power previously devoted to solving unproductive PoW puzzles for the training of high-quality federated learning (FL) models. An online third-party platform (e.g., Kaggle or Codalab) is used to delegate FL tasks to users, after which mining pool members collaborate to create the requested FL model before the specified deadline. Subsequently, different pools vie for rewards using the trained models as

proofs. While this study has effectively utilised waste energy, several significant challenges still need to be addressed. Developing a robust, fully decentralised PoFL scheme that eliminates the need for a central platform remains a concern. Moreover, there is a challenge in dynamically creating optimised pool structures with stable miner-pool associations for various FL tasks. It poses a formidable challenge to design accurate incentives for heterogeneous miners to optimise the consensus process because of their innate self-interest and diverse behaviour.

In addressing the challenges associated with PoFL, the authors of [149] put forth an innovative platform-free proof of federated learning (PF-PoFL) scheme aimed at establishing a resilient and sustainable blockchain ecosystem. This is achieved by eliminating the central platform and creating a dynamically optimised pool structure for AI model training. Taking their inspiration from PoFL, the researchers propose an energy-recycling consensus mechanism that allows computing power to be repurposed for practical FL tasks instead of being wasted on solving difficult yet inefficient PoW puzzles. Under the PF-PoFL framework, the authors develop a unique block structure, introduce new transaction types, and establish credit-based incentives to facilitate FL model ranking and enable efficient consensus within the blockchain.

In [150], the authors propose a new consensus algorithm called Proof of Training Quality (PoQ) which merges data model training and consensus processes to fully recycle the necessary energy to achieve consensus among all of a blockchain's nodes. They propose that a consensus committee should be established for improvements in operational efficiency, with a selection of members occurring through the retrieval of related nodes for each request for shared data within the blockchain. The chosen members would be responsible for training the data model and initiating a consensus process on the basis of collaborative training processes. This would significantly reduce communication overheads because only those nodes selected for the committee would receive consensus messages instead of every node receiving them. Nevertheless, such a system could have insecurities because there is no guaranteed way of generating a global randomness beacon in order to create consensus committees.

The paper [151] suggests employing optimisation problems for PoW rather than the cryptographic puzzles more frequently employed nowadays. The alternative solution pro-

poses ensuring that the energy required for PoW is employed for useful purposes, i.e., solving real-world optimisation challenges. Using the Travelling Salesperson Problem (TSP) as their model, they suggest the iterative use of optimisation algorithms, providing the PoW required for expanding a blockchain through the addition of a new block. We refer to this scheme as TSP-PoW. The central concept is that the cost of the best tour revealed for block N may be improved by adding an extra city required for the new block to be included in the chain.

Unlike PoW, which demands the consumption of energy and investment in mining machines, Proof of Generation (PoG) [152] demands investment in distributed renewable energy generation. PoG was created for the I-Green blockchain. This employs electricity data supplied through I-Green. PoG demands that users invest in the generation of distributed energy. Candidates are selected voluntarily through Prosumer nodes. On the basis of electricity data submitted through I-Green in the previous period, verification candidates are selected from the nodes that provided the highest energy. Of the N candidates fulfilling the criteria, a proposal will be chosen through random selection; this proposer will offer verification for all transactions and create a new block which will then be broadcast to every candidate. Should the chosen proposer not respond within a waiting time T , the selection of a fresh proposer will occur.

In [153], the author proposes a Proof of Search (PoSearch) protocol to deal with the difficulties of substantial quantities of energy being wasted in blockchain mining processes. PoSearch uses computational power to assess multiple candidate solutions of an optimisation problem submitted by a client (node) and to search for the best solution. Rewards by the corresponding clients are given to the nodes that offer optimal candidate solutions. Also, the protocol rewards those miners that added the block to the blockchain in the same way as PoW.

It is demonstrated that crowdsourcing can be used for networking-intensive tasks of high complexity by employing the incentive model used by Bitcoin. WebCoin [154], a new form of distributed digital currency using networking resources instead of computational ones, is proposed, with mining only being possible by using Web indexing. Those who undertake

Web indexing, scraping, and crawling will be rewarded financially through WebCoin.

It has been suggested that employing deep-learning processes as PoW could theoretically allow the power to be employed for useful processes [155]. The authors suggest a protocol called (Coin.AI) based on Proof of Useful Work. Coins are awarded when miners surpass the lowest performance threshold. It is also suggested that proof of storage mechanisms could be employed for storing deep learning models within “keepers”, distributed nodes that receive rewards in this model for retaining models in secure storage. Although the concept of energy savings achieved in this manner is attractive, the suggested model does not consider several significant elements. One of these is that training/validation data must be securely protected. The model proposes sharing data with a number of entrusted miners for its solution, which clearly presents challenges regarding how the data can be protected.

Game: In [156], the authors propose a novel Proof of Play (PoP) motivated by Huntercoin ¹ and Motocoin ². PoP is an integrated P2P gaming system with blockchain technology where players act to add new blocks to the chain. Relying on the game results, the player with the most competitive result broadcasts the new block. The authors claim the consensus algorithm can be power-efficient because it uses a lower hashrate.

Trust and Reputation: Although most proposed alternatives rely on either having mining devices (e.g., PoW, PoL) or making a substantial financial investment (i.e., stake) in the blockchain (e.g., PoS), other algorithms depend on a trust model.

In [157], the authors propose a new consensus algorithm called Proof of Trust (PoT). It is a blockchain-based system relayed on peer trust that is evaluated by the network through trust graphs created in a decentralised manner; these become part of the coding and management of the blockchain. The trust embedded is employed as a waiver for the problems of PoW. In other words, the difficulty level of solving the cryptographic puzzle and finding an appropriate hash is determined by the trust value held by the node that mined the new block.

¹Huntercoin offers players a multiplayer environment where they compete to collect coins from a map. <https://xaya.io/huntercoin-legacy>

²Motocoin has a virtual motorbike driving game in which participants collect coins. <https://motocoin-dev.github.io/motocoin-site>

The higher the trust rating you can attain, the less work is required. Although these alternatives certainly use less energy than PoW, there are a number of difficulties related to their algorithms in public blockchains, including problems with scalability, fairness and security.

An alternative PoT mechanism (Alt-PoT) is proposed in [158]. This alternative suggests a consensus algorithm used for crowdsourcing services. The validators for transactions are selected based on node trust values. The design employs two algorithms: RAFT leader election and Shamir's secret sharing algorithm. Alt-PoT does not require PoW and introduces additional trust into the mechanism. Nevertheless, choosing a leader to manage a blockchain raises problems of centrality and single failure points. Furthermore, the researchers do not detail what would motivate nodes to participate in this process, and the differences in local trust databases are not detailed, including whether there are variations between nodes. The researchers also regard every transaction as an element of the blockchain without undertaking checks on transaction trustworthiness.

Proof of Reputation (PoR) is a consensus algorithm suggested in [159] in which the reputation of nodes is evaluated on transaction activities, assets and consensus participation for a node. In the algorithm, the node that has gained the highest reputation value will be responsible for creating a new block. Then, the new block will be validated and confirmed through reputation-based voting processes. The researchers look at a trio of essential measurements affecting the PoR mechanism: the social interaction, the currency age and the regularity of participation in consensus building for each node. The extent of the node's social interaction is found through assessment of the number of its friends, how regularly it has interactions with its friends, the size of its transactions and its friends' reputation.

In [160], the authors suggest modifications to PoW to make the mining process more efficient and achieve significant power usage reductions. They propose a Proof of Contribution (PoC) protocol. Unlike the coinage in PoS, the stake in this protocol is related to the honesty of the miner, which is calculated from the number of valid blocks added by the miner to the blockchain, and based on that, it determines the miner's mining difficulty. It makes calculations of what each miner contributes and incentivises block mining by providing diffi-

culty rewards for any miners that pass extended periods without being rewarded with blocks. Although the authors claim that this algorithm is energy-efficient, they do not present any analysis of its energy consumed.

Proof of Authentication (PoAh) [161] represents a relatively energy-efficient consensus algorithm in which miners are referred to as trusted devices, receiving the block and checking on the source's identifier. Should the token be on the list retained locally with trusted nodes, the node adds it to the local chain and passes it forward through the network. The other devices in the network then add the validated block. This protocol is useful in networks with resource constraints (e.g., IoT), but analysis has not been undertaken into how applicable it would be for a heterogeneous mobile network, e.g. a vehicle network. Also, the authors claim that the proposed consensus algorithm minimises energy consumption, but they do not show to what extent it can minimise energy consumption.

The study [162] proposes a blockchain-based system intended to support the charging of electric vehicles that are entities within Private Charging Pile Sharing Networks (PCPSNs). The blockchain-based system leverages a reputation-based PoW by including the rating, behaviour, and fading effects. Such a reputation model represents a decentralised reputation method that facilitates an evaluation of the reliability of the respective consensus nodes (i.e., local aggregators (LAG)) in PCPSNs. A consensus node with the highest reputation value is selected to run PoW and add a new block. This chapter refers to this consensus algorithm as (PoR-LAG)

In [163], the authors suggest a new consensus mechanism called Proof of Negotiation (PoN), a fair multi-miner participation mechanism. This mechanism designs an evaluation methodology to decide on proposal trust values (PT) and validator trust values (VT). The trust values rely on the number of false and real block proposals, and they also rely on the number of wrong and correct votes. Using a trustworthy algorithm that randomly selects miners, honest miners that hold high trust values can be chosen at random from the available miners to act as proposers or validators when blocks are being created. The creation of multiple blocks may be effected either synchronously or asynchronously, making PoN even more

efficient in production. Nevertheless, the problem of finding an effective and efficient resolution for selfishness problems in blockchain networks in order to improve consensus mechanism performance remains highly challenging.

3.5.1.2 Vote-based Consensus Algorithms

In these consensus algorithms, the consensus is reached among nodes by votes. Nodes joining the network are predefined, and they can not join freely. Also, the number of nodes is limited.

For distributed systems, the property known as Byzantine Fault Tolerance (BFT) means that there is toleration within the system for a particular type of failure—specifically for the Byzantine Generals Problem (BGP) [56]—when there is no solution for it. Byzantine failures are considered the greatest threat and most problematic to address of all failure classes because they do not make assumptions or offer restrictions to the behaviour of nodes at any specific point. Practical Byzantine Fault Tolerance (PBFT) [164] is one algorithm based on the BGP utilised as a consensus algorithm for blockchain-based systems. With this methodology, every node should engage in the voting process to provide the next block; consensus is achieved when over two-thirds of the total nodes are in agreement for the block. Hyperledger fabric ³ is one example of a type of blockchain that relies on PBFT. Hyperledger fabric is the most common blockchain platform of the Linux Foundation’s Hyperledger project [165]. This algorithm has a critical reliance on network timing assumptions, does not handle increases in participant numbers well, and its liveness can only be guaranteed when every participant behaves predictably.

Delegated Byzantine Fault Tolerance (DBFT) operates in the same way as PBFT, but it is not necessary for every node to participate in adding a block, which enhances its scalability. In DBFT, certain nodes are selected as delegates for other nodes, and following a set of rules, they implement a consensus protocol similar to PBFT. The cryptocurrency NEO [166] employs this consensus methodology. Federated Byzantine Fault Tolerance (FBFT) can be regarded as the most innovative solution for the BGP. All the participants keep lists of the significant

³<https://www.hyperledger.org/projects/fabric>

nodes that they trust. Once a majority of trusted nodes are in agreement on a transaction, it is regarded as settled. Nodes make their own decisions as to whom they trust. Ripple [167] and Stellar [168] employ proprietary versions of FBFT. These methodologies mean that it is necessary to maintain lists of those involved or the relationships of trust between those involved.

The first public blockchain project incorporating a BFT consensus layer is Tendermint [169], inspired by the DLS protocol [170] and PBFT [164]. This project operates using consensus cycles, with each cycle involving multi-round PBFT consensus processes for the finalisation of a single block. Each round has a trio of phases: Propose, Prevote and Precommit. During the Propose phase, a deterministic algorithm designates one validator to be the block proposer using a round-robin method so that the frequency with which a validator is selected is in proportion to the level of stake they have on deposit. The validator will continue to iterate the triple-phase rounds until a single block has received over two-thirds of Precommits. The Commit votes are then broadcast for the block, and the validator counts the Commit votes of other validators. After more than two-thirds of the Commit votes have been received, the block will become a confirmed part of the blockchain. Tendermint safety can be achieved in this way as long as over two-thirds of validators in each round are honest parties.

Proof of Vote (PoV) [171] is a type of PoW with greater efficiency. A voting method is used to verify the network's blocks. The PoV is used for the creation of unique security identities for each participating node. The algorithm assigns each node a role: commissioner, butler, butler candidate or ordinary user. This method guarantees security, lessens power requirements and ends any bifurcation of a blockchain. Nevertheless, it has not been proved through any mature implementation, practical applications, or empirical evidence of its theoretical claims.

In [172], the author introduces a methodology based on a distributed voting process named 'RDV: register, deposit, vote'. He claims that because the RDV algorithm does not require mining, it will work well with devices that consume low levels of energy and the IoT.

In the consensus mechanism, every registered node has the right to vote for transactions, with almost every node being permitted registration. Each node is acknowledged through a pairing of a ‘MAC address’ and a ‘public key’. As a consequence of using a MAC address, the privacy of nodes in this network is lost, even when using random MAC addresses [173].

A consensus algorithm called proof of participation (PoP) is proposed in [174]. This consensus algorithm serves as the consensus mechanism for “BlockTour”, a blockchain-based smart tourism platform. The main goal of PoP is to persuade nodes to confirm transactions that exhibit higher levels of participation. At the end of each round, the blockchain network confirms that a block has exhibited PoP. All nodes taking part in the system elect a leader that is subsequently in charge of adding new books. This chapter refers to this consensus algorithm as (PoP-BlockTour).

3.5.2 Blockchain Structure

Many researchers have proposed ways of making blockchain-based systems more efficient regarding blockchain structure; they have suggested using different structures, such as a Directed Acyclic Graph (DAG) [175], sharding protocol [176] and Greedy Heaviest Observed Subtree (GHOST) [177]. Since the present chapter focuses on environmental sustainability, we discuss only the structures that aim to improve the environmental sustainability of blockchain-based systems by saving energy.

3.5.2.1 Directed Acyclic Graph

DAG is an architecture used in distributed ledger approaches. In a DAG, nodes are acyclic, meaning no directed path begins at one node and then loops back to itself.

IOTA is intended to offer ways of incorporating blockchains into IoT networks. IOTA was created based on Tangle technology [178], having no chains, blocks or fees. Tangle differs from blockchain in its data structure, allowing the implementation layers of DAG systems to incorporate elements of blockchain. These flexible structures reduce energy consumption and the necessary work for block mining [179]. Tangle is a DAG with nodes representing the

transactions and edges indicating the path of confirmation travelling between them. Asynchronous transaction confirmation occurs, allowing for parallel validation and no mandatory time gaps between confirmations. This means that the time a transaction is confirmed and finalised depends on the scope of the Tangle. A central feature of Tangle is that a coordinator must be integrated, and this may be problematic. Also, the large confirmation delay in the low trading traffic load can be a weakness.

Hashgraph [180] represents a consensus algorithm on a DAG that provides distributed applications with a low consensus latency, high throughput of transactions, resilience to DDoS attack, fair absolute transaction ordering and no PoW. It is also asynchronous and achieves a consensus using probability in a nondeterministic manner. It employs a gossip protocol that creates gossip about gossip procedures. New information is distributed across the network through a random selection of members, supplying them with full information. In this concept, the distributed gossip incorporates the actual hashgraph. Every gossip event for a participant is incorporated, guaranteeing BFT. Although this algorithm does not involve mining, extensive confirmation delays due to low communication frequencies are a drawback.

3.5.3 Decision Making

Decision-making (sometimes without hyphenation) is seen as a cognitive process that results in the choice of beliefs or actions out of many alternative options. Decision-making involves the identification and choice of an alternative based on the beliefs, values and preferences of the decision-makers. All decision-making processes create final choices, which might lead to action.

3.5.3.1 Decision Models

Decision Models (DM) can be used as guidelines for the assessment of blockchain-based solutions. These DMs already exist to support researchers and practitioners in checking if a blockchain-based approach is reasonable. In [181], 30 blockchain decision schemes are analysed. Five schemes are assessed through a questionnaire. The other 25 are illustrated as flow

diagrams where a sequence of binary selections results in a final state that offers the best outcome for a specific scenario. The extant DMs mainly concentrate on deciding if blockchain technology or alternative technologies, such as centralised databases, are more suited to particular environments. The majority of DMs omits any consideration of sustainability and generally do not provide sufficient coverage of potential design decisions.

A systematic decision model for evaluating and planning blockchain adoption is provided in [7]. It provides a DM that can assist stakeholders in selecting the best consensus method for their blockchain project in line with energy usage. By extending the decision tree suggested in [182], the authors create a decision-supporting framework for the initial energy assessment of anticipated projects.

3.5.4 Adaptive Techniques

Adaptive blockchain networks can be regarded as one of the best techniques for improving the environmental footprint of blockchain technology. In [183], the authors present a case for understanding and designing blockchain networks in the form of adaptive systems. Using the example of the consensus mechanism for Bitcoin, the work identifies the variables that influence the sustainability of the consensus mechanism, encompassing the environmental variables and other variables that are susceptible to direct configuration from the governance of a network. The research offers a simplified model of the relationships between these variables and how they influence one another. In the study, the problem is formulated as a standard control engineering problem, where the controller (blockchain governance) selects the optimal parameters that allow the controlled system's output (blockchain network) to satisfy certain objectives.

Although the reconfiguration behaviour of blockchain networks can increase their resilience, security and energy efficiency, there are many challenges in designing pragmatic controllers unique to blockchain networks. The first challenge is related to how observable node characteristics are. A controller should be completely knowledgeable about every possible participant's power and the cost implications; this information is not directly available within

a public open-access network. Also, node-level decisions are a complex matter. For example, we cannot assume rational behaviour for nodes. In other words, they will be perfectly set up to exit the competition when it ceases to be profitable [183].

To alleviate the heavy burden of Mobile Edge Computing hosts and prevent systems from being dominated by a minority, the study [184] has considered the adaptivity technique for PoW. The paper proposes an alternative consensus algorithm called Adaptive Proof of Work (APoW). It derives an appropriate difficulty from fulfilling PoW condition according to device capability. For modifying the difficulty of finding blocks' hashes, a Target Adapter is applied. Although the consensus algorithm can mitigate the energy consumption of blockchain-based systems, concerns regarding their security are not properly discussed (such as a 51% attack).

The study [185] proposes a consensus algorithm called nonlinear Proof of Work (nlPoW). During every block mining, miners get a random dynamic target. This target is a random number generated by the consensus algorithm uniformly between 0 and 2^{256} , which represents the possible outcomes of the SHA256 hash algorithm. This algorithm has two-fold rationales. First, miners assigned to lower difficulties for mining blocks can mine blocks quickly with a few computations compared to other miners. Thus, the amount of energy for the network can be reduced. Second, miners assigned to higher difficulties for mining blocks may be discouraged from participating in mining new blocks. Although this algorithm shows promising results, more studies are required to determine the ideal distribution of dynamic targets among miners within a blockchain network.

In [186], the authors introduced a novel consensus algorithm for blockchain systems termed Green Proof of Work (Green-PoW) to enhance the energy efficiency of the traditional PoW method. In Green-PoW, time is segmented into epochs, each comprising two distinct mining rounds. The initial round mirrors traditional PoW mining but with a slight increase in energy expenditure to identify a select group of miners eligible to participate in the subsequent round. The second round, characterized by significant power conservation, allows only the pre-selected miners from the earlier round to compete for the creation of a new block. A

unique difficulty level is established with a marked reduction in total hash power during each second-round mining in Green-PoW.

3.5.5 Extra Block Structure

In [187], the authors propose a protocol called “empty blocks”. This protocol is a block generation scheme that does not require a nonce for Proof of Work. This protocol is novel because it employs a “call” field for regulating the creation rate for regular blocks as well as empty blocks. The regular blocks contain transactions, with the empty blocks holding none. The format of the regular blocks resembles that of the Bitcoin block format with the aforementioned replacement of the nonce field with the call field. The necessary criteria for the following hash value field are dictated by the call field.

In [188], the study describes a new way of addressing the PoW challenges using an alternative consensus mechanism still based on PoW. In this Alt-PoW mechanism, all parties can view how each miner performs to solve the blocks’ puzzles through monitoring “round blocks” mining. Round blocks are solely proposed to represent the miners’ progress in the transaction blocks’ mining phase. Every participant in the network can see all round blocks at any time. When every party on the network can see the progress of all others, they can save resources by making decisions to withdraw from specific block races that they have little chance of winning, which promotes reductions in energy consumption. However, there is no discussion of the protocol’s security in resisting possible attacks.

3.5.6 Blockchain Hash Algorithm

The degree of difficulty determines the amount of work required to calculate PoW. As the difficulty level increases, greater amounts of time are needed for calculating PoW, which requires greater energy levels. The research [110] suggests an energy-efficient means of computing PoW that has greater applicability to IoT systems through simplification of the PoW puzzle. Standard blockchain systems specify difficulty levels through simplification of the initial hexadecimal digits, e.g. D , to be 0(s). The research proposes that the first D hexadecimal digits

should represent a value of the hexadecimal set (0-F). Thus, this modified solution permits a sixteen-fold increase in eligible hashes, implying that less computational time will be needed to discover eligible hashes. It means that less energy is used than in standard blockchain processes.

The paper [189] proposes a pair of novel blockchain consensus protocols, CHB-consensus and CHBD-consensus, both of which are based on a consistent hash algorithm. This provides fair opportunities for block creation to honest miners. No additional computing power is required to create a new block, and these nodes can be fairly confirmed with a consensus of the entirety of the blockchain. Malicious miners would have to invest enormous computing power to attack this new way of creating blocks. Blockchain networks using CHB-consensus and CHBD-consensus employ identical security assumptions to those used by Bitcoin systems, saving enormous quantities of power with no compromise of security or decentralisation.

3.5.7 Assist Methods

Several other methods can assist in the improvement of the sustainability of blockchain-based systems. In this section, we discuss four methods that are proposed for more sustainable blockchain-based systems.

3.5.7.1 Renewable Energy

Because there are dangerous effects in using blockchain-based systems regarding these systems' effects on global warming, alternative energy sources have become important. Digital currency advocates claim that the ultimate environmental effect of Bitcoin, as an example, is limited. Their primary defence is that Bitcoin mining can be largely powered by the wasted excess of green sources. Thus, using renewable energy can be considered a method for developing the environmental sustainability of blockchain-based systems.

According to [190], Bitcoin mining mainly takes place in parts of the world where there is an excess of renewable energy, such as Quebec, Norway, Oregon and Washington. Consequently, this allows miners to exploit the existence of cheap renewable energy. Although there

has been significant progress in renewable energy sources over the last few years, renewable energy supplies are unpredictable, fluctuating and dependent on weather conditions. This creates new challenges for electrical system operation and management, with additional measures needed to ensure that mining operations can be undertaken safely and stably. It does not appear at present that renewable energy will solve all the issues related to Bitcoin and its sustainability, especially considering the area is not well examined.

3.5.7.2 Regulations and Fiscal Policies

The study [9] discusses current fiscal policy and regulatory approaches that allow digital currencies to provide a framework for additional legal and policy methods to mitigate blockchain energy consumption. This could result in extensive advantages by developing blockchain-based systems that are environmentally sustainable and that enhance the profits of financial technologies. The author identifies several suitable financial policy proposals that could improve blockchain's environmental sustainability. However, there is a challenge with such an approach. Finding the correct fiscal tool depends on where it is intended to operate, whether it is legally available and where its boundaries should be. Decisions must also be taken as to which parts of the process are under the jurisdiction of which national entity. Numerous political, practical, economical and jurisdictional difficulties must be overcome in this area.

3.5.7.3 Mining Devices

Mining hardware is one of the core components of blockchain-based systems, and its technology has a major impact on energy consumption. The significant financial incentive gained from Bitcoin mining has attracted many miners. These have led to fierce competition between miners. Consequently, blockchain mining hardware has developed remarkably, and large companies have quickly engaged in creating ever more sophisticated technological ways of mining Bitcoin.

At the start of Bitcoin's development, mining was undertaken by employing Central Processing units (CPUs). After Bitcoin had been in existence for a year (2009), it became

apparent that mining could be accomplished by employing Graphic Processing Units (GPUs). Video processing involves large amounts of repetitive tasks like mining involves large amounts of repetitively generated hashes. GPUs have greater Arithmetic Logic Units (ALUs) than CPUs. Identical ALUs are employed for Bitcoin mining for the generation of SHA-256 hashes. This means that a GPU can mine Bitcoin more rapidly than a CPU. Shortly afterwards (2011), miners began using Field-Programmable Gate Arrays (FPGAs). In 2013, they moved on to Application-Specific Integrated Circuits (ASICs). As the name implies, ASICs are specifically designed for one dedicated form of calculation (while FPGAs are reprogrammable for mining any indicated entity). This guarantees optimisation of resources in the generation of hashes [190].

These new generations of mining devices provide high levels of performance and are more energy efficient, which has led to improvements in the environmental sustainability of blockchain-based systems. However, it is predicted that future performance and energy efficiency improvements for these mining devices will not see a rapid improvement [46].

3.5.8 Characterisation of Methods for an Environmentally Sustainable Blockchain

We have presented a thematic map regarding the methods proposed to improve blockchain design's environmental sustainability, summarised in Figure 3.2. This map covers the current state-of-the-art research extracted from the primary studies. The thematic map constructs a taxonomy for the methods of enhancing blockchain environmental sustainability.

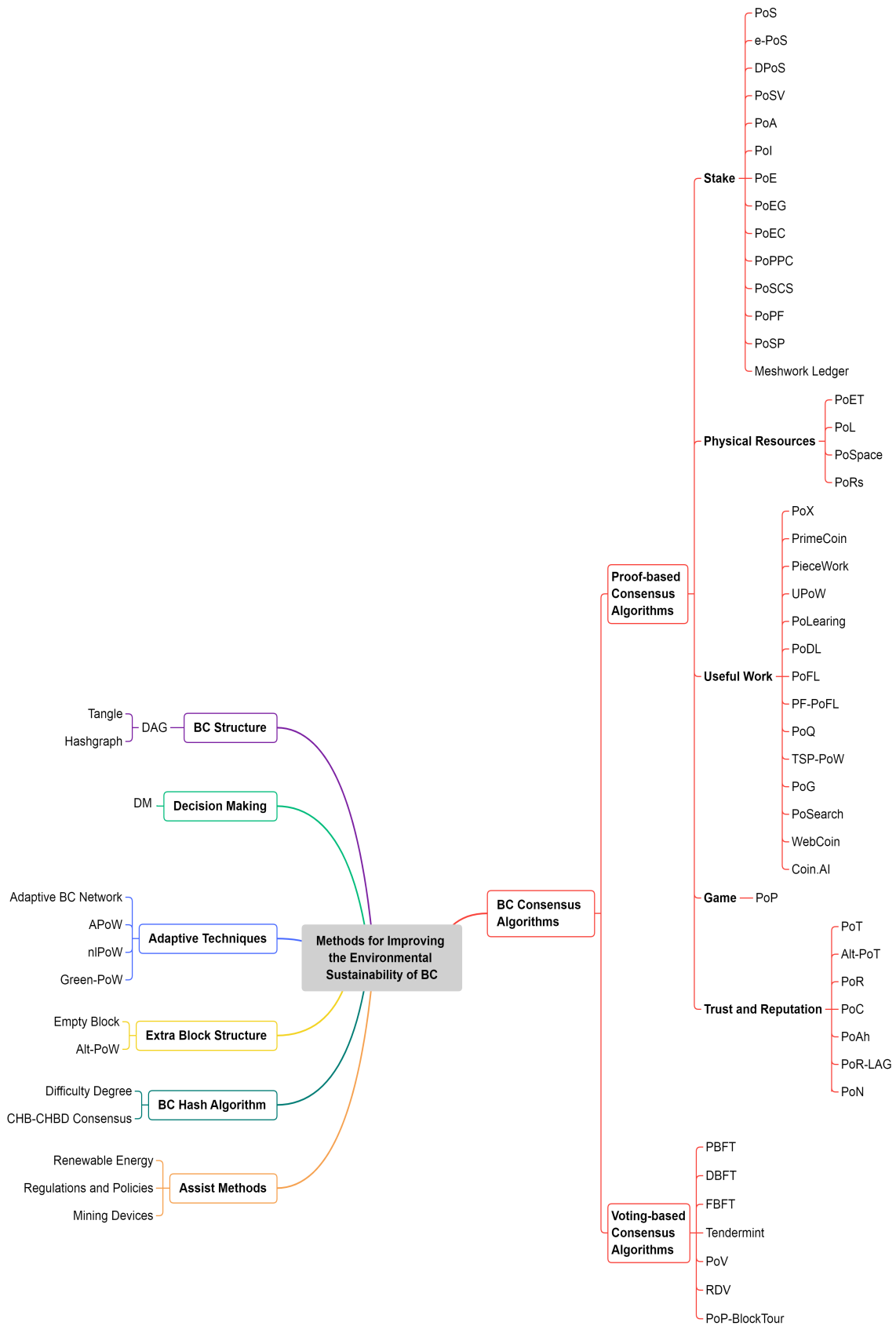


Figure 3.2: Thematic Analysis of Methods for Developing Blockchain Environmental Sustainability

3.6 Existing Measurement Tools for the Environmental Sustainability of Blockchain

3.6.1 Measuring Energy Consumption

Measuring the amount of electricity that Bitcoin mining machines produce is still challenging. Although it is possible to estimate the computer power employed by the Bitcoin network as a whole, it is not so simple to assess the underlying machines and their energy consumption. On the whole, the existing estimations of energy consumption are based on the Bitcoin cryptocurrency. The analysis for electricity consumption that is commonly seen is based on assumptions. Also, the estimates published in the scientific literature vary considerably.

In [44], the author proposes Bitcoin's energy consumption calculation from an economic view. The calculation makes an estimation based on the percentage of revenue gained from mining spent on energy costs. It assumes that 60% of revenue is spent on energy costs for the network, producing a state where even mining by devices provided by BITMAIN, the biggest manufacturer that offers new Bitcoin mining machines, cannot earn profits [44]. This estimation assumes that electricity will cost five cents per kilowatt-hour.

Although the validity of the results may decrease as the number of assumptions rises, the author has numerous assumptions that can be potential shortcomings of his estimation. One assumption that may be a weakness is the assumed electricity price (five cents per kilowatt-hour). However, numerous miners pay a lower rate than this for energy, particularly in China, while small-scale miners may pay higher rates. An additional shortcoming with these assumptions is that the price of mining hardware can vary in terms of retail and resale costs, depending on the value of coins and demand.

Bitcoin's energy footprint in terms of mining has been analysed in [94]. The authors root their analysis in the premise that the power consumed by networks (P), which is measured in Watts, can be calculated from the Bitcoin network's hashrate (R), which is measured in hash/second; the last factor is the energy efficiency of the Bitcoin mining device (D), which is measured in hash/Joule, $P = R/E$. The Bitcoin network's hashrate is $R \approx 2^{32}D/600$. By

combining the energy efficiency (E) with the hashrate (R), the amount of power consumed by the Bitcoin network can be estimated as $P = R/E \approx 2^{32}D/(600E)$.

Clearly, on any specific day, we can only make an accurate estimate of power consumption by thinking of what hardware is available for that period because any standard computer with the right software can participate in Bitcoin mining. Another challenge that could affect the accuracy of the estimation is the situation of the miners, such as the location of mining devices. Also, cryptocurrencies have been designed not to be traceable, which leads to varying difficulties in tracing mining activities.

In [95], the authors experiment with how efficient mining is performed for nine forms of cryptocurrency and ten hash functions. The data are compared statistically with benchmark experimentation using Monero mining. The research provides estimations of the amount of electricity consumed globally by Monero mining and discusses the amount of energy consumed by cryptocurrency mining as a whole. The experimental and theoretical results are used to estimate the amount of electricity other cryptocurrencies consume quantitatively.

Although the research quantitatively estimates energy consumption and environmental impacts, it has several limitations. First, the currency is encrypted to anonymise the correct number of miners and their locations. To undertake general estimations, the assumption was made that miners are only connected with local pools and that the pools do not have servers anywhere except in their birthplace. It is known that miners do not necessarily undertake mining activities in their local pools, and pools can own servers in different countries, allowing miners to connect with overseas facilities. This means that it is very difficult to produce an accurate estimate.

Levels of blockchain energy consumption are determined in [96]. Employing estimations, the authors show that modern PoW cryptocurrencies' energy consumption may be seen as outstripping the usefulness of the currency. Nevertheless, they contend that even if PoW cryptocurrencies become widely adopted, they will not threaten the climate significantly. The authors calculate that Bitcoin is likely to consume between 60 and 125 *TWh* per year, this being the equivalent of yearly electricity consumption for medium-sized countries like Austria

and Norway.

In [191], the authors propose a “green efficiency” characteristic that is incorporated within a quality model for the Bitcoin industry in [191]. This characteristic aims to create the highest-quality cryptocurrency model from the energy consumption perspective. Furthermore, the model seeks to delineate methods of ensuring green efficiency in the early phases of building and developing a worldwide cryptocurrency. This research paper is a work in progress and broadly examines the suggested green quality model for the cryptocurrency industry.

3.6.2 Measuring Carbon Emission

In [45], the authors use empirical evidence for the analysis of the carbon footprint of Bitcoin. They rely on data taken from recent filings with the IPO for major hardware manufacturers, the compositions of mining pools and the operations of mining facilities. As well as making an estimate of overall power consumption, the researchers have determined a geographical footprint for mining activities on the basis of IP addresses. The researchers demonstrated that during November 2018, Bitcoin’s yearly electricity consumption came to 45.8 *TWh*. Based on this, they extrapolate a calculation that Bitcoin’s annual carbon emissions are between 22.0 and 22.9 *MtCO₂eq*, more than Jordan and less than Sri Lanka, somewhere around the levels of Kansas City.

Climate model projections have been used to estimate the quantity of *CO₂* needed to exceed a global warming figure of 2°C [47]. This figure is compared with the total emissions that Bitcoin would use if it became a mainstream currency, in line with the rates of adoption of other widely-accepted technology and on the assumption that Bitcoin mining conditions would be the same in the future as they are now. The researchers state that Bitcoin mining could increase this figure within several decades should Bitcoin replace cashless transactions and still be mined as it is today. Whilst much research, such as [192]–[194] agree that Bitcoin’s electricity consumption is rising, questions have been asked by a number of studies [92] about the methodology employed in [47], indicating that there is a need for greater accuracy in measurement.

In [195], researchers present a pair of methodologies for assessing the carbon footprint associated with Bitcoin transactions. The initial approach is relatively straightforward, attributing weight to the origins of coinbase contributions in a transaction according to their proximity to the originating block. In the subsequent method, the weighting of coinbase contributions is adjusted to reflect input and output values for each intermediate transaction. By employing these techniques, the authors can link individual transactions and unspent transaction outputs to precise amounts of atmospheric carbon emissions.

3.6.3 Measuring Electronic Waste

Electronic waste (E-waste) poses a severe threat to the environment. It can pollute water and air because of its toxic chemicals and metals contaminating the soil resulting from improper recycling. Most studies on the environmental sustainability of blockchain technology focus on the energy consumption or carbon emissions of this technology and ignore the growth in global E-waste. In [196], the authors demonstrate a methodology for estimating blockchain technology e-waste by focusing solely on Bitcoin. They develop a framework to assess the current state of the network's e-waste generation. They use the lifetime of Bitcoin mining devices to keep track of available device types. They combine this with publicly available product specifications that reveal computational power, power efficiencies and equipment weight of a given device. They use this data to evaluate the duration of profitable operation per mining device, assuming that devices become e-waste once they turn unprofitable. The study shows that each Bitcoin transaction produces about 0.272 *kg* of e-waste. It also shows that Bitcoin could produce up to 6.44×10^7 *kg* of e-waste in early 2021, one of the peak Bitcoin price levels.

3.6.4 Environmental Sustainability Assessment Systems

A sustainability assessment is essential and should be an integral part of the planning and organising of any blockchain-based system. Sustainability can be evaluated through the use of indices or sets of indicators. Whatever metric is used to assess sustainability, all have the same purpose: to assist decision-makers in evaluating environmental sustainability, provid-

ing information for planning subsequent action, revealing trends that are not immediately apparent to offer future forecasts and to compare places and situations.

In [99], a measurement framework is proposed that provides a broad overview of the environmental problems linked with blockchain technology used for producing cryptocurrencies, specifically Bitcoin. This is a new type of framework that gives consideration to environmental sustainability elements that go beyond the energy consumption levels, for example, the type of energy source producing the electricity, how much hardware is reused and/or recycled, and how scalable the technology is. For the development of this framework, the authors found pertinent indicators of green performance in scientific literature and linked them with the essential elements of blockchain technology that are responsible for its environmental impact. Whilst this paper is the first time that an attempt has been made to develop a broad framework for the evaluation of the sustainability of blockchain, it does have limits in that it is solely focused on blockchain technology that uses PoW and, even more specifically, just on Bitcoin.

In [100], the authors employ the widely-recognised Life Cycle Assessment methods to undertake a rigorous analysis of the causes of the environmental impact of Bitcoin mining, both in the past and in the future. The research demonstrated that in 2018 the Bitcoin network's consumption was 31.29 *TWh* and its carbon footprint was 17.29 *MtCO₂eq*; this estimate falls towards the bottom end of the findings of past research. The primary factors affecting this environmental impact were demonstrated to be miners' geographical locations and how efficient the mining equipment was. Unlike past research, this research demonstrated that the useful lifetime, production and disposal of this equipment did not make a significant difference to the overall impact, and that although the total hashrate is predicted to rise, it is also predicted that the amount of energy consumed and the environmental impact per hash will fall.

3.6.5 Predicting Effects on Environmental Sustainability

Although predicting the core factors responsible for the environmental sustainability of blockchain-based systems is critical, our SLR has yet to find one study that discusses this gap. In [97], a model for predicting future values of E-waste and energy consumption associated with traditional PoW is described. With the underlying intention of identifying and explaining patterns in E-waste creation and energy use, the authors create two predictive models that leverage Facebook’s Prophet algorithm and Deep Neural Networks. The models rely on a number of explanatory elements related to the Bitcoin market and the microstructure of the blockchain. By leveraging insights into daily E-waste generation and energy usage and eleven essential input variables, they evaluate the predictive performance of the two frameworks. They subsequently describe how these inputs can anticipate and manage E-waste generation and energy consumption using local interpretable model-agnostic explanation (LIME) and Shapley additive explanation (SHAP). The results can inform forecasts on future energy consumption and E-waste accumulation in the current Bitcoin mining setup.

3.7 Discussion

In this section, we summarise the main findings, discuss the consequences of the SLR for academic researchers and report on the challenges and limitations to the review’s validity.

3.7.1 Principal Findings

We conducted this review to answer the five research questions described in Section 3.2. Below, the main findings of this review are summarised.

3.7.1.1 RQ1.1

It is important to emphasise that the purpose of the current SLR is to focus only on one dimension of sustainability, the environment, not the other dimensions, such as economic or technical ones. Therefore, the results of the current study summarise only the factors

affecting the environmental sustainability of blockchain technology (see Figure 3.1). Some of these factors are argued by some as the reasons for the rise of energy consumption of this technology but without proving this experimentally. They do not explain how these factors increase energy waste, to what extent they do so and how that can affect the environmental sustainability of blockchain-based systems. Also, existing research does not investigate other factors that may be impacted, such as land use (the size of mining devices) or the atmosphere (the heat dissipated by mining devices).

3.7.1.2 RQ1.2, RQ1.3 and RQ1.4

The results have shown that most current research enhances the environmental sustainability of blockchain-based systems by focusing on finding improvements to the PoW consensus algorithm. A large number of these alternative consensus algorithms have only been subject to online discussions (i.e. not well documented and not publicly available implementation), with just a small number reaching the level of formal research publications. Also, some of these algorithms that try to save energy disregard some key characteristics of blockchains, such as anonymity, security and decentralisation. We discuss the limitations and weaknesses of these consensus algorithms in Section 3.5.

After analysing all of the related papers retrieved from scientific databases, we have categorised the current state-of-the-art methods and techniques for developing environmentally sustainable blockchain technology. Seven main categories are presented that include more than fifty subcategories (see Figure 3.2). A few papers have improved the sustainability of blockchains by considering new methods not related to consensus algorithms, such as using DAG structures and renewable energy. However, these ideas need further improvement and investigation. Also, many methods that could increase the environmental sustainability of blockchains are missed. We discuss some of these in Section 3.8.

3.7.1.3 RQ1.5

The ever-increasing number of blockchain-based systems that are spreading across multiple domains leads to rising energy consumption and carbon footprints. Although it is important to measure and monitor sustainability, especially the energy consumption of such systems, we have identified just a few articles that measure energy consumption or propose a framework to measure environmental sustainability. Most of the reviewed papers measuring energy consumption rely on an estimation of energy wasted by Bitcoin and its mining process without examining other factors, for example, the energy consumed by storage.

Regarding the sustainability metrics, the field still needs more effort. In this review, we identified just two papers that present frameworks for measuring the environmental sustainability of blockchain-based systems. However, the studies miss a lot of factors that should be considered, such as cooling systems, CO_2 emissions and land usage of miners, especially mining pools. Also, they focus only on Bitcoin cryptocurrency and its consensus algorithm, PoW.

3.7.1.4 RQ1.6

Our SLR helps in understanding the current research gaps. While reviewing the related papers for this SLR, we identified some gaps in the area of blockchain environmental sustainability. These research gaps can enable practitioners and other researchers to concentrate on areas that need more investigation. These gaps are identified as a result of RQ1.1–RQ1.5 and discussed in Section 3.8.

3.7.2 Implications of the Review on Research

The aim of the current SLR on the environmental sustainability of blockchains is to investigate how current research has enhanced the environmental sustainability of blockchain design. This chapter provides a comprehensive review that summarises the relevant studies and reports some gaps in the literature. The findings can provide future potential directions for researchers who are interested in developing green blockchains. The discovered challenges and limitations

of the existing research can guide researchers to direct their future research accordingly to find solutions to address the identified gaps.

3.8 Future Research Directions for more Environmentally Blockchains

Initial keyword searches indicate that there are a limited number of articles related to blockchain environmental sustainability. Therefore, this section provides suggestions for academic scholars and practitioners who are working in the field of sustainable blockchains and are searching for new ideas.

3.8.1 Factors Related to Blockchain Sustainability

Although the identification of the elements affecting the environmental sustainability of blockchains has been discussed in several papers, these factors need more research to show the consequences for the sustainability of blockchains. Also, it is important to integrate some factors with others to better understand their impacts. There are some factors that are not covered in the literature, such as the ambient temperature of warehouses full of mining machines, the availability and age of such machines, storage usage and transaction throughput.

3.8.2 Methods for Developing Blockchain Sustainability

Although blockchain technology emerged a decade ago, many major directions for developing the environmental sustainability of blockchains have not yet been covered. In this section, we discuss some methods that could improve blockchain sustainability.

3.8.2.1 Consensus Algorithms

The consensus algorithm plays a crucial role in reducing the energy consumption of blockchain-based systems. Hence, many researchers concentrate on proposing energy-efficient consensus algorithms. Consensus algorithms that rely on miners' trust or reputation have already been

proposed. However, these algorithms utilise reputation or trust models that may not be appropriate for evaluating the behaviour of miners within blockchain networks, or they compute reputation and trust values based on metrics that have not been validated for blockchain-based systems. Therefore, building reputation and trust models for calculating miners' reputation or trust values within blockchain-based systems is very important as a future research topic. We have addressed this limitation in Chapter 5.

Today, Artificial Intelligence (AI) and blockchain are considered key factors behind technology development. The integration of these techniques is promising. AI can help optimise the energy efficiency of blockchain-based systems by building machine learning systems that assign the process of mining to miners based on context-aware or situation-aware systems. One potential research avenue could be using a machine learning system to determine miners based on their energy consumption or their effect on the environment. Also, we can build reinforcement machine learning algorithms to determine the ideal behaviour within a specific context to minimise its energy consumption. Another research idea is to use machine learning to minimise miner numbers based on, for example, their reputation level, which could lead to reducing wasted energy.

3.8.2.2 Sharding

Although sharding is commonly used in distributed databases, as first proposed in [197], sharding is a principle that can be applied to blockchain networks. It refers to the way in which processing transaction overheads can be split amongst large or small groups of nodes, called "shards". Such a methodology was first put forward to tackle the problems of scaling blockchains. Shards work alongside each other to optimise blockchain performance (increasing the number of transactions processed for every consensus round) by splitting up the various overheads of running a blockchain network. These overheads include the costs of storage, computing and communication. Much research has been done into sharding in traditional distribution systems to increase transaction throughputs when scaled up [198]. However, there is a lack of studies on the benefits of using this protocol to reduce the energy consumption of

blockchain technology.

3.8.2.3 Many/Multi-Objective Optimisation

Based on our literature review, there is a lack of optimising and modelling blockchain-based systems using many-objective and multi-objective optimisation algorithms. In particular, there is a need for minimising energy consumption and its consequences without compromising the inherent properties of blockchain technology.

Depending on the particular scenarios, blockchain-based systems may have several objectives and trade-offs need to be made to build an overall optimisation. For instance, the energy efficiency and security for blockchain-based systems can be conflicting because a high number of miners will increase both the systems' security and energy consumption. Therefore, a many-objective or multi-objective optimisation model can help decision-makers choose the optimal solutions based on their needs. There can be many objectives to trade off, such as energy, carbon emissions, security and performance. Numerous evolutionary algorithms, such as genetic algorithms and goal programming, can be considered to optimise the environmental sustainability of blockchain-based systems. In addition, optimisation models can benefit from machine learning in several ways, such as predicting optimal miners for an optimisation model. Solving the problem of blockchain-based systems' environmental sustainability as an optimisation problem can be a good future direction for research in promoting blockchain sustainability. Therefore, we have considered and addressed this gap in Chapter 4.

3.8.2.4 Adaptive Blockchain

An adaptive blockchain architecture may improve the environmental sustainability of blockchain technology. Most of the work related to adaptation in blockchains has focused on improving difficulty adaptation [199] or reward adaptation [200] without regarding energy consumption and environmental sustainability as possible variables.

Adaptive consensus algorithms can be interesting future research areas. They can be built based on energy-aware algorithms that can provide information for adaptivity in

many different ways. For example, the number of miners or hash algorithms can be changed dynamically based on the information that is statistically analysed. In addition, we can take advantage of the adaptivity approach to construct self-adaptive blockchain-based systems that can switch between existing consensus algorithms, for example, between PoW and PoS, or between blockchain types, for example, between public, hybrid and private, relying here on context-aware systems. Many factors can be taken into account to propose self-adaptive consensus algorithms and self-adaptive blockchain-based systems, such as the factors identified in section 3.4. We have contributed to addressing the lack of designing self-adaptive models for blockchain-based systems in Chapter 6.

3.8.2.5 Renewable Energy

The adoption of renewable energy in blockchain technology is a research challenge that is worth studying. There is a lack of methods that utilise renewable energy to reduce energy consumption and carbon footprints. Maximising the adoption of renewable energy for mining can be a good way of reducing environmental problems. Hence, there are many different ideas that researchers can work on regarding the use of renewable energy. To operate mining devices with green energy produced from various resources, such as sun, wind and water, we should investigate how the challenges of generating green energy can be addressed because such energy is unpredictable, and the ideal locations and good climatic conditions must be identified.

Renewable energy can be bought from off-site companies or can be produced by harnessing on-site equipment. The consequence of using these techniques may raise some opportunities that should be investigated. Because a large amount of power may be lost while being transmitted from renewable energy sources to blockchain-based systems, a study on this issue is necessary. Cooling equipment and other computing devices related to blockchain-based systems also have an impact on environmental sustainability. Thus, it is crucial to conduct research about the benefits of using green energy instead of brown energy for such equipment and devices.

3.8.2.6 Regulations

Because of the decentralisation of blockchain architecture, it does not rely on any central third authority. This leads to a need for enforcing government regulations and industry standards. Indeed, it is necessary to formulate regulations for determining which kind of applications can be built using blockchain technology. Also, we need to create industry standards to specify some parameters related to the environment, such as an acceptable amount of energy consumption or carbon emissions.

3.8.2.7 Mining Techniques

Quantum computing, which is a modern technology within Computer Science and Physics, can potentially solve a computational task more quickly and efficiently compared with classical computing by leveraging quantum-mechanical concepts, such as entanglement and superposition. Because quantum computers are designed to work faster than traditional computers when it comes to solving specific difficult problems, we can use them to perform mining for blockchain-based systems. Because it is not clear if quantum computers are capable of reducing energy consumption, we need to explore the impact of using such computers on the environment. In other words, quantum computers may be able to find nonces for blocks faster, but we do not know how much energy the quantum computers consume to find the nonces. Future research can examine this issue, which could provide a new direction regarding the mining process.

Integrating cloud computing with blockchain technology can be one direction for enhancing the environmental sustainability of blockchain-based systems. For example, cloud-based mining may reduce these systems' energy consumption, carbon emissions and E-waste. Also, cloud computing can be used to store blocks while mining devices store essential information. In addition, consensus algorithms can be modified to dynamically shift mining blocks to cloud computing considering specific requirements, such as energy usage. Such ideas should be investigated to show their impact on the environmental sustainability of blockchain-based systems.

3.8.3 Measuring Blockchain Sustainability

Because of the absence of research regarding measuring environmental sustainability, we present several future potential recommendations. Many factors affect the energy consumption of blockchains, so we need to cover several factors or integrate different factors to accurately determine energy consumption. These factors can impact consumption directly or indirectly. A list of factors affecting energy consumption and affecting sustainability is discussed in Section 3.4. These factors can be taken into account while monitoring energy consumption. In addition, they can help build a comprehensive framework to measure blockchains' energy consumption and environmental sustainability.

In general, the existing papers estimate energy consumption based on Bitcoin. Therefore, the field requires research to measure the energy consumption of blockchain-based systems directly and precisely based on real-world data instead of estimations of energy consumption based on Bitcoin. Also, the acceptable levels of energy consumption for particular blockchain components and for every context should be investigated.

Recently, different communities have started to rapidly shift towards adopting blockchain-based systems. However, the environmental sustainability of most of these systems has not been analysed as part of their evaluation. Since there are no benchmarks for measuring and comparing the environmental sustainability of blockchain-based systems, developing a benchmarking framework will help in understanding the effects of these systems on our environment.

3.9 Conclusion

In this chapter, we conducted an SLR to investigate the state-of-the-art concepts around the environmental sustainability of blockchain design. We have focused solely on the environmental dimension of sustainability, as it is regarded as one of the determinant factors for the successful adoption of blockchain-based systems and a key contributor to its long-term economic viability. We have considered five of the most relevant data sources in the field to

conduct the search and found 104 related papers. The review identifies and classifies various factors that relate to and negatively affect the environmental sustainability of blockchain-based systems. We have reported on several mechanisms and measurement tools for evaluating blockchain energy consumption for their support in understanding the likely environmental sustainability of these systems. In addition, our survey shows many open concerns and research gaps. We discuss ideas for future research that can be conducted to enhance blockchain sustainability.

There are a variety of ways in which our SLR can be pushed further: the surveys can pave the way for a better understanding of the relationship between blockchain components and sustainability dimensions, including environmental sustainability. It can also steer further research on “Blockchain for Green systems”, as excessive energy consumption is often cited as a major obstacle to the adoption of this technology. The review can also help in understanding how to develop systematic engineering methods, techniques, approaches and metrics for environmentally-aware, dependable and sustainable blockchain-based systems grounded on a solid understanding of the current state of the art.

Chapter Four

A NEW PROBLEM FORMULATION FOR OPTIMISING THE ENVIRONMENTAL SUSTAINABILITY OF BLOCKCHAIN-BASED SYSTEMS

Context. Proof of Work (PoW) requires an enormous amount of energy and produces considerable carbon emissions that can affect the environmental sustainability of blockchain-based systems. Enhancing the environmental sustainability of these systems without compromising the fundamental properties of blockchain technology, for instance, decentralisation, trustworthiness, scalability and security, is a challenging problem. The solution has to consider how energy consumption and carbon emission can be minimised whilst ensuring decentralisation and trustworthiness.

Objective. This chapter formulates the problem of balancing the environmental sustainability of blockchain-based systems (i.e., energy consumption and carbon emissions minimisation) and their decentralisation and trustworthiness as a Search-Based Software Engineering (SBSE) problem. It represents the problem of selecting miners for mining blocks in a blockchain-based system as a subset selection problem.

Method. We propose a model composed of multiple fitness functions. The model can be used to explore the complex search space by selecting a subset of miners within a blockchain-based system to minimise its energy consumption and carbon emission without drastically impacting its decentralisation and trustworthiness. We integrate our proposed fitness functions into five evolutionary algorithms (EAs) to solve the problem of blockchain miners' selection. Several experiments are conducted to demonstrate the effectiveness and applicability of the model in

enhancing the environmental sustainability of blockchain-based systems.

Results. Our results show that the environmental sustainability of blockchain-based systems can be enhanced with little degradation in other competing objectives. Also, the results show that the selected EAs outperform the baseline algorithm. However, the comparisons among these EAs expose that no one algorithm is consistently outstanding for all fitness functions.

Conclusion. The proposed model is used to optimise the sustainability of blockchain-based systems but can potentially be used for optimising other objectives of these systems, such as security and scalability.

Contribution to Literature. This chapter is contributed to the research literature through our published poster paper "*Selecting Miners within Blockchain-based Systems Using Evolutionary Algorithms for Energy Optimisation*" and our published full paper "*Optimising the Energy Consumption of Blockchain-based Systems Using Evolutionary Algorithms: A New Problem Formulation*". This chapter is written based on these papers.

4.1 Introduction

Despite the great potential of blockchain technology, there is an essential issue regarding its environmental sustainability. In the current debate concerning sustainability and global warming, such a perspective could constrain or limit the global adoption of this technology [9]. Therefore, the question of optimising and finding solutions for this issue is currently receiving much attention. Researchers have proposed more sustainable and energy-efficient mechanisms for trustworthy verification, as discussed in Chapter 3. However, Chapter 3 demonstrates that research has not utilised SBSE techniques to solve the environmental sustainability problem of blockchain-based systems. In addition, different well-developed optimisation techniques are available and show promise to address optimisation problems in many fields. However, minimising the energy consumption and carbon emission of these systems has not been formulated as an optimisation problem and solved using EAs.

This chapter addresses this gap by reformulating the miners' subset selection problem in blockchain-based systems as an SBSE problem to optimise the environmental sustainability of these systems. In this context, this chapter aims to answer the second research question introduced in Chapter 1: **RQ2: How can the environmental sustainability of a blockchain-based system be optimised without compromising its inherent properties, such as decentralisation and trustworthiness?**

In this chapter, we reformulate the problem of the environmental sustainability of blockchain-based systems as an SBSE problem: miners subset selection problem. We represent the problem as a set of participating miners within a blockchain-based system where each miner consumes energy and emits carbon to add blocks and has a level of reputation. The system becomes more trustworthy with many miners, leading to massive energy consumption and carbon emissions. The features of miners in a set constitute a decentralisation score, and as the score decreases, the system becomes a centralised system. With such trade-offs, we propose a model that uses EAs to optimise the environmental sustainability of these systems by selecting miners that minimise energy use and carbon emissions while maximising other conflicting objectives. In this chapter, we use four different fitness functions: energy consumption versus

trustworthiness, energy consumption versus carbon emissions versus trustworthiness, energy consumption versus decentralisation versus trustworthiness, and energy consumption versus carbon emissions versus decentralisation versus trustworthiness.

The main contributions of this chapter are summarised as follows:

- We formulate the problem of selecting miners within blockchain-based systems as an SBSE problem.
- A novel optimisation model for the problem of selecting miners within blockchain-based systems is proposed using four different fitness functions for optimising the environmental sustainability of blockchain-based systems.
- We conduct an experimental evaluation to show the efficacy of the proposed model in saving energy and reducing carbon emissions.
- A comparison among EAs is presented to analyse their performance in solving the problem of selecting miners within blockchain-based systems.

The rest of the chapter is organised as follows: Section 4.2 presents an overview of the optimisation concept, and Section 4.3 introduces the related work. The details of our optimisation problem are presented in Section 4.4. The experiment design is explained in Section 4.5. We present our results and discussion in Section 4.6. Finally, Section 4.7 presents our conclusions.

4.2 Optimisation Overview

Nowadays, optimisation is widely used since it is a powerful tool for developing different fields. It is a fundamental technique in applied mathematics, engineering, computer science, economics, and other sciences. Optimisation seeks to select an “optimal” solution from a set of solutions. The degree of optimality for the solution is measured using single or multiple objective functions of a problem that is to be maximised or minimised. The search process for the optimal solution is undertaken subject to constraints. These constraints take the form of

expressions of equality and inequality. Furthermore, solving some problems requires multiple objective functions; thus, conflicts may occur between these functions. In this section, we present a brief overview of the optimisation concept.

4.2.1 Optimisation Using Meta-heuristic Algorithms

The most recent advancements in the previous few decades have relied mainly on meta-heuristic algorithms. Indeed, meta-heuristic algorithms are used in the great majority of modern optimisation techniques in all important engineering and science disciplines, as well as industrial applications. The majority of meta-heuristic algorithms are inspired by nature, such as Particle Swarm Optimisation (PSO), Genetic Algorithm (GA) and Ant Colony Optimisation (ACO) [201]. In addition, GA is the most popular algorithm of Evolutionary Algorithms (EAs) that has become increasingly powerful in tackling complex optimisation problems and searching for optimised solutions [202], [203].

EAs belong to the group of bio-inspired algorithms [204]. They are inspired by the concepts of Charles Darwin's evolutionary theory, which incorporate selection and variation. EAs explore the search space through random perturbations and create a set of candidate solutions called a population. Individuals within a population are evolved using a combination of crossover and mutation operators to create a new generation. Crossover is a process of mating two parent solutions to produce new offspring by mixing the parent's genetic materials. A mutation occurs in individual solutions by randomly altering their genetic materials and introducing new ones. Individuals for the new generation are chosen using a survival selection mechanism. Although it usually prefers elite individuals (i.e., fitter), selection does not prevent the survival of unfit solutions. Such preservation diversifies the new generation.

4.2.1.1 Selected Evolutionary Algorithms

As we introduce a new optimisation problem (blockchain miner selection problem), we integrate our proposed fitness functions into five EAs, each with different mechanisms to preserve solution diversity. For example, Non-dominated Sorting Genetic Algorithm II (NSGA-II) cre-

ates niches by computing a crowding distance for each solution and uses the crowding distance in its selection operator to promote diversity [205].

To diversify solutions, Strength Pareto Evolutionary Algorithm 2 (SPEA2) [206] uses an external archive to store the non-dominated solutions. Then, for each solution, it calculates how many solutions dominate it and the number of solutions it dominates. SPEA2 also uses a nearest neighbour density estimation technique to guide the search efficiently.

Similarly to SPEA2, Pareto Archived Evolution Strategy (PAES) [207], which is a mutation-only algorithm, uses a d -dimensional archive ($d =$ the number of objectives) as a reference set when it creates new solutions. To promote diversity, PAES divides the objective space into grids and places each solution in a certain grid according to the solution's objective values. Then, a crowding measure is computed using the density of solutions in each grid. Finally, the crowding measure is used in ranking the non-dominated solutions in a way that prefers non-dominated solutions belonging to the least crowded regions.

One of the main performance indicators is the hypervolume, which computes the dominated proportion of the search space by the found solutions [208]. The greater the hypervolume is, the better performing the algorithm is. Indicator-based Evolutionary Algorithm (IBEA) [209] uses the hypervolume indicator to rank solutions. It calculates how much volume each solution contributes to the overall Pareto front's hypervolume. Solutions with higher hypervolume values are preferred. As a result, this process maximises the final Pareto front domination of the search space.

We also use Non-dominated Sorting Genetic Algorithm III (NSGA-III), an improved version of NSGA-II for many-objective problems [210]. To preserve diversity, the NSGA-III algorithm uses a set of well-spread reference points representing interesting directions in the fitness landscape and virtually representing the Pareto front. As the search process progresses, the algorithm updates the set and niches created around these reference points. Furthermore, predefined points divide the search space into multiple targeted searches for the algorithm instead of one massive search space. This alleviates the problem of computing a diversity score for every solution by selecting solutions from different niches instead of computing the

crowding distance. In addition, it reduces the massive number of non-dominated solutions in many-objective problems, as each optimal solution corresponds to a targeted search segment.

In this thesis, we use NSGA-II, SPEA-2, PAES, IBEA and NSGA-III because they have different mechanisms for preserving solution diversity, which helps navigate the search space efficiently [211]. According to [202], [212], EAs can be loosely classified into three categories based on their fitness assignment rules or objectives: Pareto-based, indicator-based, and decomposition-based. NSGA-II and SPEA-2 exemplify Pareto-based algorithms, IBEA and SMS-EMOA exemplify indicator-based algorithms, and NSGA-III and MOEA/D exemplify decomposition-based algorithms. In this thesis, we have excluded MOEA/D and SMS-EMOA from our evaluation because they have shown difficulty converging their solutions, even when the number of objectives is as low as four [213]. Additionally, we have included PAES in our evaluation because it is a well-established algorithm usually used as a baseline for comparing different algorithms [207], [214].

Moreover, selecting these algorithms as the chosen MOEAs for this research results from their availability as we focus on the native algorithms implemented within a Multi-Objective Evolution Algorithms framework called MOEA Framework and supported by the framework for all functionality provided. Also, they are well-suited for solving similar problems to ours [215]–[219]. Their compatibility with our problem representation is another reason for selecting these algorithms, as the solution encoding in our model is Binary-coded (Boolean), and these algorithms can be used with binary-coded solutions.

4.2.2 Search-Based Software Engineering

Developing effective and dependable software frequently involves tedious and costly work, which software engineers try to circumvent through automation. However, automating software is a viable and efficient approach because it considerably reduces the time and effort required for software development.

In SBSE, optimisation algorithms are often used to address conventional software engineering problems, which tend to demand a balance between the competing aims of vastly

different objectives. The problems encountered in SBSE possess extensive solution spaces that are difficult to examine via traditional software engineering techniques. When software engineering problems are addressed using SBSE methods, they require reformulation as search problems; these are then solved using search-based optimisation algorithms to find optimal or near-optimal solutions. Potential solutions in a solution space primarily differ in their quality, that is, the degree to which they can offer a solution to a given problem. Therefore, a fitness function that assesses each candidate solution can be used to shape the search process. Various methods can be employed to develop solutions in line with the search methodology.

Notably, the performance of SBSE techniques can reach - and potentially even exceed - human performance. For instance, the review [220] surveys SBSE research on the problems of work-group formation, test case selection and next release. It compares the solutions presented in the reviewed works with solutions developed by professionals and academics. The study revealed an overall greater consistency among the machine-produced solutions.

4.2.2.1 Blockchain and Search-based Software Engineering

Several problems brought by blockchain technology are NP-hard problems and have a time complexity of $O(2^n)$. These problems can be formulated and solved by utilising SBSE techniques. Many blockchain-based systems involve optimisation problems, including performance, security, decentralisation and scalability. They are like many other real-world applications where there are trade-offs between many competing objectives. Although SBSE has grown rapidly, there needs to be more work on SBSE as a means of addressing blockchain-based systems challenges. Like many technologies, SBSE has the potential to benefit from blockchain technology and vice-versa.

The Literature has presented some conflicting blockchain objectives and linked them to blockchain components. In Table 4.1, we have summarised some of these conflicting objectives and their related blockchain components that can be utilised to optimise blockchain-based systems.

Table 4.1: Examples of Blockchain Objectives for Optimisation Models

Blockchain Component	Objectives		
	Environmental	Security	Performance
Mining Device	[9]	[221]	[221]
Number of Nodes	[222]	[222]	[222]
Consensus Algorithm	[9]	[223]	[223]
Blockchain Type	[4]	[223]	[224]

4.3 Related Work

Due to the excessive energy consumption of PoW, several consensus algorithms, such as PoT [157] and PoR [159], have been proposed to reduce energy consumption and improve environmental sustainability by reducing the number of miners in the competition to find the nonce. These algorithms track the miners' behaviours over some time and then calculate their reputation or trust values. Finally, these values are used to allow miners to add blocks. Unlike these studies, our work does not change the architecture of the blockchain-based systems that rely on PoW. Instead, it changes the mechanism of choosing the appropriate miners that improve the environmental sustainability of mining blocks. In addition, it does not require investing in specific hardware, such as PoSpace [139] or PoL [138].

Several optimisation models are proposed in the literature to reduce the environmental impact related to energy consumption. For example, the problem of scheduling is one of the problems that has been formulated as a multi-objective optimisation problem for optimising energy consumption in many areas, such as heterogeneous computing systems [225], cloud computing [226], wireless sensor networks [227], and multi-core processors systems [228]. Also, another energy-efficient optimisation problem is formulated in various works regarding the offloading process. These studies aim to reduce the energy consumption of offloading processes in diverse domains, including cloud computing [229] and mobile edge computing for the IoT [230]. Furthermore, clustering techniques are employed to optimise energy consumption in different fields, such as cloud computing [231] and wireless sensor networks [232].

Other work solves blockchain-based system problems using EAs. For example, [233] proposes a Pareto-based technique to detect significant influencers in a blockchain-based sys-

tem. In addition, [234] proposes a transaction selection process using a combination of large deviation theory and Lyapunov optimisation.

SBSE techniques have been utilised successfully to improve the non-functional properties of software. For example, the study by [235] applied Genetic Improvement (GI) of software for trading-off energy consumption with the functional properties of software running on a Raspberry PI; the study presented in [236] utilises *in-vivo* optimisation using GI to achieve a trade-off between the energy consumption of Rebound (an animation library for Android, written in Java) and its output accuracy; the study [237] implements a multi-objective approach to optimise the energy use of Android applications by changing 'GUIs' colour palettes; in [238] they fix object-oriented and energy anti-patterns by finding an optimal set of refactoring sequences to maximise the number of fixed anti-patterns.

Additionally, software run-time and memory consumption have been optimised using SBSE. For instance, the study [239] has applied GI on the Viola-Jones algorithm (a face detection algorithm in the OpenCV library) to trade off its functionality with its run-time. Also, the study [240] has utilised a multi-objective approach to speed up the run-time of shader software by degrading its output graphics.

Our work differs from the above studies as none solves or discusses the most serious problem of blockchain based-systems, environmental sustainability, using SBSE techniques. In addition, we trade off two of the main objectives related to the environmental sustainability dimension: energy consumption and carbon emission. We compromise these objectives with other non-functional properties of blockchain-based systems, namely decentralisation and trustworthiness. Table 4.2 shows a summary of each study in this section representing the problem solved by the study, the optimisation technique used, and its area.

Table 4.2: A Summary of Related Work

Reference	Problem Considered	Optimisation Technique	Area
[157]	Energy consumption	New consensus algorithm	Blockchain technology
[159]	Energy consumption	New consensus algorithm	Blockchain technology
[139]	Energy consumption	New consensus algorithm	Blockchain technology
[138]	Energy consumption	New consensus algorithm	Blockchain technology
[225]	Energy consumption	Scheduling with multi-objective optimisation	Heterogeneous computing
[226]	Energy consumption	Scheduling with multi-objective optimisation	Cloud computing
[227]	Energy consumption	Scheduling with multi-objective optimisation	Wireless sensor network
[228]	Energy consumption	Scheduling with multi-objective optimisation	Multi-core processors system
[229]	Energy consumption	Offloading with a meta-heuristic algorithm	Cloud computing
[230]	Energy consumption	Offloading with stochastic optimisation	Mobile edge computing
[231]	Energy consumption	Clustering with Meta-heuristic algorithms	Cloud computing
[232]	Energy consumption	Clustering with multi-objective optimisation	Wireless sensor networks
[233]	Bitcoin network's influencers	Multi-objective optimisation	Blockchain technology
[234]	Bitcoin utility	Multi-objective optimisation	Blockchain technology
[235]	Energy consumption	Genetic Improvement	Applications
[236]	Energy consumption	Genetic Improvement	Mobile application
[237]	Energy consumption	Multi-objective optimisation	Mobile application
[238]	Energy consumption	Multi-objective optimisation	Mobile application
[239]	Execution time	Deep parameter optimisation	Face detection
[240]	Performance	Loop perforation	Applications

4.4 Optimisation Problem Formulation for Blockchain-based Systems

Similarly to many real-world systems, blockchain-based systems have trade-offs among different objectives that are considered as one kind of optimisation problem. According to [15], many conflicting blockchain objectives, such as trust and energy consumption, can be used to optimise blockchain-based systems.

We posit that trust provisioning within blockchain-based systems is expensive computationally and in terms of energy. We consider energy consumed and carbon emitted for managing trust within these systems to be an optimisation problem. The problem is represented as a subset selection problem of miners participating in a blockchain-based system. To solve the above problem, in which there is a trade-off between energy consumption, carbon emission and other conflicting objectives, we present a novel optimisation model that can enhance the environmental sustainability of blockchain-based systems. Our model is generally applicable to scenarios where miners are predefined and controlled. Consortium and private Blockchain-based systems can benefit from our model as the participating miners are often

managed and predefined. Moreover, public blockchain-based systems can still benefit from our model if a global standard or policy for selecting miners to mine blocks is specified. Our model employs a static optimisation style that performs optimisation first and then applies. However, it can be employed to perform a dynamic optimisation that can select optimal miners during run-time (i.e., select optimal miners after each mined block).

In this chapter, we reformulate the problem of minimising the energy consumption and carbon emissions of blockchain-based systems by reducing the number of miners. Moreover, this formulation includes maximising the trust level of these systems not only by selecting miners with high reputation values but also by the degree of decentralisation in the blockchain network, where decentralised trust is fundamental to the operations of these systems. We follow the definition of trust and reputation described in Chapter 2. There is an inherent trade-off between the number of miners, energy consumption, carbon emissions, decentralisation, and miners' reputations within blockchain-based systems [64]. The more miners a blockchain network has, the more energy is consumed, the greater the levels of carbon emissions, and the more decentralised and trusted it becomes. Furthermore, better decentralisation of miners leads to greater resistance against censorship of individual transactions and, consequently, greater trust in the system. In addition, a high number of reputable miners makes a blockchain-based system more trustworthy. We use miners' reputations to identify the trustworthiness of blockchain-based systems.

4.4.1 Solution Representation

Solution representation determines how the problem is structured in the EAs and the genetic operators that can be used. In the proposed model, the chromosome representation is an array of nodes representing a set of miners in a blockchain network. The length of chromosomes (number of genes) is equal to the number of miners participating in the mining process. Each gene X_i holds a *Boolean* value which determines whether a miner is included.

Table 4.3: A List of Notations

Notation	Description
EM	The energy consumption for each miner (<i>kilowatt – hour</i>)
P	The amount of power used by a mining device (<i>watt</i>)
T	The hours of participating in the blockchain network per day (<i>hours</i>)
mD	The number of mining devices
ET	The total energy consumption of all participating miners in a Pareto front’s solution (<i>kilowatt – hour</i>)
m	The number of miners that compose the network of a blockchain-based system
X	The value of each gene in a Pareto front’s solution representation ($X \in \{1, 0\}$)
CM	The greenhouse gas emissions produced by a miner (<i>gram</i>)
EF	the emission factor of electricity in the miner’s location (<i>gCO₂eq/kWh</i>)
CT	The total carbon emission generated by all participating miners in a Pareto front’s solution (<i>gCO₂eq/kWh</i>)
D	The degree of decentralisation
FH	The fraction of the hashrate of a miner in a solution
h	The hashrate of a miner
h_t	The total hashrate of all participating miners in a Pareto front’s solution.
RM	The reputation value for a miner
B	The total number of mined blocks in the blockchain
b	The number of blocks mined by a miner
s	The total of fees and rewards a miner has
RT	The total reputation of all participating miners in a Pareto front’s solution
H_c	The hashrate for a miner that will be compared to other miners’ hashrate in a solution
TL	The percentage of tolerance level in a blockchain-based system

4.4.2 Optimisation Model for Blockchain-based Systems

In this model, we devise four objective functions that are mathematically formulated to minimise the total energy consumed and the total carbon emissions produced by blockchain-based systems. These also maximise trust levels based on maximising the degree of decentralisation and the reputation values for miners within blockchain-based systems. A list of notations used and their description are presented in Table 4.3.

4.4.2.1 Energy Consumption Objective

This chapter focuses on enhancing the sustainability of blockchain-based systems by saving energy used in computing procedures by miners, which accounts for the bulk of blockchain-based systems’ energy consumption. Power is a measurement of the rate at which energy is used, or a system performs work over time [241]. From this definition and due to the relationship between power, energy, and time, the energy consumption for each miner EM (*kilowatt – hour*) can be calculated by:

$$EM = \frac{\sum_{i=1}^{mD} (P_i \times T_i)}{1000} \quad (4.1)$$

where P_i is the amount of power used by a mining device i that is needed for all mining device components, including processor and memory (*watt*), T_i is the hours of participating in the blockchain network per day (*hours*), and mD is the number of mining devices since one miner could have more than one device.

As the optimisation objective is to minimise the total energy consumption ET (*kilowatt – hour*) of all participating miners in a Pareto front’s solution, the smaller the energy value is, the fitter the solution is. Therefore, we optimise the energy consumption as follows:

$$\text{Minimise: } ET = \sum_{i=1}^m X_i \times EM_i \quad (4.2)$$

where m is the total number of miners that compose the blockchain network, and X_i is the value of each gene in a solution representation. It can be either ‘1’, which denotes the miner is selected for participation in the mining process for the next block, or ‘0’, which denotes a non-selected miner.

4.4.2.2 Carbon Emission Objective

The carbon emission of electricity is the greenhouse gas emitted for producing or using a certain amount of electricity, which indicates that lowering the energy use by blockchain-based systems can reduce greenhouse gas emissions. Thus, the carbon emissions caused by the electricity used by a mining device can be defined as:

$$CM = EF \times EM \quad (4.3)$$

where CM is greenhouse gas emissions produced by a miner in grams (g), EF is the emission factor of electricity in the miner’s location (gCO_2eq/kWh), and EM is the energy consumption for each miner (*kilowatt – hour*) calculated using Equation 4.2.

We optimise the total carbon emission CT generated by all participating miners in a Pareto front’s solution as follows:

$$\text{Minimise: } CT = \sum_{i=1}^m X_i \times CM_i \quad (4.4)$$

4.4.2.3 Decentralisation Objective

As discussed in Chapter 2, decentralisation means that systems do not rely on a central party among connected and distributed nodes or peers. In blockchain-based systems, one way of quantifying decentralisation is based on the number of miners participating in the mining process. Specifically, it is useful to look at the number of miners, or how many organisations control the nodes, and their power expressed in hashrate. The hashrate power held by miners controls a network's destiny. Thus, there is no benefit of having 1000 miners competing if one miner has a 51% hashrate in the network. This is because this miner would then have the chance to control the whole network. The critical point is determining which individual has the highest hashrate or creates the most blocks. Decentralisation is essential for how the system is controlled. When a blockchain-based system has a high degree of decentralisation, it means the system has greater strength against attacks and tampering, which leads to a high level of trust in the system [64].

It is critical to have scientific decentralisation measurements to assess the level of decentralisation for blockchain-based systems. Several fields have used entropy to quantify the randomness or uncertainty of a specific mechanism or event [64]. Taking a blockchain-based system as a source of information, modelling can be used with the system serving as a random variable. In this case, the quantity of information a source puts out represents uncertainty before releasing information. For example, in blockchain-based systems, estimations can be made of how probable it is that a miner can mine the next block based on its hashrate. Following the models proposed in [64] and [65], we can calculate the self-information of the event mining blocks for a miner to use with Shannon's entropy [242].

Since decentralisation is one of the core features of blockchain technology, we use this valuable feature as one objective of our model. We use Shannon's entropy to quantify decentrality D based on the distribution of miners' hashrate to prevent one miner from mining all

blocks and taking control of the blockchain-based system (i.e., 51% attack). The optimisation of this objective is defined as:

$$\text{Maximise: } D = - \sum_{i=1}^m X_i \times (FH_i \times \log_2 FH_i) \quad (4.5)$$

where m is the number of miners in a blockchain-based system, and FH_i is the fraction of the hashrate of a miner in a Pareto front's solution. The FH_i is calculated using the following:

$$FH_i = \frac{h_i}{h_t} \quad (4.6)$$

where each miner's hashrate is represented by h_i , and the total hashrate of participating miners in the solution is h_t .

4.4.2.4 Trustworthiness Objective

In our model, the number of miners will be reduced, so we need to support the PoW consensus algorithm by increasing the trustworthiness of blockchain-based systems. The trustworthiness can be raised by calculating the reputation value for each miner. Furthermore, we can use specific trustworthiness evaluation models to compress a miner's historical activities into a reputation value for each miner. Since building a trust or reputation model is not an essential contribution of this chapter, we adopt a simple model inspired by the ideas of PoW and PoS.

In our optimisation model, we use a sigmoid function to evaluate the trustworthiness of a blockchain-based system after each published block. We collect two features about each miner and use them to calculate their reputation values. The first feature is the number of blocks a miner has added to the blockchain, while the second is the miner's stake. Similarly to PoW, we assume that the miner will not assault the network after doing much work with significant requirements. Furthermore, the miner's ownership of the amount of currency should protect against attacks on the network because miners do not want to lose their coins, as with PoS. In this model, the reputation value for the miner is the sum of the sigmoid function for each feature. Thus, the reputation value for each miner RM within a blockchain network can

be calculated as:

$$RM = \sum_{i=1}^B \left(\frac{1}{1 + e^{-b}} + \frac{1}{1 + e^{-s}} \right) \quad (4.7)$$

where B is the total number of mined blocks in the blockchain, b is the number of blocks mined by a miner, and s is the total of fees and rewards the miner has.

The last objective to maximise is the total reputation RT of participating miners in a Pareto front's solution, which maximises the trustworthiness of the blockchain network. It is worth mentioning that the level of trust of a Pareto front's solution does not follow the number of miners. Therefore, some Pareto front's solutions show a lower level of trust with a higher number of miners than other solutions with fewer miners. However, a blockchain-based system's highest trust can be achieved when all miners participate in mining processes.

$$\text{Maximise:} \quad RT = \sum_{i=1}^m X_i \times RM_i \quad (4.8)$$

4.4.2.5 Fitness Functions Constraints

Equations (4.2), (4.4), (4.5), and (4.8) share same constraints, as follows:

$$\begin{aligned} H_c &< TL\% \sum_{i=1}^m X_i \times h_i - H_c \\ \sum_{i=1}^m X_i &> 1 \\ X_i &\in \{1, 0\} \end{aligned}$$

where h_i is the hashrate for a miner i in the blockchain network, H_c is the hashrate for a current miner that will be compared to other miners' hashrate, and TL is the percentage tolerance level that a decision-maker must identify for the system. So, for example, the decision-maker can determine the TL to be 50% or less.

These constraints ensure that a miner's hashrate should be less than the TL , such as

50% or 30%, of the total hashrate for all other miners in the individual solution. When a malicious miner has a total hashing power above 50% or 30% of the whole network's hashing powers, a double-spending attack or a selfish mining attack can be launched [243], [244]. Therefore, this constraint ensures avoiding such a vulnerability. Also, they ensure that more than one miner should participate in the mining process to prevent centralisation.

We use the above objectives to form four fitness functions. We have at least one pair of conflicting objectives in each fitness function.

4.5 Experiment Design

This section discusses the design of experiments to show how our model can improve the environmental sustainability of blockchain-based systems using evolutionary algorithms by selecting a set of miners. First, section 4.5.1 presents the research questions we aim to answer in this chapter. Then, Section 4.5.2 introduces the evaluation procedure applied to answer the research questions. Finally, Section 4.5.3 shows the implementation details.

4.5.1 Research Questions

This chapter intends to show the advantages of reformulating the miners' subset selection problem in blockchain-based systems as an SBSE problem in improving the environmental sustainability of these systems. The chapter endeavours to answer the second research question introduced in Chapter 1: **RQ2: How can the environmental sustainability of a blockchain-based system be optimised without compromising its inherent properties, such as decentralisation and trustworthiness?**

To answer this question, we need to answer some sub-questions:

RQ2.1: To what extent can our static optimisation model balance the energy consumption and carbon emission of a blockchain-based system with its core properties: decentralisation and trustworthiness?

RQ2.2: Are the selected evolutionary algorithms effective in solving our blockchain miner

selection problem compared with Random Search (RS)?

RQ2.3: Among the used algorithms, which algorithm can achieve the best performance?

4.5.2 Evaluation Procedure

Now, we present the evaluation procedure used to answer our research questions.

4.5.2.1 Evaluating the Effectiveness of the model

To answer **RQ2.1**, we compare each algorithm's best solution in terms of energy use and carbon emission and the reductions in the conflicting objectives (i.e., decentralisation and trustworthiness) compared to the original solution. The original solution is the complete set of miners within a blockchain-based system (i.e., the standard PoW). We focus on comparing the algorithms solutions for the fitness function that considers the four objectives of blockchain-based systems (i.e., energy consumption vs carbon emissions vs decentralisation vs trustworthiness). Considering this fitness function, we can show the effects of minimising energy consumption and carbon emissions on decentralisation and trustworthiness.

4.5.2.2 Performance Metrics

the performance metric in this chapter means the algorithm's ability to evolve non-dominated solutions that cover as much as possible of the solution space. To compare algorithms' performance, we use the hypervolume metric, which computes the d-dimensional volume of the dominated portion of the objective space by the non-dominated solutions from a reference point [208]. We use this metric since it compares algorithms regarding diversity and convergence. This metric is widely used in the literature for evaluating algorithms' performance and for the solution selection procedures [245]. The higher the hypervolume value of an algorithm, the better the performance.

Since the hypervolume metric uses a reference point for comparing MOEAs, selecting this reference point for calculating the hypervolume is crucial. It can significantly impact the performance evaluation of algorithms and the interpretation of results [246]. Therefore, it

should be fairly determined.

There are various ways to obtain a reference point for optimisation problems, encompassing utilising the worst objective value among all identified solutions, the boundary of the optimisation problem and the nadir point from the Pareto front of all discovered solutions [247]. However, the choice of reference point remains an open issue in hypervolume-based comparisons of EMO algorithms. In addition, there is still no consensus on the best method for choosing a reference point for a given problem [246].

The hypervolume indicator generally favours knee and boundary points of the Pareto front over well-distributed ones [248]. This is because the hypervolume indicator measures the volume of the space dominated by the reference point, and knee and boundary points are often located in areas of low density. Additionally, it is necessary to establish the reference point at a fair distance from the boundaries of the solution sets; otherwise, it will not be visible to all Pareto fronts produced by each algorithm under comparison [249].

In this thesis, we have chosen a boundary point (i.e., the worst possible value for each objective) as the reference point for calculating the hypervolume indicator. This is a reasonable and fair choice for our specific problem and allows for a more robust and interpretable comparison of the MOEAs. It has several advantages regarding fairness and visibility.

Using a reference point as a boundary point, which is fairly distant from the solution set's boundaries, ensures that the reference point is visible to all Pareto fronts produced by each algorithm under comparison, including the extreme points or boundary points of the Pareto front. This makes for a fairer comparison, as all algorithms are evaluated against the same reference point. These points are often crucial for understanding the shape and distribution of the Pareto front [250].

To answer **RQ2.2**, we compare the selected algorithms' hypervolume with the hypervolume of RS's non-dominated set. The comparison includes showing statistical differences between RS and other algorithms using the right-tailed Wilcoxon rank-sum test [251]. This conservative non-parametric test makes no assumptions about the datasets' distribution. The null hypothesis states that the hypervolume values of algorithm X are greater than RS's hy-

Table 4.4: Implementation Details

Variable	Value
Number of Miners	160
Network Total Block Number	4073
Bitcoin Network Hashrate	107,611,000.0 TH/s
Bitcoin Reward	6.25 BTC
Bitcoin Fee	0.00028188 BTC
Bitcoin Average Transaction Size	250 Byte
Mining Device Hashrate	110 TH/s
Mining Device Power	3,250 Watt
Miner Running Time	24 Hours
Percentage of Tolerance Level	50%
Fitness Evaluation	40,000

pervolume values. We use the Wilcoxon test because most of the resulting datasets have non-normal distributions. The statistical technique used to determine whether an algorithm’s hypervolume values come from a normal distribution is the Shapiro-Wilk test [252].

We then use the Vargha and Delaney \hat{A}_{12} effect size to measure the approximate differences between the RS performance and the selected algorithms. \hat{A}_{12} is a non-parametric measure and calculates the proportional difference between two datasets [253]. For interpreting the effect size, this approach measures the quantity of the difference in four ranges: no difference (0.5), a negligible difference (up to 0.56), a small effect (up to 0.64), a medium difference (up to 0.71), a large difference (larger than 0.71). Furthermore, this approach calculates the expected probability that algorithm one performs better than algorithm two. For instance, if $\hat{A}_{12} = 0.8$, then algorithm one is expected to outperform algorithm two 80% of the time.

To answer **RQ2.3**, we conduct a pairwise comparison between every pair of the selected algorithms using the Wilcoxon rank-sum test and \hat{A}_{12} effect size.

4.5.3 Implementation Details

The details of the implementation used to run our experiments are presented in the sections below. Also, a summary of the implementation details is presented in Table 4.4.

4.5.3.1 Experiment Settings

We integrated our proposed fitness models discussed in Section 4.4.2 with five evolutionary algorithms. We use the Random Search (RS) as a baseline for our comparison. For the algorithm implementations, we used a Java-based Multi-Objective Evolution Algorithm framework (MOEA Framework) ¹. For each algorithm, we leave all variation operators and variation probabilities at their default values (see Table 4.5 and 4.6 for these values). Each algorithm is run with 40,000 fitness evaluations. To account for the stochastic nature of the algorithms, we run each algorithm 100 times. All experiments are performed on a Windows 10 machine with 24GB memory and an Intel i7-6700 CPU clocked at 3.4GHz.

Table 4.5: A List of Notations for Evolutionary Algorithms Parameters

Parameter	Description
populationSize	The size of the population
sbx.rate	The crossover rate for simulated binary crossover
sbx.distributionIndex	The distribution index for simulated binary crossover
pm.rate	The mutation rate for polynomial mutation
pm.distributionIndex	The distribution index for polynomial mutation
offspringSize	The number of offspring generated every iteration
k	Crowding is based on the distance to the k-th nearest neighbour
archiveSize	The size of the archive
bisections	The number of bisections in the adaptive grid archive
indicator	The indicator function (e.g., hypervolume, epsilon, crowding)
divisions	The number of divisions
epsilon	The ϵ values used by the ϵ -dominance archive, which can either be a single value or a comma-separated array (this parameter is optional)

4.5.3.2 Bitcoin Simulator Settings

Simulation methods are used in multiple fields of science. The simulations enable us to obtain insight into a system's behaviour and simplify the deployment and implementation of protocols. Simulations allow the investigation of large-scale systems with a large number of nodes using one machine and also to get findings in a reasonable time. Within large-scale blockchain networks, there are difficulties in procuring information related to the entire network, except where nodes offer information regarding themselves. Also, it is only sometimes

¹MOEA Framework version 2.13 available at <http://moeaframework.org>, accessed on December 10, 2020.

Table 4.6: The values of the Parameters for the Used Algorithms

Parameter	Random	NSGA-II	SPEA2	PAES	IBEA	NSGA-III
populationSize	160	160	160	-	160	160
sbx.rate	-	1.0	1.0	-	1.0	1.0
sbx.distributionIndex	-	15.0	15.0	-	15.0	15.0
pm.rate	-	$1/N$	$1/N$	$1/N$	$1/N$	$1/N$
pm.distributionIndex	-	20.0	20.0	20.0	20.0	20.0
offspringSize	-	-	100	-	-	-
k	-	-	1	-	-	-
archiveSize	-	-	-	100	-	-
bisections	-	-	-	8	-	-
indicator	-	-	-	-	hypervolume	-
divisions	-	-	-	-	-	4
epsilon	Problem dependent	-	-	-	-	-

possible to observe the actual behaviour within a large-scale network. For this reason, it is neither feasible nor practical to undertake experimentation within large-scale blockchain networks. Although the case study and evaluation are conducted in a controlled and simulated environment, the evaluation is careful to emulate those dynamics that can stress systems at scale.

Here, we use a blockchain simulation framework called Bitcoin-Simulator [13] that uses real and artificial data, such as the distribution of miners' hashrates and locations. It is a widely used simulator for the blockchain environment. Bitcoin-Simulator simulates the working of blockchain-based systems that use the PoW consensus algorithm and their network layers. Thousands of nodes and events can be tracked by the simulator. It replicates the PoW process for miners within a blockchain network by assigning each miner a particular mining hashrate and location. We utilise the simulator to collect data used to implement our optimisation model. The data collection involves running the simulator to mine 4073 blocks, equivalent to one month of mining. There are 160 miners in the simulation. We have set the percentage tolerance level in the blockchain-based system to be 50% to prevent miners from performing a double-spending attack.

To replicate a real-world scenario of a blockchain-based system, we use the basic properties of Bitcoin's network, such as the hashrate, rewards, and fees as shown in Table 4.4 ².

²Information was retrieved from <https://blockchair.com/bitcoin> on November 30, 2020.

Table 4.7: The Distribution of Miners’ Locations and their Hashrates Percentages.

Country	Hashrate Percentage	Country	Hashrate Percentage
Canada	0.8%	Kazakhstan	6.2%
China	65.1%	Malaysia	4.3%
France	0.2%	Norway	0.5%
Germany	0.6%	Paraguay	0.3%
Iceland	0.4%	Russia	6.9%
India	0.1%	Thailand	0.3%
Iran	3.8%	United States	7.4%
Italy	0.3%	Venezuela	0.4%

We use Bitcoin as the most widely known blockchain-based system [254]. We determine the distribution of miners’ locations and their hashrate percentages based on information retrieved from CBECI ³. Table 4.7 shows the distribution of miners’ locations and their hashrates percentages of Bitcoin’s network hashrate, divided into 16 countries where each country has ten miners.

4.5.3.3 MOO Model Assumptions

In blockchain networks, we cannot accurately estimate how much electricity is used for mining operations because it is impossible to determine the number of mining devices in a network or which devices are active at any given time [44], [190]. In order to determine the number of mining devices in a blockchain network, we first assume that all miners use the most efficient mining device and that as a miner’s hashrate increases, their number of devices increases. We base our assumption on the fact that using inefficient devices leads to leaving the network due to not receiving profits from successful mining [44], [190]. In addition, we do not assume that a miner would have a high number of traditional devices that use CPU and Graphics Processing Unit (GPU) due to their inefficiencies compared to the current state-of-art Application-Specific Integrated Circuit (ASIC). Consequently, the number of devices for each miner is found by dividing the hashrate for each miner by the hashrate for the selected mining device type. The power of this device is also used to calculate the energy consumption of each miner. We use

³<https://ccaf.io/cbeci>, retrieved on August 31, 2021.

the hashrate of Antminer S19 Pro produced by Bitmain Technology Holding Company ⁴. Its hashrate can reach 110 TH/s , and its mining power is 3,250 $watt$.

Moreover, we assume that miners try to mine blocks for 24 hours because they want to gain profit following the same assumption published in [45], [190]. For calculating the carbon emission, we first use the distribution of miners' locations retrieved from CBECI and set it into the simulator. Then, we use miners' locations to calculate the carbon emission produced by each miner using emissions factors published for miners' countries in [255].

4.6 Results and Discussion

In this section, we present the results of our experiments. First, we group our experiments based on the proposed fitness functions presented in Section 4.4.2. Then, we present our results and discuss **RQs 2.1-2.3**.

To investigate the performance of the algorithms on the real-world blockchain miners' selection problem, we need to compute the actual Pareto front. Similarly to [256], [257], we compute the Pareto front by combining the outcomes of 500 independent runs of the algorithms for each proposed fitness function.

4.6.1 Objectives Space Results

4.6.1.1 Energy Consumption and Trustworthiness Objective Space

Figure 4.1 shows the approximated Pareto front found by each algorithm during the 100 runs in blue and the Pareto front in black. The x-axis shows the energy consumption, and the y-axis presents the reputation score of miners (i.e., the trustworthiness of a blockchain-based system) calculated by Equation 4.7. As can be seen, NSGA-II, SPEA2, IBEA, and NSGA-III consistently find better non-dominated solutions from the Pareto fronts. Clearly, PAES's non-dominated solutions are distant from the Pareto front, which shows that having only a mutation operator promotes exploitation over exploration. This is because mutation operators

⁴<https://www.bitmain.com>

exploit the neighbouring areas of the current solution, whereas crossover operators create jumps in the search space to explore it better [258]. RS is the worst-performing algorithm when minimising energy use and maximising trustworthiness. NSGA-II, SPEA2, and NSGA-III obtain a better spread than IBEA. This is because the IBEA algorithm uses the hypervolume indicator in its selection operator. Most of its non-dominated solutions (85+%) occupy the regions of the search space where the hypervolume is maximised. This behaviour of IBEA has also been observed in the rest of the experiments.

It is worth mentioning that while IBEA has been shown to perform well on many multi-objective optimisation problems, it may not perform as effectively in diversifying produced solutions for some problems [259], [260]. This indicates that IBEA’s mechanism can lead to premature convergence, where the algorithm converges to suboptimal regions in the early stages of the evolutionary process before fully exploring the solution space. In other words, this method may have difficulty in effectively exploring the entire Pareto front, as it is prone to becoming trapped in specific regions of the search space. These findings are consistent with previous studies, such as [259], [261], [262].

4.6.1.2 Energy Consumption, Carbon Emissions, and Trustworthiness Objective Space

Figure 4.2 shows the approximated Pareto front found by each algorithm in the 100 runs and the computed Pareto front. The results are colour-coded by the carbon objective values calculated by Equation 4.4. The x and y-axes, respectively, represent the energy use and the reputation score. As can be seen, the non-dominated solutions created by NSGA-II and SPEA2 cover larger portions of the computed Pareto front compared to other algorithms. Interestingly, NSGA-III’s non-dominated solutions are slightly distant from the Pareto front and are more scattered than those of NSGA-II, SPEA2, and IBEA on the energy and trustworthiness dimensions. In addition, since the IBEA algorithm uses the hypervolume indicator in its selection operator, the majority of its non-dominated solutions (85+%) occupy the regions of the search space where the hypervolume is maximised. Similarly to the results of energy

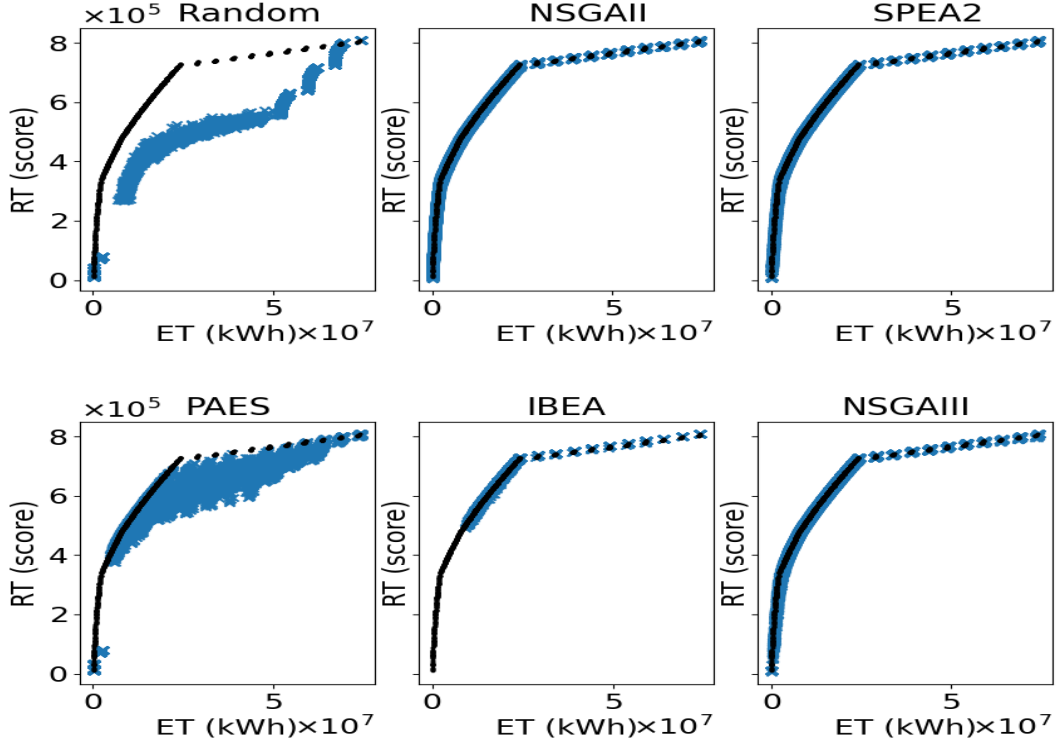


Figure 4.1: The results of trading-off energy consumption with trustworthiness using five algorithms. The Pareto front is shown in black.

consumption vs trustworthiness experiments, PAES and RS performed poorly compared to other algorithms in terms of covering the Pareto front.

4.6.1.3 Energy Consumption, Decentralisation, and Trustworthiness Objective Space

Figure 4.3 presents the results of minimising energy use while maximising the decentralisation and the trustworthiness of a blockchain-based system. The x-axis and y-axis represent the energy use and reputation score, while the colour scale of each point represents the decentralisation score calculated by Equation 4.5. The overall results of the algorithms are similar to those in Figure 4.2 except that the NSGA-III algorithm covers fewer regions of the Pareto front. In addition, it can be observed that its solutions at the end of the spectrum, where the trustworthiness is maximised, are slightly distant from the Pareto front compared to NSGA-II, SPEA2, and IBEA.

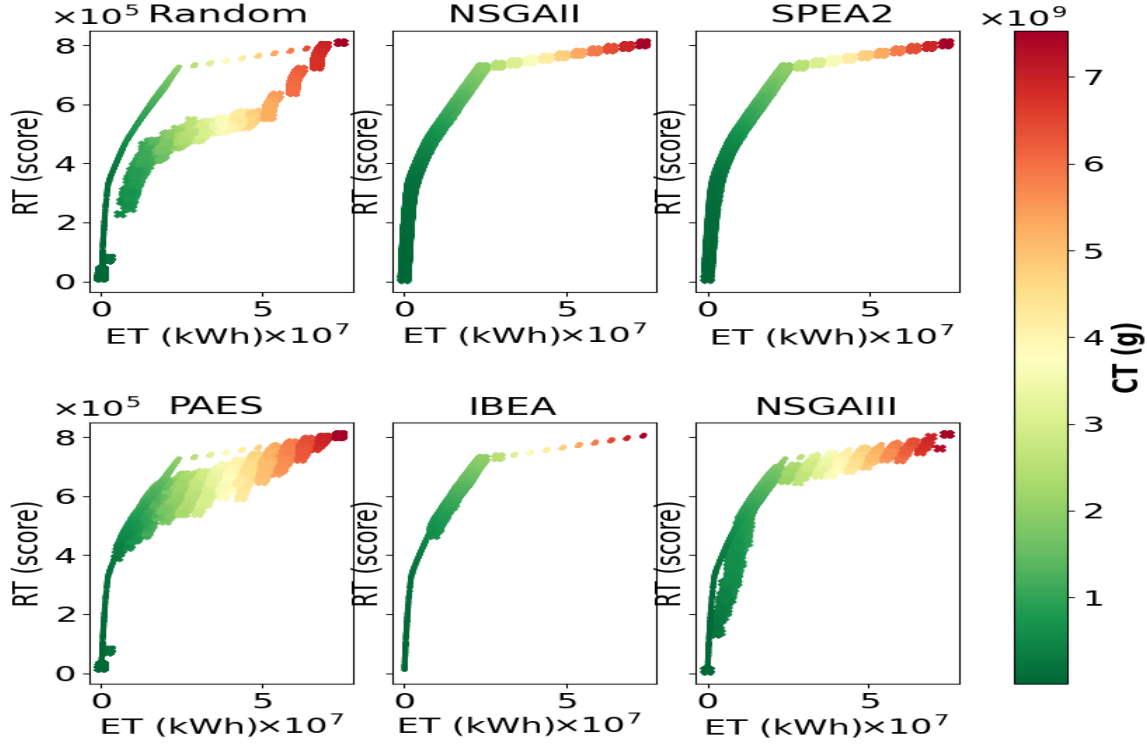


Figure 4.2: The results of trading-off energy consumption with carbon emissions and trustworthiness using five algorithms. The dot markers show the Pareto front.

4.6.1.4 Energy Consumption, Carbon Emissions, Decentralisation, and Trustworthiness Objective Space

Figure 4.4 shows the many-objective optimisation experiment results. The x-axis, y-axis, and z-axis represent the energy use, reputation, and decentralisation scores, respectively. The results are colour-coded by carbon values. As can be seen, the NSGA-II and SPEA2 non-dominated sets include more solutions of the Pareto front. However, as the problem dimensionality increases, their ability to consistently find the Pareto front's solutions degrades (i.e., they have more distant solutions from the Pareto front than IBEA and NSGA-III). On the other hand, IBEA non-dominated solutions are less diverse in terms of objective values, but they reside on the Pareto front. The NSGA-III non-dominated set covers slightly more regions of the Pareto front than IBEA's non-dominated solutions. The PAES and RS algorithms found the lowest number of Pareto front's solutions. The former is a mutation-based algorithm which effectively explores the neighbours of the promising solutions. However, as the problem dimensionality increases, the algorithm's effectiveness decreases.

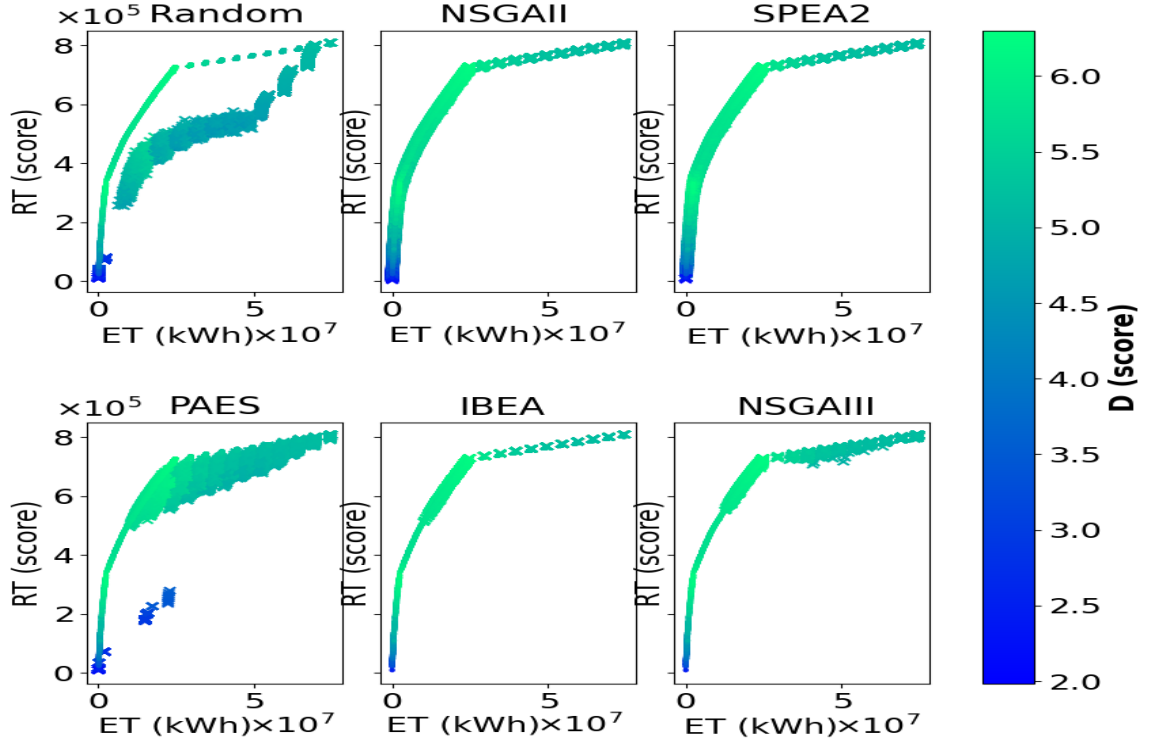


Figure 4.3: The results of trading-off energy consumption with decentralisation and trustworthiness using five algorithms. The Pareto front is shown using the dot marker.

4.6.2 Research Questions Answers

4.6.2.1 Improvement in Energy Consumption and Carbon Emission

To answer **RQ2.1**, we compare the original solution's objective value (i.e., all miners included) to the objective values of the solutions found using EAs. The reported results are the ratio of a solution's objective score to the original solution's objective score. Overall, using the proposed fitness functions helps the optimisers to explore the search space and find optimal solutions balancing energy consumption and carbon emissions (i.e., efficient solutions for energy consumption and carbon emissions) without compromising the properties of blockchain technology: decentralisation and trustworthiness. Indeed, energy savings and low carbon emissions are achieved with some reductions in the conflicting objectives. It is worth mentioning that Pareto-based algorithms are used to produce non-dominated solutions considering decision-makers' preferences. To discuss the reduction of improving energy consumption and carbon emissions on decentralisation and trustworthiness, we focus on the fitness function:

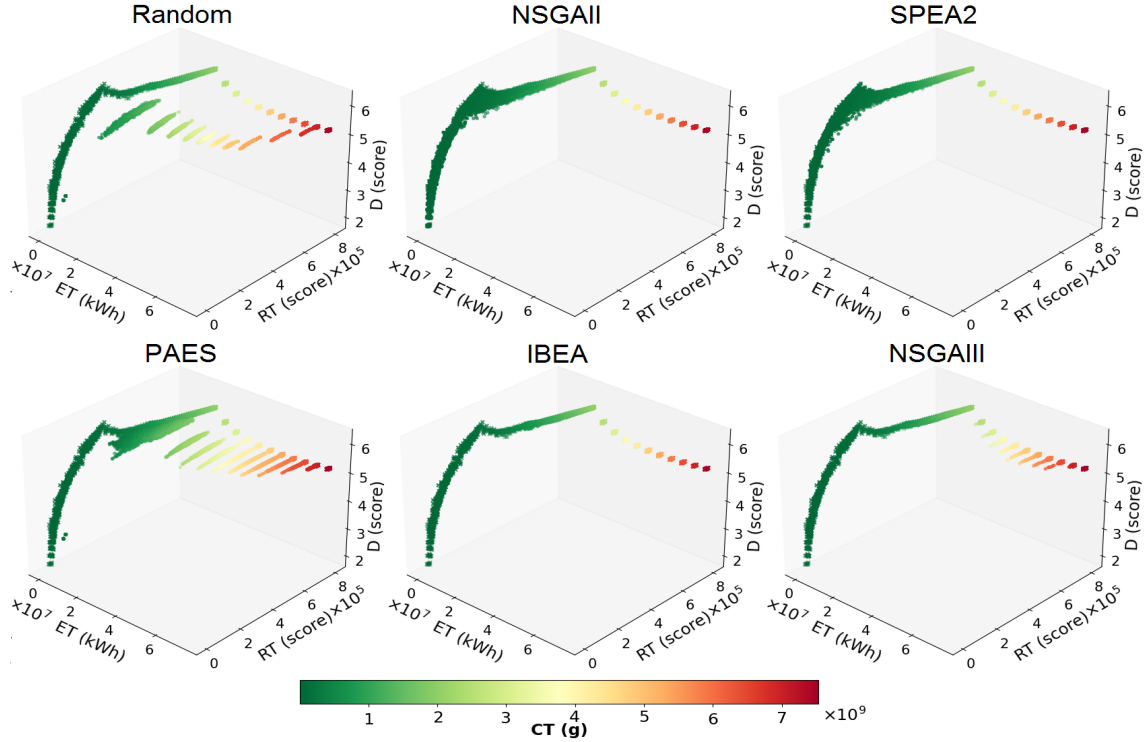


Figure 4.4: The results of trading-off energy consumption with carbon emissions, decentralisation, and trustworthiness using five algorithms. The Pareto front is shown using the dot marker.

energy consumption vs carbon emissions vs decentralisation vs trustworthiness.

NSGA-II and SPEA2 non-dominated sets for this fitness function include more Pareto front solutions than other algorithms. They include solutions that can enhance the environmental sustainability of blockchain-based systems by improving energy efficiency, carbon efficiency and decentralisation with a slight reduction in trustworthiness. For example, there is a solution in NSGA-II non-dominated sets that can minimise energy consumption by 78.1% and carbon emissions by 82.4%, with 13.6% improving in decentralisation at the cost of only 25% of overall trustworthiness. Also, SPEA2 non-dominated sets include a solution that improves the energy efficiency by 78% and reduces the amount of carbon emissions by 82.1% while increasing decentralisation by 13.8%. With all these improvements, trustworthiness is still not less than the first quantile of the trustworthiness of blockchain-based systems that use the original PoW. It is worth noting that IBEA is managed to find solutions similar to NSGA-II and SPEA2 although its non-dominated sets are minimal compared to those of other

MOEAs. In addition, these algorithms include other solutions that substantially reduce energy use and carbon emissions with a slight improvement in decentralisation; however, the trustworthiness is decreased by more than 75%. Solutions with such objective values can be used in private or consortium blockchain-based systems. This is because miners are already known to organisations employing such kinds of blockchains.

Although the carbon emissions rate seems to strictly follow the increase of energy consumption at the same rate in Figure 4.4, this does not mean that miners that consume high energy will produce high carbon emissions compared with other miners that consume low energy. In some cases, we can have a miner that consumes a low amount of energy but is located in a country with a high carbon intensity, leading the miner to produce high carbon emissions and vice versa. As a result, energy consumption and carbon emission can be considered as conflicting objectives. Nevertheless, having the carbon emissions results in Figure 4.4 that follow the energy increase shows that the optimiser has favourably selected miners from the same regions with the same carbon intensity.

4.6.2.2 Performance Analysis

For answering **RQ2.2**, we compare the hypervolume of the non-dominated set of each algorithm with the RS's non-dominated set's hypervolume. We use the two-tailed Wilcoxon rank-sum test with a threshold of $p \leq 0.05$ to conduct the comparisons. The null hypothesis is that algorithm X's hypervolume is significantly greater than the RS algorithm's. To compute the difference, we use Vargha and Delaney effect size. In addition, we conducted a comparison between every pair of algorithms (pairwise comparison) to answer **RQ2.3**.

Figure 4.5 presents the statistical test results and the effect size for each algorithm's performance using the four proposed fitness functions. The label S in each cell denotes a significant difference, whereas label I indicates a non-significant difference. The cell colour shows the effect size. As seen in Figure 4.5, across all fitness functions, each algorithm's hypervolume is significantly greater than that of RS (see the first column of every heatmap). In addition, the difference between RS performance and other algorithms is large. This is consistent with

the visual representation of the algorithms' non-dominated set in Figures 4.1, 4.2 and 4.3.

Now, we answer **RQ2.3**. In the first fitness function (i.e., energy consumption vs trustworthiness) and the third fitness function (i.e., energy consumption vs decentralisation vs trustworthiness), their figures show that NSGA-II's performance is the best among all algorithms. It indicates that it produced the most diverse non-dominated sets that cover the largest portion of the search space among other non-dominated sets. PEAS has the second-worst performance due to its mechanism in exploring the search space. Among all algorithms used, IBEA's performance is the best in exploring the search space using the second fitness function (i.e., energy consumption vs carbon emissions vs trustworthiness). We have investigated its non-dominated solutions and found that they are centred in the region where the hypervolume is maximised. This is due to the algorithm selection preference among solutions which prefers a larger hypervolume. However, as can be seen in Figure 4.3, such a mechanism restricted the solution diversity in the fitness landscape.

Interestingly, SPEA2 has the best performance among other algorithms in exploring the solution space using the fourth fitness function (i.e., energy consumption vs carbon emissions vs decentralisation vs trustworthiness). However, it is worth noting that in terms of run-time, SPEA2 has the second-worst run-time after the PAES algorithms. Our results indicate that the expensive mechanism in determining the strength of solutions enables SPEA2 to outperform other algorithms in our proposed many-objective problem.

Although NSGA-III is designed for many-objective problems, it does not perform well in our many-objective problem. We conjecture that the NSGA-III lightweight niching mechanism, which is based on reference points, is not as effective as other algorithms' (i.e., SPEA2, NSGA-II, and IBEA) expensive diversity-preservation mechanisms. It depends on reference points being created to virtually represent how the Pareto front would look in the objective space. The quality of the created niches dramatically influences the performance of the algorithm. It is worth mentioning that the performance of NSGA-III is worse than NSGA-II and SPEA2 in [263], as well.

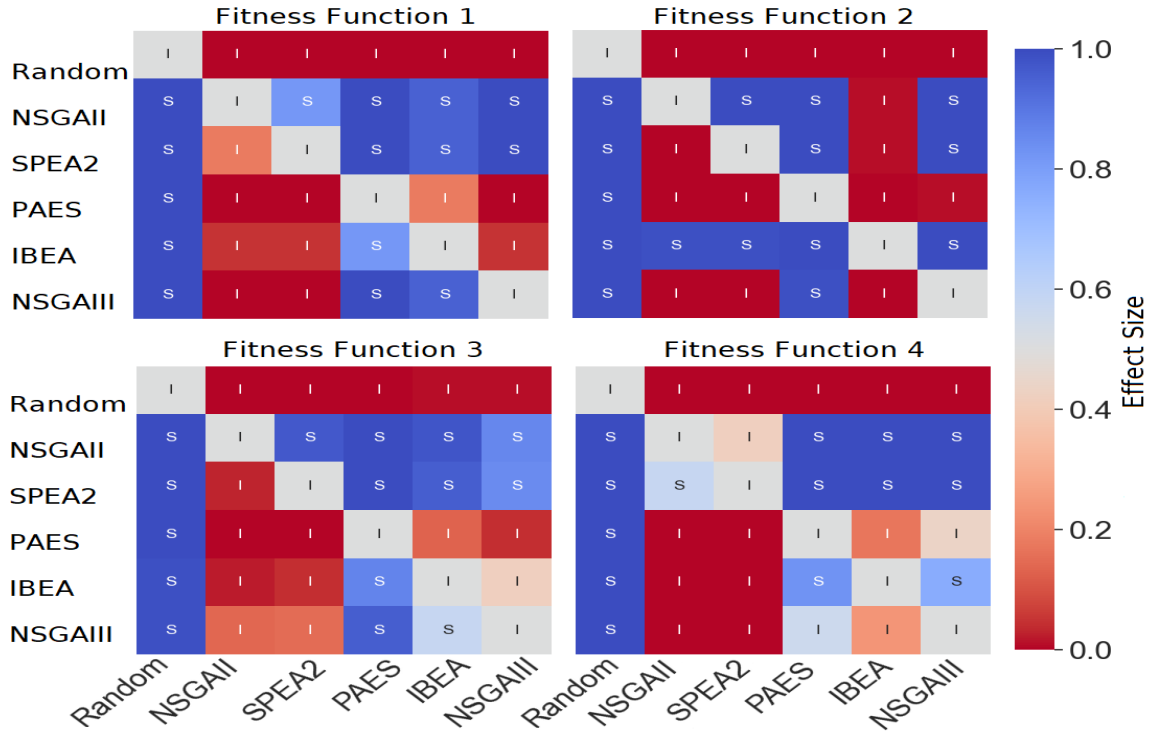


Figure 4.5: Algorithms effect sizes and P-values. The letter S indicates significant differences, and the letter I denotes insignificant differences.

4.7 Conclusion

In this chapter, we have reformulated the problem of optimising the environmental sustainability of blockchain-based systems as a multi-objective optimisation problem. We attempt to minimise energy consumption and carbon emission while considering the decentralisation and trustworthiness of blockchain-based systems. To solve the problem, we have proposed four different fitness functions. Our results show that energy usage and carbon emissions can be reduced by 78% and 82%, respectively. These improvements come with increasing in decentralisation by 13.8% and a reduction in trustworthiness by 25% (non-functional properties). Moreover, using private blockchain-based systems, where miners are known, can save energy and carbon emissions by more than 90%. Finally, we have compared five evolutionary algorithms with different diversity-preservation mechanisms to evaluate our proposed model. The comparisons revealed that no algorithm is consistently superior using its default settings.

As with every model, our proposed model has some limitations. For calculating the

reputation value for miners, we have adopted a simple model inspired by the ideas of PoW and PoS. However, such a model may suggest false Pareto fronts due to the need for more knowledge about the miners, such as their behaviour in mining blocks. For example, the used reputation model cannot differentiate between old miners, newly joined miners or miners that repeatedly leave and join the network. Also, it cannot predict malicious miners. These call for a reputation model that can more effectively measure miners' reputation within blockchain-based systems (Addressed in Chapter 5). In addition, the current model is static, and we use it in an offline optimisation scenario (i.e., optimise first, then deploy). Also, it does not consider environmental changes and the use of green energy. Therefore, this calls for a self-adaptive model that can be used in dynamic optimisation scenarios, where the environment changes over time, including green energy usage, with consideration of decision-makers' requirements (Addressed in Chapter 6).

Chapter Five

A REPUTATION MODEL FOR MINERS IN BLOCKCHAIN NETWORKS

Context. Many researchers have proposed solutions to enhance the environmental sustainability of blockchain technology, such as using alternative consensus algorithms that rely on existing trust or reputation models to only allow reputable miners to create new blocks. However, choosing those miners remains challenging because of the architecture of blockchain technology, which offers a free and open environment for miners to take part in mining new blocks. Therefore, there is a great need for a dynamic reputation model to evaluate miners' behaviour within blockchain-based systems that use mining-based consensus algorithms.

Objective. This chapter proposes the first reputation model that influences how reputation is fundamentally managed within blockchain-based systems. Also, it introduces several important properties required to design reputation models for blockchain-based systems. The reputation model aims to promote the environmental sustainability of blockchain-based systems when it integrates with existing consensus algorithms to select miners based on their reputation values.

Method. We propose a novel reputation model that dynamically assesses the reputation of individual miners by reflecting the miners' behaviour within a blockchain-based system that uses the traditional Proof of Work consensus algorithm. The model is evaluated analytically and compared to other trust and reputation models for miners. In addition, we perform experimental evaluations to represent the performance of our model and its accuracy in detecting malicious miners. Finally, we have evaluated the effectiveness of using the model regarding the energy consumption and carbon emissions of blockchain-based systems.

Results. The evaluation shows that our model fulfils several desirable properties that should

always be satisfied by reputation models for blockchain-based systems. In contrast, other models do not always meet these properties. Also, our experiments demonstrate the model's effectiveness in detecting malicious miners with more than 93%. Regarding the environmental sustainability of these systems, the model can reduce the energy consumption to 51% on average of the total energy consumed in the standard PoW consensus algorithm. In addition, the carbon emissions of the systems can be reduced to 77% on average compared to PoW.

Conclusion. Our model is used to assess the reputation of miners within a blockchain-based system. It can be potentially integrated with any consensus algorithm that uses a mining process. Also, it has the potential to enable environmentally sustainable mining processes.

Contribution to Literature. This chapter is contributed to the research literature through our published full paper "*MinerRepu: A Reputation Model for Miners in Blockchain Networks*". This chapter is written based on this paper.

5.1 Introduction

In blockchain-based systems, there is no middle or hub node to ensure the correctness of the ledgers on distributed nodes. Also, nodes do not need to trust other nodes. This leads to proposing consensus protocols that ensure the consistency of ledgers in different nodes. Thus, consensus algorithms play an essential role as they are trust or reputation models for selecting miners to mine blocks within blockchain-based systems. The most common algorithm to reach a consensus in blockchain-based systems is PoW, but this consensus algorithm is not energy-efficient. Therefore, researchers have attempted to enhance the energy consumption of PoW by integrating it with reputation systems that build trust among a miners' community by utilising the past experiences of each miner. The idea of this integration is to assist in making judgements and recommendations on selecting reputable miners, which can enhance the energy consumption efficiency of blockchain-based systems that use PoW.

Since a blockchain network is a structured P2P network, much research has developed centralised and decentralised trust and reputation models for P2P networks that could be used. However, these models are not applicable to blockchain communities due to the architecture of blockchain technology, where mining activity is the vital role of miners within blockchain networks rather than the interactions between nodes. In addition, a few consensus algorithms are proposed to calculate the trust or reputation of miners within blockchain networks based on trust or reputation metrics (see Chapter 3). However, these algorithms rely on existing trust or reputation models that may not be suitable for evaluating miners' behaviour within blockchain-based systems that use mining-based consensus algorithms. Also, they compute trust and reputation values based on metrics not evaluated for blockchain-based systems. Therefore, Chapter 3 demonstrates that research is needed to investigate how trust and reputation models can help define trusted and malicious miners within blockchain networks, considering blockchain technology characteristics and miners' dynamic behaviour. Also, there is a need to see how these models can improve energy efficiency and reduce carbon emissions, leading to blockchain-based systems' overall sustainability.

This chapter answers the thesis's third research question introduced in Chapter 1:

RQ3: How can we evaluate the reputation of miners within blockchain-based systems, considering the dynamic of miners' behaviours, to support the environmental sustainability of these systems?

To answer this research question, we develop MinerRepu, a novel reputation model for assessing the reputation of individual miners by reflecting the miners' behaviour within a blockchain-based system that uses the traditional PoW consensus algorithm. To the best of our knowledge, our model is the first reputation model to influence how reputation is fundamentally managed within blockchain-based systems. The model can be applied to blockchain-based systems that use mining-based consensus algorithms such as PoW. Also, it can be integrated with other trust architectures for other domains, such as the proposed architecture for IoT in [264]. The most important advantage of this model is that it can promote energy consumption efficiency for blockchain-based systems when it overlies existing consensus algorithms to select trusted miners based on their reputation values.

The main contributions of this chapter are summarised as follows:

- We review the state-of-the-art trust and reputation models for blockchain-based systems and identify the general lack of any similar model.
- Drawing on the conclusions of this review, a novel model for calculating and evaluating the reputation of miners in blockchain-based systems is proposed.
- An analytical framework for evaluating and comparing trust and reputation models for miners in blockchain networks is presented, and criteria against which a model might be evaluated are identified.
- We conduct several experiments to show the changes in miners' reputation values over time, and we demonstrate how malicious miners can be detected.
- Experimental evaluations are performed to demonstrate how using our model for blockchain-based systems can save energy and reduce carbon emissions compared to PoW.

The rest of the chapter is organised as follows: First, Section 5.2 gives an analysis of the existing literature on consensus algorithms for blockchain. Next, Section 5.3 describes our reputation model, and the evaluation of the model is presented in Section 5.4. Finally, Section 5.5 concludes the chapter.

5.2 Related Work

Several alternative consensus mechanisms have been put forward to tackle energy consumption inefficiencies in blockchain, particularly concerning PoW. These algorithms can be classified into proof-based consensus algorithms and vote-based consensus algorithms as presented in Chapter 3. This chapter focuses on algorithms under the first category. These algorithms utilise trust or reputation models to select miners to mine blocks within blockchain-based systems. These kinds of algorithms can be grouped into trust-based consensus algorithms and reputation-based consensus algorithms. We have discussed most of these consensus algorithms in Chapter 3. However, a brief discussion is presented in this section.

5.2.1 Trust-based Consensus Algorithms

Although the majority of proposed alternatives rely either on owning physical resources such as PoW or having a significant monetary investment (i.e., stake) into the blockchain, such as PoS, a few algorithms are available that rely on trust metrics with some limitations.

In Proof of Trust (PoT) [157], miners' trust values are used to serve as a waiver for the required energy for mining blocks. They claim that the literature contains many trust metrics that could be used to calculate nodes' reputations. They have used the Pagerank algorithm to evaluate PoT. However, more discussion is needed to show how these metrics can be adjusted or applied within blockchain-based systems.

In [158], another PoT mechanism (Alt-PoT) is proposed that uses naive Bayes to calculate the honest probability of nodes. It relies on three elements, including the total number of transactions the node has conducted on the crowdsourcing platform, the number of

times a miner participates in validating blocks and the number of complaints about a miner. However, the model needs to include some critical properties of designing trust models. For example, it does not observe transactions' trustworthiness used for calculating the honesty of nodes.

The authors in [265] present a trust-dependent consensus (TCON). The trust model of this scheme relies on the number of blocks that were validated and successfully added to the blockchain by a miner. However, it needs to consider the changes in miner behaviour over time and the sensitivity of the reputation value.

5.2.2 Reputation-based Consensus Algorithms

Several reputation-based consensus algorithms have been proposed. However, most of these algorithms use reputation features that can only be applied to some blockchain-based systems. For example, some of these studies calculate reputation values for miners based on features that are related to vehicular ad hoc networks (VANETs) [266], wireless sensor networks (WSNs) [267] or P2P networks [268]. We do not discuss these studies because they do not distinguish miners' behaviour within blockchain-based systems and are specified for a particular domain.

Proof of Reputation (PoR) is a consensus algorithm proposed in [159], where a node's transaction activity, asset and consensus participation are evaluated to construct its reputation. PoR is a hybrid reputation-based approach that is vulnerable to all the drawbacks of such consensus algorithms, for example, denial of service attacks and a lack of fairness of access.

Proof of Reputation X (PoRX) [269] is a reputation model that is combined with the proof of something (PoX) mechanism. PoRX employs two measures when selecting a block issuer. The first criterion is reputation, while the second is work or stake, as stipulated by the base PoX. The reputation values for miners in this model rely on the number of blocks successfully produced by miners during a competition cycle. This model penalises miners when they do not submit blocks for a period of time or do not submit the expected number

of blocks by themselves. Although the model has a technique for punishing miners, it does not consider whether those miners are malicious or not.

RepuCoin [270] attempted to use a PoR mechanism. By assessing miners' behaviours, the authors determined miners' reputations, and they developed a reputation-based weighting scheme consensus. In RepuCoin, every miner has a reputation score, and miners with high reputation values are chosen to participate in the consensus process. These reputation values are determined by evaluating the extent and regularity of the valid work the miner has provided to the system. One of the downsides of this approach is that it consumes a significant amount of energy. According to [271], this algorithm is a proof-based consensus algorithm, not reputation-based.

In [272], an alternative to Delegated Proof of Stake (DPoS) consensus algorithm is proposed. It replaces stake based on coins with a reputation ranking system that depends on ranking models, such as NCDawareRank, PageRank and HodgeRank. For calculating reputation, three elements are combined: the amount of stake, the usage of resources, and the activity of the transactions. This consensus algorithm needs a mechanism to calculate nodes' reputation values instead of repeating computation after each block.

5.3 Reputation Model for Miners within Blockchain-based Systems

In this section, we describe our reputation model, a novel model that monitors the behaviour of individual miners within a blockchain network. In this chapter, we define reputation as described in Chapter 2. In blockchain-based systems, we expect miners to submit trusted blocks based on their previous behaviours that reflect their honesty.

The main goal of this chapter is to design and develop MinerRepu, a dynamic reputation model for measuring and evaluating the reputation of miners in blockchain networks after each mined block. Our model computes situational reputation in miners based on the general satisfaction with miners' behaviour. General satisfaction is the satisfaction that one miner

gains based on all previous contributions in all block mining. The model is built on a well-known blockchain consensus algorithm called Proof of Work. Thus, it can be combined with any consensus algorithm for blockchain-based systems with a mining process. We observe miners' activities and evaluate the satisfaction toward each miner based on different reputation features. To the best of our knowledge, our model can be considered the first reputation model for individual miners that is evaluated and compared with other trust and reputation models for blockchain-based systems.

We assume that a reputation management system is responsible for the dissemination mechanism. This mechanism helps anyone interested in obtaining miners' reputations, which can be derived from the calculation, to access them. Such a mechanism can include storing the reputation values and distributing them to anyone who needs them. For example, the reputation management system could use a distributed hash table to store the miners' reputation values with a gossip protocol for distributing updated information. This mechanism, though, is out of the scope of the thesis.

In the following sections, we describe the properties of our reputation model and the features used for calculating the reputation values. Also, we show how to aggregate these values in a manner that leads to an elegant interpretation.

5.3.1 Reputation Model Properties

Reputation is widely used as an indicator of the trustworthiness of nodes in decentralised systems. However, to promote their adoption, reputation models should be able to address the reputational issues and needs of these services. Therefore, the design of reputation systems requires identifying the properties that such models fulfil. Based on the literature, we have determined several desirable properties that should be satisfied by all trust and reputation models. According to [273], the properties can be categorised into three groups. The first group of properties focuses on the formulation dimension. The second and third groups are related to the calculation and dissemination dimensions. In this chapter, we identify particular properties that focus on the formulation dimension since the chapter aims to build

a formulation to calculate reputation values for miners (see Table 5.1). We classify these properties into two groups. The first group of properties describes the input and mathematical model for evaluating reputation values. The second group contains properties that ensure newcomers and older miners are treated fairly.

The properties in the first group (P1 to P5) concentrate on the information and aggregation methodologies employed to assess reputation values. P1 requires ratings and reputation values to discriminate miner behaviour accurately. Properties P2 and P3 cope with the type of information utilised for assessing reputation values. A block within a blockchain-based system can be mined in different ways, which leads to difficulty in reaching conclusions about miners' reputations. However, our model aggregates two types of features and comparable reputation information that can accurately reflect the reputation of miners within blockchain-based systems that use PoW. P3 relies on temporal elements because the behaviour of miners might vary over time. Also, reputation is based on the experience of past mining processes. For example, a malicious miner could act adequately for some time to create a positive reputation, which could then be used to deploy an attack. Therefore, the evaluation of miners' behaviour should be captured over time to reflect reputation accurately. P4 reflects the evolution speed of the reputation relationship with the variations of miners and network behaviours. The sensitivity factors under evaluation encompass the speed of change in the level of reputation values for miners. Finally, P5 aims to force a miner to exhibit rational behaviour by utilising a sufficient penalty.

The second group of properties (P6 to P8) ensures that the treatment of new and old miners is fair. When a new miner joins the system, there is no knowledge regarding their behaviour. Some reputation systems generally provide new miners with a default reputation value. Nevertheless, this value should not penalise new miners simply for being new (P6). If new miners are regarded as low-reputation users, they will never be chosen to do mining, so it will be impossible for them to build their reputation. Equally, a reputation system must stop miners from exploiting their new status (P7). Indeed, miners with a bad reputation may adopt new identities to avoid the repercussions of their acts by joining again as new miners.

P8 relates to the miners’ longevity, which makes it difficult or impossible for miners to adopt pseudonyms or new identities to remove any connections with previous bad behaviour.

Table 5.1: Properties for Trust and Reputation Models

ID	Property	Reference
P1	Reputation should distinguish miner behaviour.	[273]
P2	Gathering reputation features should be meaningful.	[273]
P3	Reputation should show the changing of miner behaviour over time.	[273]
P4	Reputation should be sensitive.	[274]
P5	The penalties should be sufficiently severe.	[275]
P6	The system should not penalise new miners for their status.	[273]
P7	The system should not give advantages to newer miners.	[273]
P8	The system should discriminate miners’ longevity.	[51]

5.3.2 Reputation Derivation

In MinerRepu, a miner’s reputation is based on satisfaction with the miner’s behaviour. The satisfaction information regarding miners can be gathered by analysing the behaviour of miners in previous mining processes. This satisfaction reflects the degree of reputation that miners in the community have. We use one of the main important factors for such evaluation, which is miners’ availability.

The availability of a miner in a blockchain network is considered necessary, especially at the beginning of a blockchain-based system, because the system needs to have many miners to avoid the centralisation problem. Availability is composed of mining time and propagation time. Miner’s availability means that the miner should be available to participate in mining blocks and propagate blocks to other nodes.

The first feature related to availability is mining time, which defines the time a miner takes to mine a block. There is an expected mining time for miners based on their hashrate and the difficulty of finding hashes in the network. The satisfaction associated with mining time is evaluated after each submitted block as a way to monitor miners’ behaviour. To compute the satisfaction based on the mining time, we compare the time a miner took to mine the block in the current round with its expected time for mining blocks. This feature

tracks how long miners did not participate in the network. It catches miners that might leave the network and shows how miners are available to do mining. Also, it is used to differentiate between new and old miners.

Propagation time represents the time a miner takes to receive and verify blocks and then broadcast them in a blockchain network. The satisfaction is calculated by comparing the lowest propagation time that appeared in the current broadcasting time of the mined block to the propagation time for that miner. We include the propagation time in calculating the reputation values because a delay in information propagation can be responsible for inconsistencies in the blockchain network, leading to slower block verification. Also, attackers can take advantage of the inconsistencies to perform double-spending attacks, which are more difficult to discover in a slow network. The satisfaction related to propagation time shows the probability that the miner will be up and running and able to deliver valuable services to other nodes. Using this feature gives miners that have not mined any blocks a chance to gain a level of reputation over time instead of keeping their reputation values at zero. If we keep them at zero, we may affect the network because those miners may decide to leave the network, which leads to a reduced number of nodes in the network. As a result, centralisation can occur.

5.3.3 Reputation Quantification

Since the behaviour of miners in the blockchain network may change over time, the representation of reputation value must be shown as a continuous range to distinguish the reputation levels for miners in a comparable way. In MinerRepu, we represent reputation from zero to one, signifying a continuous range from unknown to completely reputable. Basically, every miner's reputation value is set to zero from the beginning. This value goes up and down according to the miner's behaviour within the blockchain-based system. When it behaves well, this value goes up and vice versa.

5.3.4 Reputation Computation

The reputation value for a miner $R(m)$ is based on satisfaction regarding its availability. We design our model to define the reputation value in an accurate and parameterisable way. Three objectives are taken into account to calculate miners' reputation values. First, miners should be monitored carefully at the beginning stage, and their reputations should gradually increase at the beginning. Second, mature miners can be potentially rewarded with a rapid reputation increase in the middle part of their participation. Third, over-control should be avoided by imposing slow increases at the peak. Therefore, three factors are considered for calculating the increment ratio for a miner's reputation value.

The first factor is the sigmoid function calculated using a parameter x that controls the increment or decrement of miners' reputation. It ensures that a new miner can slowly increase its reputation, even when the satisfaction value of its availability is strong. A miner must remain within the system and act honestly for sufficient time to gradually raise its reputation. Once this has been reached, the turning point is where its reputation value is enough to be motivated by increasing its reputation quickly to a level of greater interest. Ultimately, the curve tapers off again, ensuring that reputation does not continuously grow but achieves a plateau that allows for a fair share of power between miners. The reputation function also has set parameters (α, λ) that determine these points precisely. These parameters can be adjusted to allow miners' reputations to increase more quickly or slowly as appropriate.

Second, we use satisfaction about the number of blocks a miner has mined and broadcast (i.e., the satisfaction of mining time and propagation time) to control the increments of the reputation value of each miner's behaviour. This factor can motivate miners to increase the number of highly satisfied blocks to gain high reputation values. Also, satisfaction controls the decrements of the miners' reputation values, which ensures that miners with many satisfied blocks will try to avoid losing a high reputation value by working regularly. Also, this can prevent malicious miners from performing attacks as they will lose a high reputation value while mining in their private blockchain. In other words, this ensures that miners that do not submit or broadcast any block for some time will be punished by decreasing their reputation

values.

Thirdly, we consider the hashrates for a blockchains network, miners and tolerance level. First, we use the percentage of a miner’s hashrate of the total network hashrate to control the increment of the satisfaction about mining time for the miner. It is used to detect a possible selfish mining attack. Second, the reputation function is parameterised to precisely determine the level of risk within the blockchain network; namely, the parameter t can specify the hashrate percentage that can become the tolerance level within the network. In MinerRepu, we assume that the parameter is decided by decision-makers who are responsible for a blockchain-based system.

In this chapter, we establish a general reputation metric that dynamically uses two features (i.e., mining time and propagation time for a block). The general metric computes the reputation value of a miner using the total amount of increment the miner obtained for the satisfaction of the miner’s contribution during a given period. We formulate the calculation for mining time and propagation time features separately.

5.3.4.1 Mining Time

To compute the increment rate for a miner’s reputation value based on its behaviour of mining a block, we first find the satisfaction about the miner’s mining time $satMt$, which determines how good the miner’s mining time Mt is for the mined block compared with its expected mining time $expMt$. The value Mt would not be zero because $satMt$ is just calculated for the miner that produced the current block. Therefore, $satMt$ is equal to zero for the rest miners. The satisfaction based on the mining time $satMt$ is computed as follows:

$$satMt = \begin{cases} \frac{expMt}{Mt} & \text{if } Mt > 0 \\ 0 & \text{otherwise} \end{cases} \quad (5.1)$$

where the expected time to find a block by the miner $expMt$ can be calculated using an equation based on [94], as follows:

$$expMT = \frac{D \times 2^{32}}{MHR} \quad (5.2)$$

where D is a number that controls the time miners take to add a new block to a blockchain-based system (i.e., it is called difficulty), and MHR is the hashrate for the miner.

The change rate in the miner’s reputation value has three different cases based on a miner’s behaviour (Selfish-miner, Non-miner and Honest-miner).

Selfish-miner. The first case is the increment of reputation value for a selfish miner. According to [244], selfish miners can gain unfair rewards for their mined blocks. Specifically, if a miner has computational power over 33%, the miner can make unfair gains by maintaining a private blockchain and withholding mined blocks. This means honest miners will be forced to waste computation on a stale public branch. One thing that may indicate selfish mining activity, as mentioned in [244], is the time gaps between sequential blocks. Practically, a selfish miner suppresses an honest chain of length N by using a chain of a length $N + 1$ and then submitting a block that appears very soon after the previous block. Since standard mining events should be independent of each other, there should be an exponential distribution of block discovery times. Any deviations from this distribution could suggest that selfish mining is occurring. In MinerRepu, a selfish miner is a miner that has a percentage of network hashrate greater than or equal to the tolerance level and has submitted two blocks following each other in a short time. The short time means the time between these blocks is less than the miner’s expected mining time for generating a block. The selfish miners will gain ‘-1’ for the change rate of satisfaction based on mining time which is used as a sign of misbehaviour. We believe this will stop malicious miners from misbehaving because it catches miners that try to perform either a 51% attack [8] or a selfish mining attack.

Non-miner. The second case is related to miners that did not mine the current block. Those miners get zero for the ratio of changes in reputation value based on a miner’s mining time which influences the final reputation values for the miners. This can motivate miners to

mine blocks regularly.

Honest-miner. Regarding a miner that submits a block honestly, the miner will gain a higher increment ratio up to one if the satisfaction about the mining time $satMt$ is high and vice versa.

The formula we propose to calculate the ratio of changes in reputation value based on a miner's mining time RMt by considering the above factors is as follows:

$$RMt = \begin{cases} -1 & \text{if } Mhr\% \geq t, y_m = 1, satMt > 1 \\ 0 & \text{if } satMt = 0 \\ satMt & \text{if } 0 < satMt < 1 \\ 1 & \text{otherwise} \end{cases} \quad (5.3)$$

where y_m is the number of mined blocks in the blockchain since the last block published by the miner.

5.3.4.2 Propagation Time

To calculate the increment rate for the reputation value a miner received from the satisfaction about its propagation time of a block RPt , we first find satisfaction about the propagation time for a block $satPt$ that is broadcast by the miner that shows how much time the miner took to receive and verify the block Pt . We then compare it to this round's lower propagation time LPt . The value $satPt$ is measured for all miners in the network. However, it is equal to zero for the miner that produces the block since there is no propagation time. Other miners that did not participate in broadcasting the mined block get '-1'. This can encourage those miners to keep sending blocks and not leave the network. When this value goes higher, the miner is more satisfactory. Consequently, we define the equation as follows:

$$satPt = \begin{cases} \frac{LPt}{Pt} & \text{if } Pt > 0 \\ 0 & \text{if } RMt > 0 \\ -1 & \text{otherwise} \end{cases} \quad (5.4)$$

Hence, the ratio of increments for the reputation value for the miner based on the block's propagation time RPt is formulated as follows:

$$RPt = satPt \quad (5.5)$$

Using the above equations, the updated miner satisfaction $satRound$ can be calculated as:

$$satRound = \begin{cases} 0 & \text{if } RMt = -1 \\ RMt + RPt + PSatRound & \text{otherwise} \end{cases} \quad (5.6)$$

where $RMt + Rpt$ is the satisfaction of the current round, and $PSatRound$ is the satisfaction of previous rounds for the miner. The value $satRound$ for a malicious miner becomes zero each time the malicious miner submits a suspicious block which means losing a high amount of reputation value.

5.3.4.3 Final Reputation Value

The new reputation value for a miner $R(m)$ based on the above equations can be represented as follows:

$$R(m) = \frac{1}{1 + e^{-\alpha(satRound-\lambda)}} \quad (5.7)$$

The previous equation (i.e., sigmoid function) ensures that the reputation value for a miner does not exceed one and does not go below zero. Also, it indicates a continuous range from an unknown miner to a completely reputable miner.

5.4 Evaluation

There are several ways of approaching the evaluation of trust and reputation models. These encompass custom-made experiments, general experimentation in restricted situations, or common evaluation frameworks, which include one or both theoretic criteria and simulation frameworks [276]. This thesis applies an analytical approach to compare our reputation model to some existing trust and reputation systems and examine how our model addresses attacks. Also, we adopt experiments to present how the model performs and evaluate the correctness of predicting malicious miners. In addition, we investigate how our model can save the energy consumed by PoW.

5.4.1 Analytical Approaches

In this section, we compare our model with trust-based and reputation-based consensus algorithms because they are, to some extent, comparable to our model. In addition, we compare MinerRepu with the reputation model proposed in Chapter 4, which is considered as one objective of selecting miners. We have called that model, Ch4Repu.

5.4.1.1 Criteria Framework-based Analytical Evaluation

Some studies offer several measures or criteria that can be employed for analysing trust and reputation models. We introduce several major characteristics and properties obtained from a number of dimensions of reputation evaluation systems (see Table 5.1). Criteria framework-based analytical evaluation approaches offer a basis for comparing models based on specific indicators. We examine and compare our reputation model with other models for blockchain-based systems regarding these properties. The analysis results are summarised in Table 5.2.

All approaches do not fulfil property P1 except MinerRepu because trust and reputation models should meet three requirements: capturing the range of user behaviour (trust/distrust), capturing the confidence of entities on trust information (certainty/ uncertainty) and the absolute reputation values [273]. Most of these approaches consider the regularity of participation in the consensus as one feature of miners' trustworthiness. However, these approaches do not take into account uncertainty. For example, some use the number of generated blocks without considering the expected mining time of the miner that mined the current block and other miners to distinguish the miners' behaviour.

Table 5.2: Evaluation of Trust and Reputation Models for Miners within Blockchain-based Systems

Properties	[157]	[158]	[159]	[265]	[269]	[270]	[272]	Ch4Repu	MinerRepu
P1	⊗	⊗	⊗	⊗	⊗	⊗	⊗	⊗	•
P2	⊗	⊗	•	•	•	⊗	•	•	•
P3	⊗	⊗	•	⊗	•	•	•	•	•
P4	⊗	⊗	⊗	⊗	⊗	⊗	⊗	⊗	•
P5	⊗	⊗	•	⊗	⊗	•	⊗	⊗	•
P6	•	•	•	•	•	•	•	•	•
P7	•	•	•	•	•	⊗	•	•	•
P8	•	•	•	•	•	•	•	•	•

- P1: Reputation should distinguish miner behaviour.
- P2: Gathering reputation features should be meaningful.
- P3: Reputation should show the changing of miner behaviour over time.
- P4: Reputation should be sensitive.
- P5: The penalties should be sufficiently severe.
- P6: The system should not penalise new miners for their status.
- P7: The system should not give advantages to newer miners.
- P8: The system should discriminate miners' longevity.

Others use a subjective evaluation to measure the satisfaction towards miners in the consensus. Both ways lead to no support or limited uncertainty. Thus, they must provide the information necessary to distinguish miners' behaviour. As a result, these approaches do not fulfil property P1 because they do not meet one or more of the above requirements.

The primary features needed for fulfilling P2 reflect miners' behaviour. In Table 5.2, the reputation systems that use the features that can present miners' behaviour fulfil this property. However, the reputation system [157] utilises features using information referring to a weighted trust graph (i.e., Pagerank Algorithm), and [158] and [270] use information about the miner within different blockchain architectures. Thus, we consider these as not meeting P2.

Most of the analysed trust and reputation systems for miners in blockchain-based systems use timestamps to show the changes in miners' reputations over time. The systems that meet the property P3 show a change in trust or reputation values after each generated block. However, [157], [158] and [265] do not fulfil property P3. The models proposed in [157] and [158] use temporal aspects with features not reflected in the miners' behaviour. Also, the system in [265] uses binary values after each block to present the reputation values that do not display an update of the miners' behaviour.

Systems with techniques to control the speed of the change of miners' reputation fulfil P4.

These systems use a sigmoid function or some parameters to control the sensitivity of increments and decrements of miners' reputations. However, the remaining systems do not utilise such techniques or use them in a way that affects their mechanism. For example, [270] and Ch4Repu use a sigmoid function for calculating reputation values, but they aggregate the results of this function with other values, affecting the reputation model's sensitivity. Others use binary values to evaluate miners' behaviour after each block.

The property P5 is captured using a sufficient penalty towards miners for misbehaviour. Although most of the analysed techniques penalise miners for misbehaviour, they exploit this factor only partially. Indeed, most reputation systems penalise miners for misbehaviour based on the number of valid and invalid blocks generated by miners without taking into account the hashrate of miners, or else they punish malicious miners using methods unrelated to the miners' behaviour. Because of these limitations, we consider these systems as not fulfilling P5. Proof of Reputation [159], ReputCoin [270] and MinerRepu are the only reputation systems in our analysis that can penalise miners sufficiently for misbehaviour.

New miners can gain fair treatment (P6 to P8) by employing technical solutions and some features. All analysed systems meet these properties except [270], which does not fulfil the property (P7). The systems use a default value for new miners that is carefully specified so that new miners can be distinguished from older miners; these systems use reputation values that can express the entire range of miners' behaviour regarding good and bad behaviour. Thus, they do not use bad initialised values or only negative evaluations that can lead to the inactivity of new miners or give new miners a chance to receive a high reputation automatically. Also, they use costly techniques that stop miners from re-entering the system as new miners. Regarding [270], the reputation model uses an initial value for new miners, where this value is extracted from an external resource. Such value can give advantages to new miners.

5.4.1.2 Threat-based Analysis

Attacking reputation systems usually has the aim of performing attacks against the reputation systems' goals. The purpose of this evaluation is to present how our reputation system is invulnerable to particular threats; this includes the behaviours of self-promoting, whitewashing, slandering, and traitors attacks. We discuss these threats because they fundamentally target the reputation system's

formulation. Nevertheless, we ignore a denial of service attack because it is related to disseminating reputation values, which is outside this thesis's scope.

Self-promoting attacks represent malicious behaviours in which attackers attempt to enhance their reputation. Self-promoting attacks are essentially an attack on the formulation. Attacks of this nature are only possible in systems that operate formulations considering positive feedback [277]. In MinerRepu, formalisation considers the positive and negative values for miners' behaviours. So, the model is invulnerable to this attack.

Whitewashing attacks occur when attackers execute a short-term strategy that allows them to degrade their reputation; then, they can evade the outcomes of system abuse by exploiting a vulnerability in the system to restore their reputation. To reduce the risk of whitewashing attacks, reputation systems need to employ a formulation that prevents newcomers and good miners that participate for a long time from having the same reputation [277]. MinerRepu is not vulnerable to a whitewashing attack because it prevents newcomers from having the same reputation metrics as long-term participants. The formulation is based on long-term experiences that discriminate between new and old actions.

Slandering means that a miner manipulates the reputation of other miners by giving false information or behaving in a manner that decreases the reputation values of the victim miners. This kind of attack typically focuses on the formulation dimension of a given reputation system [277]. MinerRepu incorporates formulations purposely designed to limit the risk of slandering attacks by computing user reputation according to direct information only. As another weakness, a miner could act in a way that may affect other miners' reputations. The miner with a high hashrate may stop mining for some time to let other miners have a higher chance of submitting two blocks in a short time, which results in a reduced reputation for the victim miners. However, our model uses a defence technique towards this weakness by penalising the miner for stopping mining for that time.

A traitors attack happens when a miner behaves honestly in the system for a period to raise its reputation value and then begins to misbehave. In our model, the formulation includes positive and negative information for calculating the reputation. When attackers behave honestly for an initial period to build up a positive reputation and then start misbehaving, they will not gain reputation values for behaving dishonestly. However, they will lose a high value from their reputation values.

Table 5.3: Experimental parameters

Variable	Value
Number of miners	16
Number of blocks	1000
Network hashrate	125540000 TH/s
Difficulty	15.784217546288 TH/s
Tolerance level within the network	30% of the network hashrate
α	0.02
λ	300
Experiment running number	10

5.4.2 Experimental Approaches

To evaluate our model, we apply an experimental evaluation method that utilises a blockchain simulator, as simulations are often cheaper, faster and easier to implement than a complete product in the real world.

5.4.2.1 Blockchain Simulator

We evaluate our model through a blockchain simulator called Bitcoin-Simulator [13] using real and artificial data (similar to the simulator used for evaluating the proposed model in Chapter 4). Using this simulator, we can generate data that we subsequently use to calculate the reputation level of each miner.

We have designed ten simulation experiments to evaluate the model. We assumed a general set of related parameters for the experiments using real data, including the current hashrate for the bitcoin network and the difficulty of finding a hash ¹. We used the same settings as used by [13], such as the miners' hashrate and geographical distribution. Based on the default setting of the simulator, the number of honest miners is equal to 15, and 1 miner is considered malicious. To reflect a real blockchain network, we randomly chose one miner in each experiment to join and leave the network frequently. We also randomly chose 100 blocks to determine when the miner joined and left the network. Table 5.3 shows the Experimental parameters.

¹We have retrieved information from <https://blockchair.com/bitcoin> on the 1st of March 2021

5.4.2.2 Miners Reputation Values Variations

In this section, we discuss the results of our simulation experiments. We assess the dynamic reputations of honest and malicious miners using simulation experiments.

As depicted in Figure 5.1, the reputation values for honest miners (blue lines) increase with the increase in the regularity of their honest behaviour, taking into account the joining and leaving behaviour of the honest miners (yellow lines). We can clearly see that the reputation values between honest miners increase slowly at the beginning and faster when the miners perform honest behaviour for a sufficient number of blocks. Then, at the peak, the reputation values increase slowly again to provide a fair share of reputation between miners, especially when there are miners with a low hashrate.

On the other hand, the reputation values of malicious miners (red lines) increase slowly, like for the honest miners, since the malicious miners have yet to misbehave. However, our model penalises malicious miners immediately after performing attacks. Malicious miners lose a high proportion of their reputation once they behave selfishly. Therefore, their reputation values become like newcomer miners' reputation values. Figure 5.1 shows that some trends represent the changes in the reputation values of the honest miners, while the reputation values of the malicious miners do not show the sigmoid curve; they keep increasing and then suddenly exhibit a drastic drop.

This analysis shows that MinerRepu reflects the following nature: “reputation is hard to gain, but it is easy to lose”. Our model evaluates the reputation accurately among miners. Furthermore, it reacts when miners' behaviour changes radically and is sensitive to the changes towards malicious actions that can effectively signal malicious miners.

5.4.2.3 Malicious Miner Detection

In blockchain-based systems, the consensus mechanism, PoW, is vulnerable to a 51% attack (i.e., majority attack), which can be exploited by malicious miners with computing power over 51% to achieve total control of the blockchain. Nevertheless, recent studies indicate that even miners with computing power less than 51% are considered dangerous [244]. To be more precise, when a miner's hashing power comprises, as an example, over 25% of the total hashing power of the blockchain network, then that miner can launch a selfish mining attack [244]. Miners might attempt to perform such an attack to raise the number of their mined blocks in the blockchain, which raises their rewards.

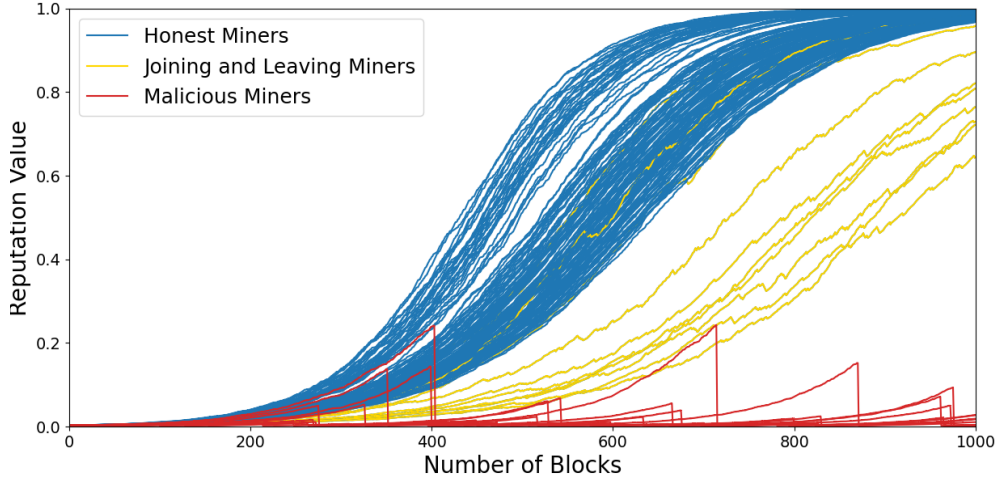


Figure 5.1: The variation of reputation values for honest and malicious miners

They perform this attack by selecting specific mined blocks and withholding them in their private blockchains. Then, they gradually publish them. Since Bitcoin’s resistance to adversaries is predicated on the assumption that the attacker cannot have more than 30% of the total hashrate of a blockchain network [13], [244], [278], in this chapter, we focus on detecting selfish miners that have hashrates equal to 30% and that perform selfish mining attacks.

To capture selfish miners, we use the ratio-to-moving-average method to show the fluctuations in miners’ reputation during a number of mined blocks (see Figure 5.2). The figure shows that the level of reputation fluctuation for malicious miners is abnormal (red lines) compared to honest miners. On the other hand, the level of reputation fluctuation for honest miners (blue lines) is stable, which indicates that honest miners’ contribution is relatively stable. Furthermore, miners that join and leave the network (yellow lines) have a relatively stable reputation fluctuation. The integration of our model with the ratio-to-moving-average method can be used to evaluate the reputation of miners: only miners with a stable level of reputation fluctuation within a certain interval (for example, [0.95, 1.05]) are considered honest miners within the blockchain network.

5.4.2.4 Model Accuracy

To calculate the accuracy of detecting and differentiating between honest and malicious miners, we have checked whether our model can correctly classify those miners after each mined block. First, the accuracy of classifying the miners is calculated by computing how often our model can accurately classify miners (i.e., the ratio of correct classifications to the total of classifications). Then, we have

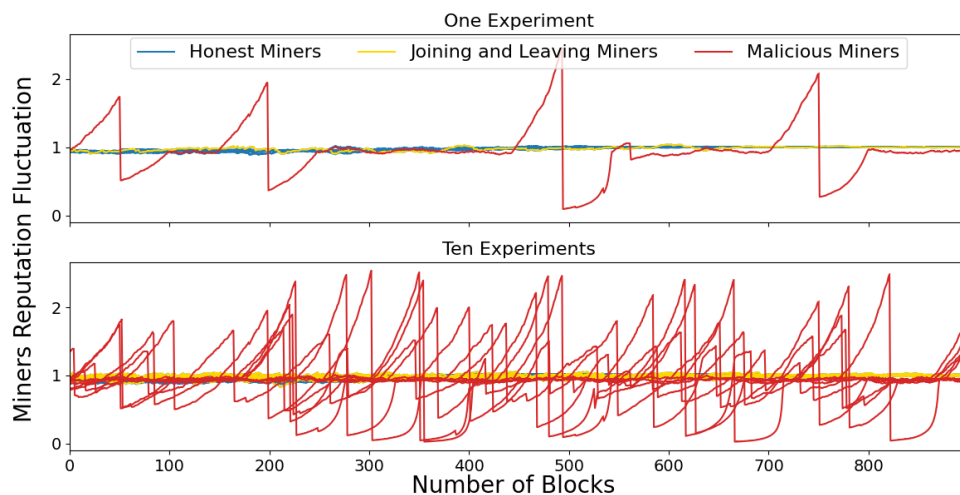


Figure 5.2: The fluctuation of miners' reputation during mining of blocks

used the experiments' average accuracy to demonstrate our model's accuracy. Finally, we have utilised the miners' reputation fluctuation intervals to detect whether a miner is honest or malicious. In other words, if the reputation fluctuation of a miner is within an interval, that means the miner is honest. If it exceeds the boundaries, then it is not. We set four intervals for our experiments $[0.95, 1.05]$, $[0.85, 1.15]$, $[0.75, 1.25]$ and $[0.65, 1.35]$.

Figure 5.3 shows the accuracy of our model in defining miners as honest or malicious. Using the intervals described above, we have observed that when the endpoints of the interval are very conservative (e.g., $[0.95, 1.05]$), the judgement about the miners is not accurate in the early stages (blue dots). Nevertheless, the detection function of the reputation model becomes more effective using these endpoints when the reputation of miners increases steeply. The remaining intervals (i.e., $[0.85, 1.15]$, $[0.75, 1.25]$, $[0.65, 1.35]$) show accuracy more than 93%, with average accuracies of 96%, 95%, and 95%, respectively. Thus, choosing appropriate endpoints for the interval used to classify miners is essential. Also, one can use two different intervals; for example, we can use $[0.85, 1.15]$ at the early stages of mining, and once the number of blocks reaches a specific value (e.g., 400), we set the interval to a more conservative one, such as $[0.95, 1.05]$.

5.4.2.5 Energy Saving and Carbon Emissions

In this section, we discuss how MinerRepu can reduce the energy consumption and carbon emissions of blockchain-based systems to understand the model's effectiveness better. The model can minimise

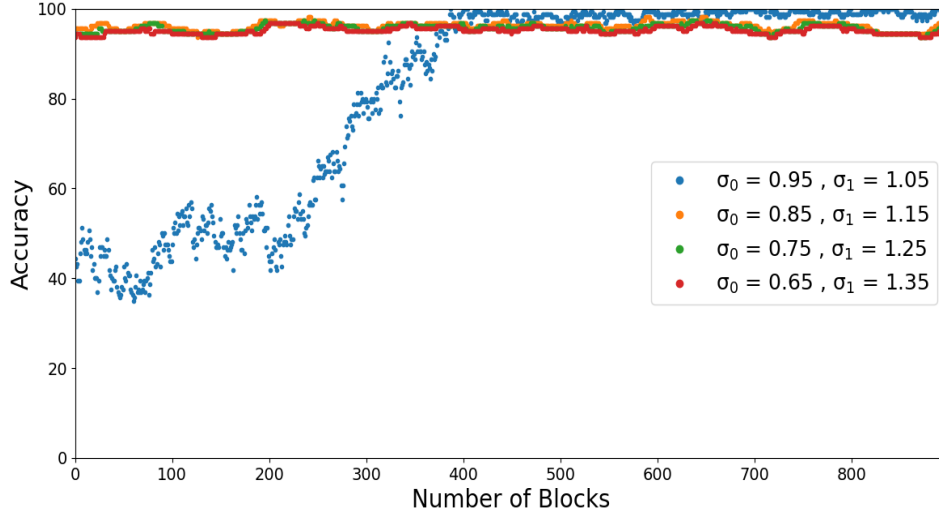


Figure 5.3: The accuracy rate of detecting honest and malicious miners with different intervals

the amount of energy spent on PoW by reducing the number of not reputable miners within the blockchain network. Also, it can minimise the carbon emissions of these systems. As a result, our model can save energy and reduce carbon emissions compared to the situation in which all miners engage in PoW.

We have calculated the energy consumed and carbon emissions by each miner after the miners have built their reputations. We chose the 1000th block as the time point for calculating the energy consumption and carbon emissions, which is computed in two different ways. First, we have calculated it for the case where all miners participated in mining the block. In the second scenario, the energy consumption and carbon emissions are determined for four different clusters based on miners' reputation values: in the 99th percentile, in the 98th percentile and above, in the 97th percentile and above, and in the 96th percentile and above.

To calculate the total energy consumption of all miners, we have used the general equation for E (kWh):

$$E = \sum_{m=1}^M P_m \times T_m \quad (5.8)$$

where P_m is the power use (kW) of a miner m , T_m is the time ($hour$) at which the miner's power is consumed, and M is the total number of miners.

We can calculate the total carbon emissions of all miners C (g) as follows:

Table 5.4: The energy consumption of a blockchain-based system using MinerRepu

Miners' Reputation	Energy Consumption		
	Range	Average	Standard Deviation
$\geq 99\%$	43-57%	51%	0.06
$\geq 98\%$	53-68%	65%	0.05
$\geq 97\%$	57-70%	67%	0.04
$\geq 96\%$	57-70%	68%	0.04
	Carbon Emissions		
	Range	Average	Standard Deviation
$\geq 99\%$	60-82%	77%	0.07
$\geq 98\%$	84-99%	95%	0.04
$\geq 97\%$	89-100%	97%	0.03
$\geq 96\%$	89-100%	97%	0.03

$$C = \sum_{m=1}^M EF_m \times E_m \quad (5.9)$$

where EF_m is the emission factor of electricity in the miner's location (gCO_2eq/kWh), and E_m is the energy consumption for each miner (*kilowatt – hour*).

Similar to the assumptions in Chapter 4, we assume that all miners use the most efficient mining device, and as a miner's hashrate increases, their number of devices also increases. We base this assumption on the fact that using inefficient devices leads to leaving the network due to not receiving profits from successful mining [44], [190]. Consequently, the power use of each miner was determined by dividing the hashrate of each miner by the hashrate of the selected mining device type. In addition, we assume that miners try to mine blocks for 24 hours to gain profit [45], [190].

The results in Table 5.4 show that the total energy consumption and carbon emissions increase as we increase the number of miners within clusters, as more miners participate in the consensus processes. However, our model can reduce the energy consumption to 43% (51% on average with a standard deviation of 0.06) of the total energy consumed by miners of the standard PoW consensus algorithm. Also, it can minimise the carbon emissions to 60% (77% on average with a standard deviation of 0.07) of the total carbon emission of PoW. These reductions are not compromising the trustworthiness of the blockchain-based system, as we have only included miners with a high reputation value ($\geq 99\%$).

5.5 Conclusion

Utilising trust and reputation models for blockchain has the potential to influence how reputation is fundamentally managed within blockchain-based systems and enable environmentally sustainable mining. To address these objectives, we have presented a novel reputation model for individual miners within blockchain networks called MinerRepu. It calculates and compares the reputations among miners, considering mining behaviours and broadcasting of blocks. We can potentially integrate the model with any consensus algorithm that uses a mining process. Our model is the first reputation model for blockchain-based systems that has been analytically evaluated and compared to other trust and reputation models for miners. Experimental evaluations have been conducted to test the performance of our model in classifying honest and malicious miners. The results show that the proposed method can effectively classify miners with an average accuracy rate of 96%. Also, we have discussed the model's energy consumption and carbon emissions. The results showed that MinerRepu could save up to 49% on average of the energy consumed and up to 23% on average of carbon emissions produced by the standard PoW.

Although our model can save energy and reduce carbon emissions, it may affect blockchain-based systems' total decentralisation. The model may limit new blocks' mining to a small number of miners. As a result, blockchain-based systems' overall decentralisation may become low. Therefore, we need a solution that uses our model without compromising the inherent trustworthiness and decentralisation of blockchain technology (We have addressed this gap in Chapter 6). In addition, taking into account the future potential of the integration of a reputation model, it may provide more options for improving the sustainability of blockchain-based systems. Integrating our reputation model with self-adaptive techniques can potentially be an option to optimise the sustainability of blockchain-based systems over time (Addressed in Chapter 6).

Chapter Six

SELF-OPTIMISING THE ENVIRONMENTAL SUSTAINABILITY OF BLOCKCHAIN-BASED SYSTEMS

Context. Several solutions have been proposed to improve the sustainability of blockchain-based systems, with an explicit focus on environmental sustainability. Most of these solutions focus on minimising energy consumption by suggesting alternative consensus algorithms. However, no previous study has proposed a self-adaptive model to enhance the environmental sustainability of blockchain-based systems without compromising the core properties of blockchain technology.

Objective. In this chapter, we propose a novel self-adaptive model to optimise the environmental sustainability of blockchain-based systems. The model balances the systems' energy consumption and carbon emission without compromising their decentralisation and trustworthiness. The model continuously monitors a blockchain-based system and adaptively selects miners, considering environmental changes and user needs.

Method. We propose a model that dynamically selects a subset of miners to perform sustainable mining processes while ensuring decentralisation and trustworthiness. The aim is to trade off four conflicting objectives by minimising energy consumption and carbon emission of blockchain-based systems and maximising the decentralisation and trustworthiness of these systems. We have implemented and evaluated the efficiency and effectiveness of the model using simulations. Also, we have investigated and discussed the correlation between these objectives and how they are related to the number of miners within the blockchain-based systems.

Results. The results show that our model can optimise the sustainability of blockchain-based systems by minimising energy consumption and carbon emission while maintaining decentralisation and trustworthiness under different operating conditions compared to similar models, including the straightforward use of Proof of Work. Compared with PoW, the results show that our model can

reduce energy consumption by 55.49% on average and carbon emissions by 71.25% on average while maintaining desirable levels of decentralisation and trustworthiness by more than 96.08% and 75.12%, respectively. Also, the results show that there are strong positive correlations between each pair of objectives except decentralisation with other objectives. It also shows strongly positive relationships between the number of miners and each objective.

Conclusion. Our model for self-optimising the sustainability of blockchain-based systems can perform better in energy consumption and carbon emissions compared to the original PoW solution and similar models with an acceptable level of decentralisation and trustworthiness under different operating conditions. Moreover, the model can be applied as a self-adaptive model for any other conflicting objectives.

Contribution to Literature. This chapter will contribute to the research literature through our full paper "*Self-Optimising the Environmental Sustainability of Blockchain-based Systems*", which is under the second round of the review.

6.1 Introduction

In Chapter 4, we have reformulated the problem of selecting miners in blockchain-based systems as an optimisation problem. The optimisation model attempts to minimise energy consumption and carbon emission while considering the trade-off with decentralisation and the trustworthiness of blockchain-based systems. It calculates the trustworthiness through the reputation of miners within the systems based on a simple model inspired by the ideas of PoW and PoS. This has motivated our work in Chapter 5, where we have proposed a dynamic reputation model for measuring and evaluating reputation by monitoring miners' behaviour after each mined block within blockchain networks. In addition, the optimisation model selects a subset of miners in an offline optimisation scenario where it first optimises and then deploys. However, as the environment is dynamic and changes over time, selecting potential miners to optimise blockchain-based systems' sustainability can change at run-time.

To improve the sustainability of blockchain-based systems, researchers have mainly focused on minimising the energy consumed by miners within these systems assuming carbon emissions linearly follow the changes in energy consumption, which may not necessarily be the case [16]. Therefore, solutions that provide environmentally sustainable blockchain-based systems in terms of energy consumption and carbon emissions are needed, as discussed in 2. The solutions should maintain the fundamental design of blockchain technology and its inherent built-in properties, such as its decentralisation and trustworthiness. Furthermore, the solutions should take into consideration environmental conditions and decision-makers' preferences. Therefore, this chapter provides a novel adaptive model for optimising the sustainability of blockchain-based systems without compromising their decentralisation and trustworthiness.

This chapter addresses the fourth research question in this thesis: **RQ4: How can we dynamically enhance the environmental sustainability of blockchain-based systems while maintaining their decentralisation and trustworthiness, taking into account environmental changes and decision-makers' requirements?**

To answer this question, this chapter develops a self-adaptive model for blockchain-based systems leveraging MAPE-K control loop (Monitor, Analyse, Plan and Execute over shared Knowledge) [279], as a reference model for self-adaptive and autonomic systems [280]. The proposed model provides automated and self-adaptive blockchain-based systems capabilities, which can help users per-

sonalise the selection and configuration of these systems according to their requirements. To the best of our knowledge, this chapter has proposed the first self-adaptive model to enhance the environmental sustainability of blockchain-based systems considering energy consumption and carbon emissions without compromising their fundamental support for decentralisation and trust. The proposed model is a self-adaptive model for blockchain-based systems that integrates the MAPE-K architecture and a MOOM. It dynamically searches for more environmentally sustainable solutions that maintain the fundamental core properties of blockchain technology. In particular, the formulation is designed to optimise the energy consumption and carbon emissions of blockchain-based systems that use the PoW consensus algorithm while balancing the decentralisation and trustworthiness of these systems at run-time.

The main contributions of this chapter are summarised as follows:

- We report on the state of art self-adaptive models and multi-objective optimisation models for blockchain-based systems to identify gaps and inform how we develop our proposed model.
- A self-optimising model for blockchain-based systems is proposed, where we make novel use of MAPE-K and MOOM to enhance the environmental sustainability of these systems. The focus is on dynamic optimisation of the trade-offs between maintaining decentralisation and trust in consensus provision, reducing energy consumption and carbon emissions, and considering environmental conditions and users' requirements.
- We conduct several experiments to evaluate the proposed model's effectiveness in reducing energy consumption and carbon emissions and maintaining the decentralisation and trustworthiness of these systems.
- We investigate and discuss the correlations between objectives and between the number of miners and each objective.

The rest of the chapter is organised as follows: Section 6.2 provides a brief background related to the concept of self-adaptive systems. Also, Section 6.3 gives a brief analysis of the existing literature on the integration of blockchain-based systems with self-adaptive models and with multi-objective optimisation models. Section 6.4 describes our self-optimising model for blockchain-based systems. The experimental design is explained in Section 6.5. The evaluation of the model is presented in Section 6.6. Finally, Section 6.7 concludes the chapter.

6.2 Self-adaptation Overview

Self-adaptive systems are the focus of many scientific and engineering efforts. These systems can adapt in different aspects, such as security, performance and fault handling. Self-adaptive systems are used in a number of different areas, such as software systems and applications. In this section, we present an overview of the basic concepts of self-adaptive to boost our understanding of the field.

6.2.1 Self-adaptive Definition

The phrase “self-adaptive (software) systems” is defined in several ways in the literature, as well as other terms that are used interchangeably, such as autonomic systems, dynamically adaptive systems, self-adaptive software systems or self-adaptive systems [281]. Here, we provide a definition that is used in this thesis.

In [282]–[284], self-adaptive systems perform ongoing assessments of their behaviour, modifying it if the assessment outcomes indicate that the efforts are not leading to the goals or if there is a likelihood of improved performance. In other words, self-adaptive systems perceive their environment and situate themselves within it, and they can modify their behaviour accordingly. As implied by the word “self”, they are able to act autonomously (i.e., with little or no intervention) when adapting to take account of contextual or environmental changes. Although several self-adaptive systems exist that require no human intervention in their operations, having high-level goals in place, such as using policies, can serve as valuable guidance.

6.2.2 Adaptation Loop

An adaptation loop refers to the closed-loop mechanism embodied in self-adaptive software. Adaptation loops involve several processes in addition to effectors and sensors. Most currently used mechanisms ensure adaptivity through the use of four distinct processes, namely monitoring, analysing, planning and executing (MAPE). However, some approaches add shared knowledge to the above (MAPE-K). Adaptation logic development for such systems essentially uses the MAPE control feedback loop as the standard [284], while researchers have put forward related feedback structures, including sense-plan-act control [285], autonomic control loop [286] and observer/controller architecture [287].

6.2.3 Self-adaptive Properties

While most adaptive or automated systems are designed to tackle the system dynamics without human intervention, it should not be assumed that this implies the presence of uncertainty. In other words, although the system experiences changes, the timing and extent of these changes are relatively predictable. In contrast, self-adaptive systems are specifically designed to deal with uncertainty in addition to dynamics. They accomplish this by modifying behaviours in line with their observations of themselves, the environment and the prevailing uncertainty. Presently, self-adaptive software remains a crucial and challenging field [288]. In line with the definition of adaptive behaviours, four properties are attributed to self-adaptivity, each with specific aims, as per [284]:

1. **Self-configuring:** The ability to respond to changes by dynamically and automatically re-configuring through software entity installation, integration, updating, or composing/decomposing.
2. **Self-healing:** The ability to identify, assess and respond to disturbances as well as predict problems and take appropriate actions to prevent failures and achieve goals.
3. **Self-optimising:** The ability to allocate resources and manage performance to meet various user demands in terms of, for example, response time, utilisation and throughput; also referred to as self-adjusting and self-tuning.
4. **Self-protecting:** The ability to identify malicious attacks and compensate for their impacts; this is a two-fold process: system defence against attackers and identifying potential problems and taking appropriate actions.

6.2.4 Blockchain and Self-adaptive

Blockchain technology has integrated with the self-adaptation concept. Researchers have attempted to develop blockchain-based systems that are dynamically adapted based on using different methods, such as based on appropriate consensus algorithms [289], [290], the number of nodes [291] or block size [292], [293].

Even though these definitions of self-adaptation cover run-time modifications for both functional and non-functional requirements, the majority of researchers in the field of software engineering

have concentrated their research on non-functional requirements [294]. Blockchain technology offers considerably extensive uses for different areas, including software engineering. Therefore, blockchain-based systems have had a share of this focus. Many researchers have focused in their endeavours on non-functional aspects of this technology. Non-functional aspects include reliability, high efficiency [289], performance, security [290], latency, throughput [291], consistency [292], [293] and scalability [295].

Blockchain technology can revolutionise handling trust in self-adaptive systems, particularly those that are decentralised and do not have a central controlling entity. Blockchain technology can help to realise trust between entities in self-adaptive systems through distributed ledgers that are tamper-proof and agreed upon among the entities [296]. Many self-adaptive systems have exploited blockchain technology to improve trustworthiness, maintain security, improve scalability, provide decentralisation, etc. This widespread adoption includes several fields, such as IoT [297], cloud computing [298], data transmission [299] and wireless sensor networks [300].

Several current blockchain-based systems have included the idea of smart contracts to build and execute agreements in a secure manner. Smart contracts are self-executing programs that can be implemented without trusted third parties. They are stored and run over blockchain technology. Correct contracts that meet contractual agreements are executed by consensus algorithms. They accomplish this by controlling and executing code automatically in a decentralised and distributed blockchain network [301].

6.3 Related Work

This chapter proposes a self-adaptive model that optimises the environmental sustainability of blockchain-based systems using MOOMs. Accordingly, this section discusses studies on the integration of blockchain-based systems with self-adaptive models and with MOOMs. Our coverage includes work on the consideration of environmental sustainability.

6.3.1 Blockchain and Self-Adaptive Models

Various efforts have been made recently to conceptualise blockchain networks as adaptive systems. However, most of these attempts have focused on adapting the difficulty of a blockchain network [302],

[303] or adapting rewards [200] without considering environmental sustainability, specifically energy consumption and carbon emissions.

The authors of [183] propose a model to investigate the relationship between the parameters that affect the network's sustainability and impact the environment. They then optimise the variable choices to enhance the system's sustainability using control engineering techniques. Although the authors claim that they identify variables that affect the environmental sustainability of blockchain-based systems, they need to indicate how the adaptation could affect the main environmental sustainability variables, such as energy consumption and carbon footprint.

In [290], the authors invest in the design of a self-adaptive management system that would automatically and dynamically switch between consensus algorithms and deployment configurations according to the requirements of the applications based on changes in the IoT data load. Although the authors evaluate and measure the performance of each consensus algorithm in terms of Central Processing Unit (CPU) consumption and response time, they fail to discuss the energy consumption of these CPUs and the potential impact of the adaptation on environmental sustainability. Another limitation of the model is the number of consensus protocols considered. The authors specifically focus on Practical Byzantine Fault Tolerance (PBFT), Proof of Elapsed Time (PoET) and Raft while not considering the common consensus algorithm, PoW.

A recent study [186] proposes a new consensus algorithm called Green-PoW. It divides the time for mining blocks into epochs, and each epoch is composed of two rounds resulting in two mined blocks. The consensus algorithm aims to reduce the energy consumption of blockchain-based systems by utilising the energy consumed during mining the first block to choose some miners for performing the second block mining. The authors show that the energy consumption during the first round exceeds the original PoW. However, it is reduced in the second round due to the fewer miners elected to mine the second block. As a result, the average energy consumption is estimated to be less than the original PoW by up to 50%. Although reducing energy consumption only sometimes results in reducing the carbon emissions of blockchain-based systems, the study does not discuss the potential reduction of this consensus algorithm in terms of carbon emissions.

6.3.2 Blockchain and MOO Models

Blockchain-based systems are like many real-world systems where compromises are made between different objectives, such as energy versus security. This type of optimisation problem can be solved using MOO algorithms. Therefore, several studies have sought to solve problems associated with blockchain technology using MOOMs. However, using MOOMs for designing energy-efficient blockchain-based systems and making an effort toward carbon neutrality is limited.

The authors of [233] propose a metric to identify the most significant influencers in the Bitcoin network. The metric uses Pareto front ranking for the trade-offs of multiple criteria: maximum balance, the minimum transaction number and minimum days active.

The work of [234] leverages large deviation theory and Lyapunov optimisation to propose a transaction selection mechanism. The proposed mechanism aims to maximise the tolerance of packaging delay and minimise the packaging cost threshold.

Another multi-objective optimisation problem is solved in [304] using the Particle Swarm Optimisation (PSO) algorithm to determine the optimal block size based on factors such as the total number of transactions and CPU power of miners. The approach aims to minimise two objectives: transaction selection time and block-building time. Similarly, the study [305] uses the PSO algorithm and a Strength Pareto Evolutionary Algorithm (SPEA) to determine the suitable block size, which is determined by the optimal number of transactions in each block.

6.4 Self-optimising Model for Blockchain-based systems

This section presents a novel self-adaptive approach that improves the environmental sustainability of blockchain-based systems without compromising the inherent characteristics of these systems, such as decentralisation and trustworthiness. Environmental sustainability is defined as the protection and preservation of natural resources for the benefit of humankind. Our approach utilises the MAPE-K architecture [279] to support the selection and configuration of blockchain-based systems during the run-time phase. Our MAPE-K management system continuously monitors the deployed system. It also analyses the decision factors (i.e., environment changes and user needs) related to the mining process. In the planning phase, the system then determines, using a MOOM, which subset of miners is most efficient to execute the next mining round. The above process is based on data and information

stored in the knowledge component.

The proposed self-optimising model is consistent with the fundamental working of blockchain-based systems. The model is most useful for private and consortium blockchain-based systems, where miners are controlled and predefined. However, public blockchain-based systems can still take advantage of the model if there is a management system that chooses a miner (i.e., controller) to be in charge of MAPE-K in a decentralised manner. This means that one miner cannot be the controller in all adaptation rounds to respect one of the inherent characteristics of blockchain-based systems (i.e., decentralisation). Selecting controllers can be implemented in a decentralised method, such as a Round-Robin fashion, or randomly. In each round, the controller will adapt the system by leveraging the MAPE-K loop processes and select a set of miners that will participate in mining new blocks. Any block mined by a not selected miner means that the miner is malicious, leading to the discarding of that block and the loss of the miner's reputation. However, a detailed discussion of the management system is outside the scope of this thesis.

In this chapter, the model aims to minimise the energy consumption and carbon emissions of blockchain-based systems and maximise the decentralisation and trustworthiness of these systems by selecting a subset of miners to perform mining processes. Our model can also be used when miners contribute to mining pools, where a set of miners is putting their resources together. Therefore, miners can be individual miners or mining pools. The target model is demonstrated in Figure 6.1. In the following sections, we discuss the five components of MAPE-K for our model in more detail.

6.4.1 Knowledge Component

During the process of self-adaptation, the monitoring, analysis, planning and execution components of the MAPE-K architecture are dependent on the knowledge component. It offers an abstract insight into the managed system's relevant aspects, environment and self-adaptation goals. Furthermore, the knowledge component is responsible for storing data and information needed to interact with the requirements and data of the blockchain-based system. In this chapter, the knowledge component is provided with data collected from different sources, such as Our World in Data [306], to be used as initial knowledge for our self-adaptive model. In line with [307], the knowledge component can be divided into four parts. The data collected falls under these parts, as follows:

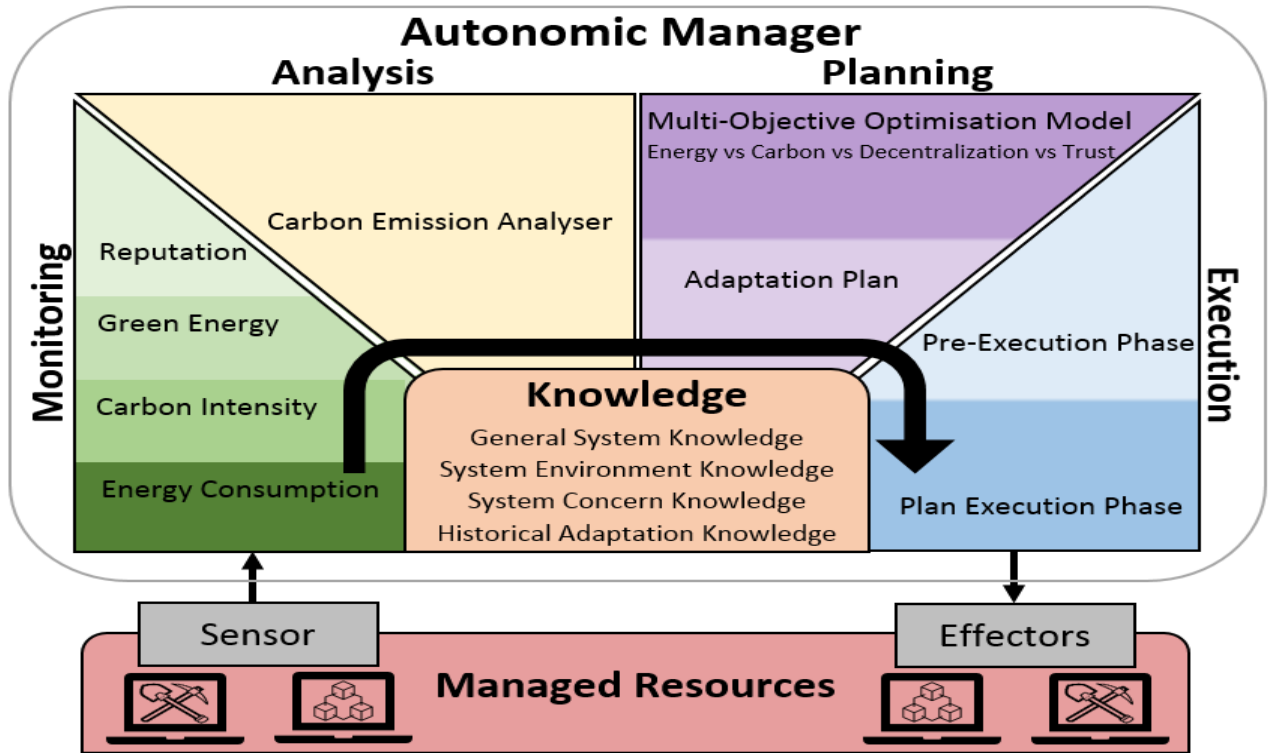


Figure 6.1: A self-adaptive model for blockchain-based systems.

6.4.1.1 General System Knowledge

General system knowledge offers an abstract view of the managed system. This kind of knowledge includes the preliminary information for operating the managed system. Additionally, it is relevant to the other components in the managed system, such as the number of miners and nodes within the blockchain-based system and the network status of the system, including difficulty, hashrate, hash algorithm, block size, transaction fee and reward.

6.4.1.2 System Environment Knowledge

System environment knowledge provides an abstract view of the environment, representing the context related to the operation and location of self-adaptive systems. This part of the knowledge refers to the environment related to the managed system and its resources. This information includes the locations of miners participating in the blockchain-based system, the carbon intensity and share of electricity from green resources in each miner's location at different times, the hashrate for each miner in the network and the mining device for each miner.

6.4.1.3 System Concern Knowledge

System concern knowledge provides relevant information regarding adaptation concerns. For example, it specifies the resources needed to accomplish the objectives of the self-adaptive system, such as the minimum number of miners within the blockchain-based system and the amount of carbon emissions and energy consumption of the system. Also, it provides related information for miners' decentralisation and reputation values within the blockchain network.

6.4.1.4 Historical Adaptation Knowledge

Historical adaptation knowledge represents run-time information shared between the MAPE components. In other words, it provides historical data, such as previous adaptation plans and historical adaptation analysis data. The other components can use this information to execute their functions. Historical adaptation knowledge can also be used for machine learning or statistical purposes.

6.4.2 Monitoring Component

The monitoring component retrieves information about the managed blockchain-based system and its environment during run-time through sensors to update the knowledge component. It may pre-process the collected data before updating the knowledge component. This pre-processing includes the normalisation, filtering and aggregation of data. Using sensors, we can retrieve precise metrics about miners within a blockchain network, such as energy consumption, carbon emission, the share of electricity from green resources and reputation.

This model uses a blockchain simulator to capture the primary monitoring information about the miners' state. This information includes the number of miners, their hashrates, their locations, the power of their devices, the number of blocks mined by each miner and network status (e.g., difficulty and hashrate). We use this information to determine the miners' energy efficiency, reputation value and carbon intensity and share of electricity from green resources in their locations.

6.4.3 Analysis Component

The analysis component establishes a need for adaptation actions based on the knowledge component contents and the monitored state of the managed blockchain-based system. It uses representations

of the adaptation goals available in the knowledge component to determine the system’s ability to achieve its goals, such as becoming more environmentally sustainable. Finally, the analysis results are used by the planning component and used to update the knowledge component, specifically the historical adaptation knowledge.

Our model aims to reduce carbon emissions that are produced by miners involved in mining blocks. The model considers the changes in the environment and decision-makers’ requirements during run-time. To this end, an analysis model is designed to assess the effectiveness of adaptation from the perspective of carbon emission produced by miners in blockchain-based systems. In other words, the analysis model calculates the carbon emissions that miners may produce while mining blocks in subsequent adaptations.

6.4.3.1 Carbon Emission Analyser

Carbon emissions related to electricity emission can be explained as the amount of greenhouse gases emitted while generating a given level of electricity; as such, reducing the amount of energy that blockchain systems use will reduce the production of greenhouse gases. However, the carbon intensity of a location, which changes over time, plays an important role in changing carbon emissions. Therefore, we should consider the value of carbon intensity for countries where miners are located.

Most electricity comes from brown resources, such as gas, coal and oil. However, it can be generated from other resources, such as nuclear and renewable resources, including solar, hydro-power, water, wind or sun, that nearly emit zero carbon emissions. Therefore, using renewable energy can mitigate the carbon emissions miners produce. Accordingly, green energy should be considered when measuring the total carbon emissions of miners. We can calculate the total amount of carbon emissions generated by a miner in a period as follows:

$$C = CI \times (E - GE\%) \quad (6.1)$$

where C is the total greenhouse gas emissions (g) that a miner produces in a time (t), and CI is the carbon emission intensity of electricity where the miner is located (gCO_2eq/kWh) in t . E is the total energy consumption of the miner (kWh), which can be consumed by more than one mining device. It can be calculated as $H \times P$, where H is the number of hours per day the miner participates in the blockchain network, and P is the total power use (kWh) of the mining devices. Finally, $GE\%$ is the

share of electricity from low-carbon resources in the miner's country in t .

6.4.4 Planning Component

In the MAPE-K, the outputs of the analysis component are sent to the plan component. Then, depending on the results of previous components and the knowledge component, this component adapts the managed system to optimise the system state taking into account environmental changes and decision-makers' requirements.

In this chapter, the plan component is triggered, and a set of plan actions is composed to improve the sustainability of the managed system. As with many real-world systems, improving one objective can affect other conflicting objectives in blockchain-based systems. Therefore, we have used a MOOM to propose an optimisation plan that finds the near-optimal solutions for enhancing the sustainability of the managed system without compromising the main properties of blockchain technology (i.e., the conflicting objectives).

6.4.4.1 MOOM for self-adaptive blockchain-based systems

To optimise the managed system, we aim to enhance the environmental sustainability of blockchain-based systems by reducing the amount of energy consumed and the amount of carbon emissions produced by the miners involved in mining blocks. Also, we aim to maintain one of the main core properties of these systems, which is decentralisation. A further goal of the model is to maintain the trustworthiness of blockchain-based systems, another main core property of these systems, by improving the miners' reputation values participating in mining processes.

To do this, we utilise a MOOM. This model selects a subset of miners to perform the mining processes in order to minimise the total energy consumption and carbon emissions while simultaneously maximising decentralisation and ensuring that the required trust level of the system is maintained. The model is designed to incorporate a mathematical fitness function formulated for four objectives to achieving this aim. The fitness function is characterised as energy consumption versus carbon emissions versus decentralisation versus trustworthiness. We discuss the objectives of this fitness function as follows:

• **Energy Consumption Objective.** Energy consumption is considered a dominant factor that impacts the sustainability of blockchain-based systems. Therefore, our model aims to enhance the sustainability of these systems by reducing the amount of energy they consume. A blockchain-based system consists of many mining data centres (i.e., miners) located at different locations, and each mining data centre has multiple mining devices. In our model, we consider minimising the energy-wasting of a blockchain-based system by reducing the number of mining data centres participating in the mining processes, which relates to the energy consumption of mining devices.

Mining devices within mining data centres consume a tremendous amount of energy during computing procedures, accounting for most of the energy consumption in most blockchain-based systems. Therefore, our optimisation objective is to minimise the total energy consumed by miners within a blockchain-based system E_{total} (kWh) that can be calculated as:

$$\text{Minimise: } E_{total} = \sum_{i=1}^{md} X_i \times E_i \quad (6.2)$$

where md is the total number of mining data centres in a blockchain network, and X_i is either 1, meaning a mining data centre is participating in the mining process, or 0, which means the mining data centre is not participating in the mining process.

• **Carbon Emission Objective.** Due to the rapid growth of mining data centres for blockchain-based systems, the energy consumption of the data centres can lead to massive carbon emissions that harm the environment. To achieve a sustainable blockchain-based system, we seek to minimise the carbon emissions produced by mining data centres. Thus, we optimise the total carbon emissions C_{total} (g) generated by all mining data centres participating in mining processes as follows:

$$\text{Minimise: } C_{total} = \sum_{i=1}^{md} X_i \times C_i \quad (6.3)$$

• **Decentralisation Objective.** Decentralisation is one core property of blockchain technology. It means that a blockchain-based system does not rely on one party or specific parties for mining processes and adding all new blocks. Therefore, it is essential to look at the number of miners within the system's network and the distribution of the mining of blocks among them. It is not helpful for the system to have many miners while only one or two miners are mining new blocks. This can make

the system more centralised since those miners control mining processes.

Allocating the mining of new blocks to specific miners can minimise the energy consumption and carbon emissions of a blockchain-based system. Nevertheless, we should consider the effects of this allocation on the system's decentralised. One way to measure decentralisation is by looking at the number of miners participating in the mining process and adding new blocks [64]. In particular, it can be measured using mining power (i.e., mining hashrate) for each miner and its hashrate fraction with the total hashrate of other miners. Similar to [16], [64], [65], [308], we measure the decentralisation of a blockchain-based system using Shannon's entropy that calculates the self-information of the event of mining blocks. Thus, we optimise and calculate the decentralisation of the system D as follows:

$$\text{Maximise: } D = - \sum_{i=1}^{md} X_i \times (MHF_i \times \log_2 MHF_i) \quad (6.4)$$

where MHF_i is a miner's hashrate fraction among all participating miners in mining new blocks. It can be calculated as h_i/h_t , where h_i is the miner's hashrate, and h_t represents the total hashrate of participating miners.

• **Trustworthiness Objective.** Reducing the number of miners to minimise energy consumption and carbon emissions can affect the trustworthiness of a blockchain-based system. The trustworthiness of this system relies on the number of miners and, more importantly, on their reputation within its network. Therefore, we should consider the total reputation of miners when reducing the number of miners within the system network. In other words, reducing miners without considering their reputations can lead to allocating the mining of new blocks to miners with low reputation values.

This chapter defines trust and reputation as described in Chapter 2. These definitions mean high reputation values of miners within a blockchain-based system lead to a more trustworthy system.

Our self-optimising system employs our reputation model introduced in Chapter 5 to maintain and ensure trustworthiness. The reputation model evaluates miners' credibility by calculating their reputations based on how they behave within a given blockchain network. It utilises the Sigmoid function to ensure that the reputation of each miner is between zero (as an unknown miner) and one (as a completely reputable miner) in a continuous range. We have used the same default values proposed in Chapter 5. The model can detect malicious miners with an average accuracy rate of 96%. The reputation value of a data centre R is calculated following the equation presented in Chapter 5

as follows:

$$R = \frac{1}{1 + e^{-\alpha(\text{satRound}-\lambda)}} \quad (6.5)$$

where *satRound* is the total satisfaction a miner gained during mining processes, and α and λ are parameters that can be adjusted to control the changes in the reputation values of miners during the mining of blocks.

As a result, we determine and optimise the total trustworthiness value for a blockchain-based system based on the reputation values of all participating miners within the blockchain network. Thus, the total trustworthiness value T_{total} can be calculated as follows:

$$\text{Maximise: } T_{total} = \sum_{i=1}^{md} X_i \times R_i \quad (6.6)$$

• **Fitness Function Constraints.** The following constraints for the MOOM should be satisfied:

1. The number of miners should be more than one for a set to mine new blocks in a blockchain-based system.
2. The hashrate for a miner in the set should be less than 50% of the total of other miners' hashrates in the set to prevent miners from performing a 51% attack.
3. Any other constraints obtained from the knowledge component, such as decision-makers' preferences regarding the amount of carbon emissions or the trustworthiness of the blockchain-based system.

6.4.4.2 Adaptation Plan

The adaptation plan uses the MOOM that finds sets of optimal miners for mining new blocks in a blockchain-based system. Then, it builds actions based on an optimal set that can be applied to meet the requirements of the decision-makers. In other words, it identifies a relevant decision to fit conditions on the knowledge component. Subsequently, a plan is generated for the selected adaptation option. Once the optimal set of miners has been selected and configured, the action is carried out by the execution component.

6.4.5 Execution Component

The execution component applies the adaptation plan proposed by the plan component using effectors to adapt the managed system status. In other words, the plan component sends a Pareto front solution to the execution component. This solution includes a list of selected miners that will perform the mining process for the following blocks until the next adaptation time, which is defined by a decision-maker for the managed system (e.g., each year). Finally, the plan is executed on the managed system without restarting it. The execute component consists of two phases: pre-execution and plan execution.

6.4.5.1 Pre-Execution Phase

First, the execute component verifies whether the managed system is ready to implement the planned actions. If the system readiness is not confirmed, the component completes pre-execution activities before executing the actions required to change miners within the managed system. The pre-execution typically includes steps, such as verifying the network's hashrate, mining difficulty and mining time for the managed system. In addition, it includes steps to ensure that the managed system is in a safe state. It is common for such preparation to include multiple steps.

6.4.5.2 Plan Execution Phase

After the pre-execution is completed, the component progresses to the second phase, in which the adaptation plan is performed. Changing miners may include completing tasks, such as updating the data stored in the knowledge component. Finally, the plan execution verifies that the plan has been accomplished and executed safely.

6.5 Experiment Design

This section discusses the design of experiments to show how our self-optimising model can improve the sustainability of blockchain-based systems by using an evolutionary algorithm that selects an optimal set of miners. Section 6.5.1 presents the research questions we aim to answer in this chapter. In Section 6.5.2, we introduce the evaluation procedure that is applied to answer the research questions, whereas Section 6.5.3 shows the settings of the MOOM. Finally, Section 6.5.4 shows the

implementation details.

6.5.1 Research questions

In this chapter, we aim to dynamically enhance the environmental sustainability of blockchain-based systems without compromising the inherent properties of blockchain technology. We propose a model that balances four conflicting objectives of these systems: energy, carbon, decentralisation and trustworthiness. Our model uses an adaptive technique that leverages the MAPE-K loop and the MOOM.

The chapter seeks to answer the fourth research question of this thesis introduced in Chapter 1:

RQ4: How can we dynamically enhance the environmental sustainability of blockchain-based systems while maintaining their decentralisation and trustworthiness, taking into account environmental changes and decision-makers' requirements?

To answer this question, some sub-questions need to be answered:

RQ4.1: To what extent can our self-optimising model decrease the energy consumption and carbon emissions of a blockchain-based system?

RQ4.2: How can the model affect the fundamental properties of the blockchain-based system (i.e., decentralisation and trustworthiness) when enhancing its environmental sustainability?

RQ4.3: How do the generated solutions using our self-optimising model improve the sustainability of the blockchain-based systems compared to similar existing optimisation models?

RQ4.4: What are the relationships between objectives and between each objective and the number of miners?

6.5.2 Evaluation Procedure

In our experiments, we consider that a blockchain-based system that uses PoW has the maximum energy consumption, carbon emission, decentralisation and trustworthiness level as all miners participate in the mining process (i.e., the system has 100% energy consumption, 100% carbon emission, 100% decentralisation and 100% trust level).

To answer the research questions, we consider there is a decision-maker who would like to optimise the environmental sustainability of a blockchain-based system (in comparison to the original values of energy consumption and carbon emission) while maintaining a level of decentralisation and trustworthiness of the system. We assume that the decision-maker desires to minimise energy

consumption and carbon emission and maximise decentralisation. At the same time, the trust level of the system is critical. Therefore, it must not be lower than the first quantile of the original system trust level (i.e., the trust level of the blockchain-based system after optimisation is not lower than 75% compared to the original system).

For selecting an optimal solution from the Pareto front generated by the MOOM, we pick the nearest solution to the decision-maker conditions. This solution can be chosen using Euclidean distance that finds the length of a line segment between two points [309]. Therefore, our model uses Euclidean to find the nearest solution for the decision-maker preferences regarding the four objectives.

We then conduct experiments to evaluate energy consumption and carbon emissions improvements for a blockchain-based system (RQ4.1). Also, we show how these improvements affect the levels of decentralisation and trustworthiness of these systems (RQ4.2). In addition, we conduct comparisons for a blockchain-based system applying our self-optimising model versus similar optimisation models (RQ4.3). We show how our model and other models improve energy and carbon and affect decentralisation and trustworthiness. Finally, we discuss the correlation between each pair of objectives and show the relationship between each objective and the number of miners within the system network (RQ4.4). We use the Kendall rank correlation coefficient to measure these relationships.

In this chapter, we have implemented a blockchain-based system that uses PoW as a comparison baseline model. Also, we have compared the self-adaptive model with similar studies, including a static optimisation model proposed in Chapter 4 and an energy-efficient PoW called Green-PoW that is proposed in [186].

The static optimisation model uses the MOOM to find the optimal set of miners (i.e., optimal solution) in a specific time and then applies the solution forever (i.e., an offline optimisation scenario where it first optimises the environmental sustainability of the system, then deploys forever). We use the same selection technique of the self-adaptive model for finding an optimal solution, which is the nearest optimal solution to the decision maker's preferences. We refer to this model as Static Model.

Green-PoW splits mining processes into iterations, each with two mining rounds. In the first round, all miners participate in mining and adding blocks, while a selected subset of miners from the first round participates in the second round. To compare this model with the proposed model, we use the best scenario of Green-PoW in terms of energy consumption.

6.5.3 MOOM Settings

The model employs an EA to obtain an optimal set of miners in a blockchain-based system that satisfies the decision-maker needs. We use the EA, NSGA-II [205], which can solve multi-objective optimisation problems. According to our discussion in Chapter 4, NSGA-II has outstanding performance for optimising the energy consumption, carbon emissions, decentralisation and trustworthiness of blockchain-based systems compared with alternative algorithms, such as Random Search, PAES, IBEA and NSGA-III. Also, NSGA-II creates non-dominated solutions for fitness functions with four conflicting objectives, where these solutions can span larger areas of the computed Pareto front compared to the alternative algorithms. Furthermore, it is well-known algorithm and well-suited for solving similar problems to ours [217].

To implement the algorithm, we use MOEA Framework ¹. In the first optimisation round, the initial population for the MOOM is designed to be random. For subsequent optimisation rounds, the initialisation uses the Pareto front generated from the previous optimisation to generate a new Pareto front. Next, the new Pareto front is used to find the optimal solution. Regarding the algorithm's variation operators and probabilities, we leave them at their default values. We run the algorithm with a population size of 160 solutions and 40,000 fitness evaluations per optimisation run. Finally, we repeat the experiment ten times to account for the stochastic nature of the used algorithm.

6.5.4 Implementation Details

The details of our experiments are presented in the sections below. We provide experimental settings and self-optimising model assumptions. A summary of the implementation details is presented in Table 6.1.

6.5.4.1 Experimental Settings

Similar to the implementation of the models introduced in Chapters 4 and 5, the proposed self-optimising model is evaluated by an empirical evaluation method, and experiments are conducted on the simulator for blockchain, Bitcoin-Simulator [13], using artificial and real data (see Table 6.1). The experiments are designed to simulate the most common cryptocurrency, Bitcoin.

¹MOEA Framework version is 2.13 and is available at <http://moeaframework.org>, accessed on August 31, 2021.

Table 6.1: Experiments Parameters

Variable	Value
Number of Miners	160
Number of blocks per year	1000
Number of miners' countries	16
Network hashrate	140.8 EH/s
Difficulty	21.66 TH/s
Mining device hashrate	110 TH/s
Mining device power	3.25 kWh
Miner running time	24 hours
α	0.025
λ	200
MOO algorithm	NSGA-II
Fitness evaluations	40,000
Number of experiments	10

We provide the model with data related to a blockchain-based system, such as the network's hashrate and the difficulty of finding a hash, from a well-known website for providing data service for global blockchain applications called BTC.com ². Data related to the hashrate for miners and the distribution of their locations are retrieved from CBECI. For analysing the carbon emissions produced by each miner at each time, we obtain the carbon intensity and the share of electricity generated from low-carbon sources for the countries where miners are located from the Our World In Data for ten years ³.

Each experiment evaluates these values after each year (i.e., adaptation round) for one decade. All experiments are completed on a Windows 10 machine with an Intel i7-6700 CPU clocked at 3.4GHz and 24GB memory.

6.5.4.2 Self-Optimising Model Assumptions

As discussed in Chapter 4, in real-world blockchain-based systems, especially public ones, it is impossible to accurately estimate the electricity usage for mining operations in these networks. This is because it is difficult to determine the number of mining machines within a given network and how many are active [16], [190] at a specific period. In addition, it is infeasible to isolate the power usage required during mining blocks from other background tasks on the same device or the energy usage

²<https://btc.com/en/btc>

³<https://ourworldindata.org>, retrieved on August 31, 2021.

of other devices operating in the same household or location. Thus, calculating electricity usage must be based on assumptions.

Similar to Chapter 4, we calculate how many mining devices are in a blockchain network based on the assumption that all miners utilise the most efficient devices where the number of devices used by each miner is linearly related to the miner’s hashrate. Underpinning this assumption is the reality that using inefficient devices results in less successful mining and fewer profits, thus leaving the network [190]. In our experiments, we especially apply one of the most efficient mining devices for Bitcoin, Antminer S19 Pro. It is generated by Bitmain Technology Holding Company ⁴ that boasts a mining power of 3.250 *kWh*, and its hashrate can reach 110 *TH/s*. Consequently, to determine how many devices each miner uses, the miner’s hashrate is divided by the hashrate for the given device. Each miner’s energy consumption is calculated based on all devices’ power. Also, as per the studies [16], [45], [190], we assume that mining is conducted 24 hours a day since miners are eager to maximise their profits, as we have mentioned before.

In real-world optimisation problems, evaluating the fitness function for solutions is commonly affected by noise. As a result, it is difficult to obtain accurate fitness function values without their noise [310]. Also, EAs are widely used to optimise problems in noisy natural environments, where such environments can change optimisation problems’ properties [236], [311]. Thus, we have modified the fitness function that evaluates the carbon emissions of blockchain-based systems $f(C)$ to replicate real-world scenarios. In particular, we have used a multiplicative noise model that multiplies the fitness function by a random value. The noisy fitness can be represented as $f^{Noisy}(C) = f(C) \times N$. We have drawn the random value N from a normal distribution that is from a range number of [0, 10].

Finally, We assume that the number of blocks mined each year (i.e., adaptation round) is 1000 blocks, and the managed system adapts after every year for 10000 blocks (i.e., one decade/ ten adaptation rounds).

6.6 Results and Discussion

This section answers the research questions **RQs 4.1-4.4**. First, we discuss the experiments’ results related to improving energy consumption and carbon emissions. Second, we show how environmental

⁴<https://www.bitmain.com>

sustainability improvements may affect blockchain technology’s inherent properties (i.e., decentralisation and trustworthiness). Third, we compare our model with similar models. Finally, we investigate and discuss the correlation between the four objectives and between each objective and the number of miners.

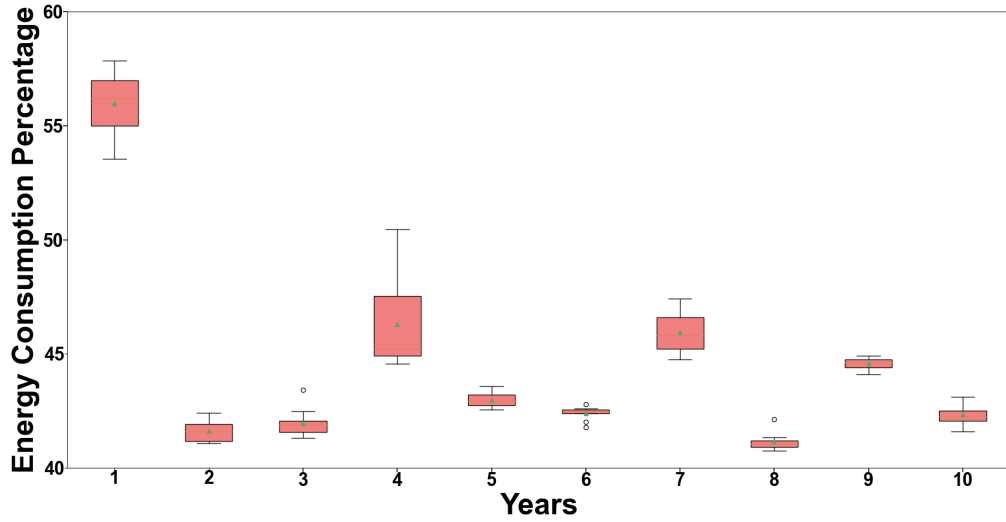
6.6.1 Improvement in Energy Consumption and Carbon Emission (RQ4.1)

Figure 6.2 shows the results of the selected solutions after conducting the self-optimisation experiment to improve the sustainability of the blockchain-based system regarding energy consumption and carbon emissions. The x-axes of the sub-figures present the rounds (i.e., years). In Figure 6.2A and Figure 6.2B, the y-axis shows the energy consumption percentage or carbon emission percentage of the solutions to the original solution (i.e., PoW) where all miners are selected for mining new blocks (for instance, $(\text{energy consumption of the PoW solution} - \text{energy consumption of the optimised solution}) / \text{energy consumption of the PoW solution} \times 100$). Each box-plot contains the result of ten experiment runs.

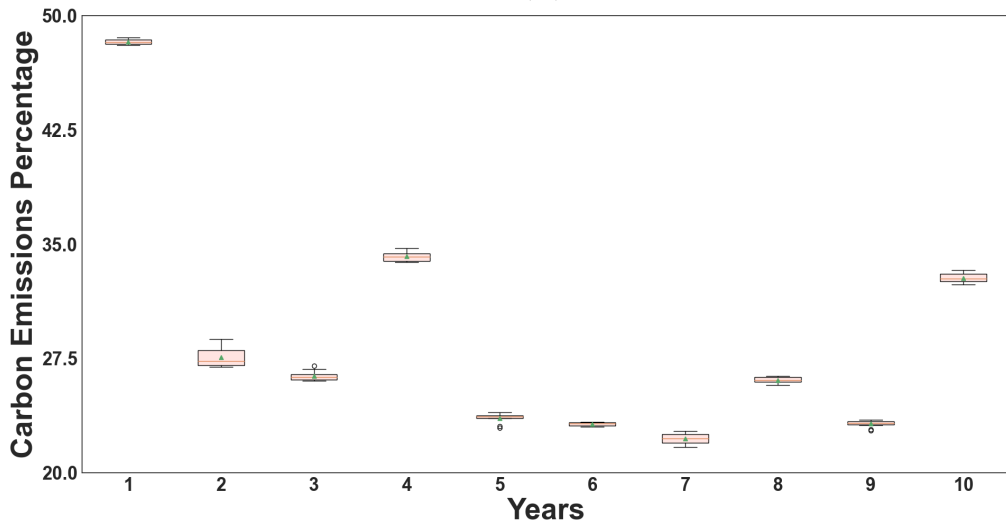
Generally, Figure 6.2A and Figure 6.2B show that the selected sets of miners in the ten experiments have obtained solutions that satisfy the decision maker’s preferences for each year in terms of environmental sustainability. These solutions are greener than the original PoW while providing acceptable solutions regarding trust level. The energy consumption of a blockchain-based system that uses our model is less than 50% in most rounds. The maximum energy consumption is less than 58% in all rounds, and the average reduction in energy per round is 55.49%. In addition, the carbon emission of the system is less than 35% in most rounds. The carbon emissions value has not exceeded 50% in all rounds, and the average reduction in carbon per round is 71.25%.

6.6.2 Reduction in Decentralisation and Trustworthiness (RQ4.2)

In our model, we aim to dynamically enhance the environmental sustainability of blockchain-based systems without compromising the fundamental properties of blockchain technology. We balance the environmental sustainability of the systems with their decentralisation and trustworthiness. Therefore, this section discusses the possible reduction in decentralisation and trustworthiness. As discussed



(A)

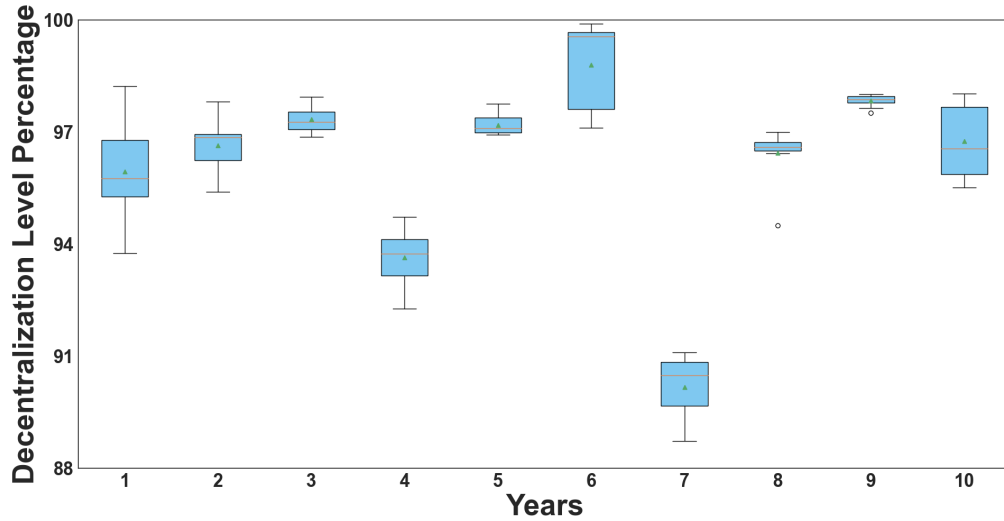


(B)

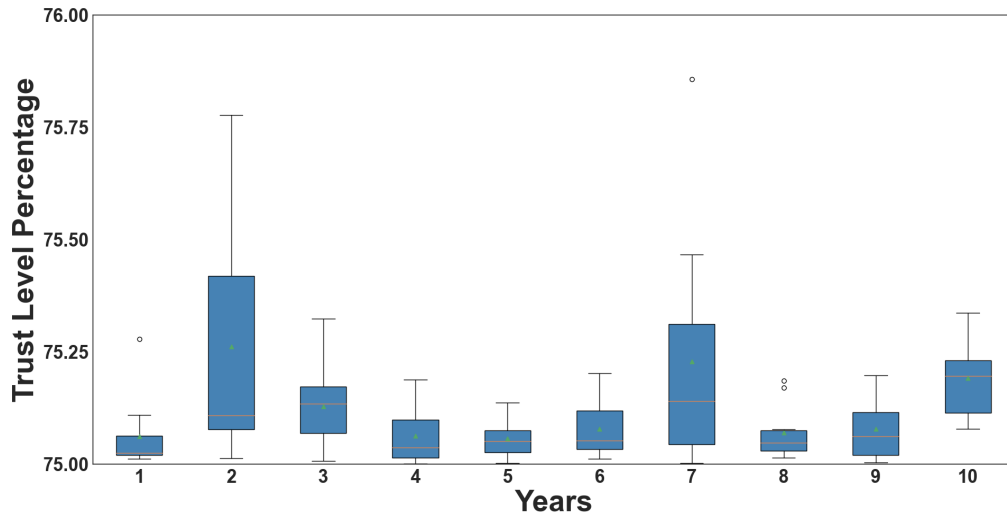
Figure 6.2: The energy consumption (A) and carbon emission (B) percentages of the ten experiments for one decade.

in Section 6.5.2, we assume the decision-maker desires to minimise energy consumption and carbon emissions and maximise the decentralisation of a blockchain-based system as much as possible. In contrast, the trust level of the system is critical and should not be lower than 75% after optimisation compared to the original system.

Figure 6.3 shows the decentralisation and trustworthiness percentages of the selected solutions by using our model. Similar to the previous section, the x-axes of the sub-figures present the rounds (i.e., years). In Figure 6.3A and Figure 6.3B, the y-axis respectively shows the decentralisation percentage or trustworthiness percentage of the solutions to the original solution.



(A)



(B)

Figure 6.3: The decentralisation (A) and trustworthiness (B) percentages of the ten experiments for one decade.

Figure 6.3A shows that most solutions have decentralisation percentages more than 94%. The percentage of decentralisation in all solutions is more than 88%, and the average reduction in decentralisation per round is 3.92%. Regarding trustworthiness, Figure 6.3B shows that the level of trustworthiness in all solutions has fulfilled the decision-maker preferences concerning the system's trustworthiness. In other words, the system still has a level of trustworthiness that is not less than 75% of PoW. The average reduction in trustworthiness per round is 24.88%. This indicates that our optimisation model evolves greener solutions in terms of energy consumption and carbon emission with an acceptable level of decentralisation and trustworthiness for the decision-maker. As seen

in Figure 6.3, optimising energy consumption and carbon emissions comes at costs that do not exceed 12% of the decentralisation value and 25% of the trustworthiness value compared to the original blockchain-based system using traditional PoW.

6.6.3 Self-optimising Model Versus Similar Studies (RQ4.3)

This section compares the reductions of a blockchain-based system’s energy consumption and carbon emissions using our self-optimisation model with similar works. Also, it discusses the effects of these improvements on the system’s decentralisation and trustworthiness.

In general, our model for self-optimising the sustainability of a blockchain-based system performs better in terms of energy consumption, carbon emissions, decentralisation and trustworthiness than the Static Model. Our model can reduce the system’s energy consumption by an additional 11.47% per round on average. Also, it can benefit an additional reduction of 22.19% in carbon emissions per round. These improvements come with increments in the decentralisation and trustworthiness of the blockchain-based system by 0.14% and 0.05%, respectively.

Compared with the Green-PoW model, the self-optimising model can enhance the environmental sustainability of the blockchain-based system more. Our model minimises energy consumption by more than 6.51% of the reduction of the Green-PoW model. In addition, our model performs better in terms of carbon emissions by more than 22.32% of the Green-PoW. Also, decentralisation and trustworthiness are higher than the Green-PoW model by 46.05% and 24.53%, respectively.

Table 6.2 summarises the results of the ten experiments for the three models (i.e., Self-optimising Model, Static Model and Green-PoW Model) compared to the systems that use the original PoW, where all miners are participating in mining blocks. In these systems, the energy consumption is $9.51 \times 10^7 \text{ kWh}$, which is constant in all years. Also, the decentralisation and trustworthiness levels are constants where decentralisation is 6.10, and trustworthiness is equal to 1.00, the highest level of trust. The PoW’s average carbon emission is $1.59 \times 10^{11} \text{ g}$ with a 95% confidence interval of 2.73×10^{10} .

6.6.4 The Relationships Between Objectives (RQ4.4)

In this section, we first discuss the correlations between every two objectives. Secondly, we show how the number of miners within a blockchain-based system is related to each objective. Figure 6.4

Table 6.2: Summary of the final improvement of the environmental sustainability of blockchain-based systems and its reductions on decentralisation and trustworthiness using Self-optimising Model, Static Model and Green-PoW model.

Model	Energy Consumption Reduction		
	Range	Average	CI
Self-optimising Model	55.89% - 54.83%	55.49%	0.16%
Static Model	46.45% - 42.15%	44.02%	0.73%
Green-PoW Model	49.03% - 48.96%	49.00%	0.01
Model	Carbon Emissions Reduction		
	Range	Average	CI
Self-optimising Model	71.37% - 71.05%	71.25%	0.05%
Static Model	51.54% - 47.17%	49.06%	0.78%
Green-PoW Model	48.98% - 48.93%	48.95%	0.01%
Model	Decentralisation Values Reduction		
	Range	Average	CI
Self-optimising Model	4.21% - 3.66%	3.92%	0.08%
Static Model	6.24% - 1.77%	4.06%	0.7%
Green-PoW Model	49.99% - 49.99%	49.99%	0.00
Model	Trustworthiness Values Reduction		
	Range	Average	CI
Self-optimising Model	24.95% - 24.79%	24.88%	0.02%
Static Model	24.99% - 24.72%	24.93%	0.04%
Green-PoW Model	49.45% - 49.43%	49.44%	0.003%

presents these correlations, where each cell shows the Kendall rank correlation coefficient results. Also, Figure 6.5 presents the correlation between the four objectives with the number of miners in one randomly selected experiment. Figure 6.5A shows the energy consumption, carbon emissions and the number of miners, while Figure 6.5B shows the decentralisation, trustworthiness and the number of miners. In Figure 6.5, we have applied a normalisation method called Unit Vector Transformation to transform values for the four objectives and the number of miners.

Figure 6.4 indicates that the correlations between each pair of objectives are strong positive relationships, except for decentralisation, where the strength of its associations with other objectives is weakly positive. In addition, the figure shows that the relationships between the number of miners within the blockchain network and each objective are strongly positive.

Although the relationship between energy consumption and carbon emissions is strongly positive, reducing energy consumption may not necessarily lead to low carbon emissions. The carbon

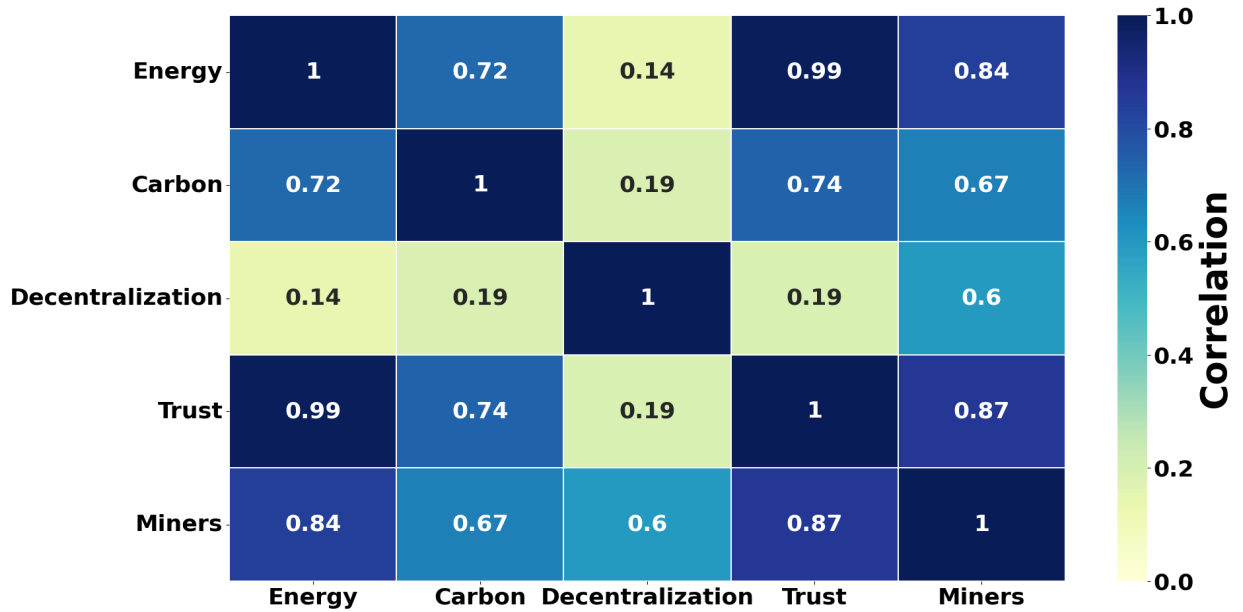
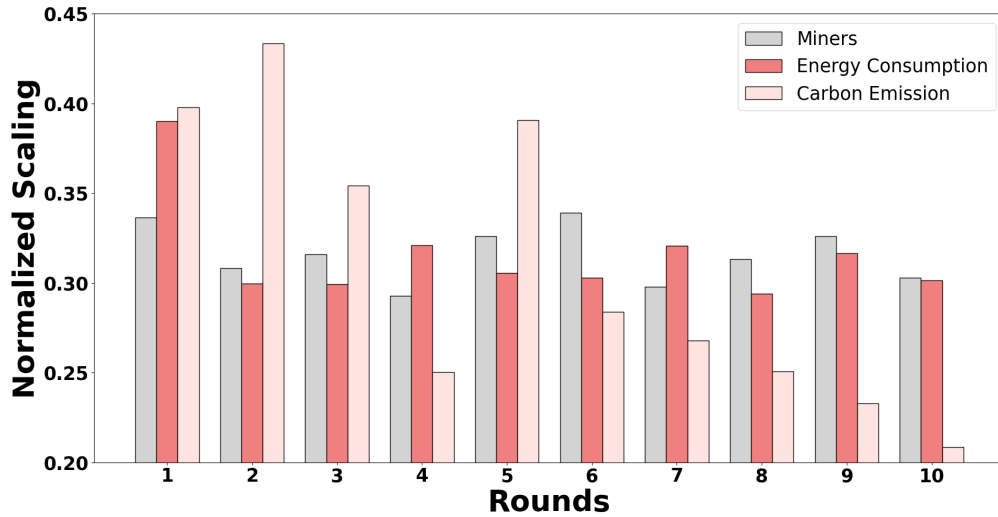


Figure 6.4: The Kendall rank correlation coefficient heatmap for every two objectives and for each objective with the number of miners.

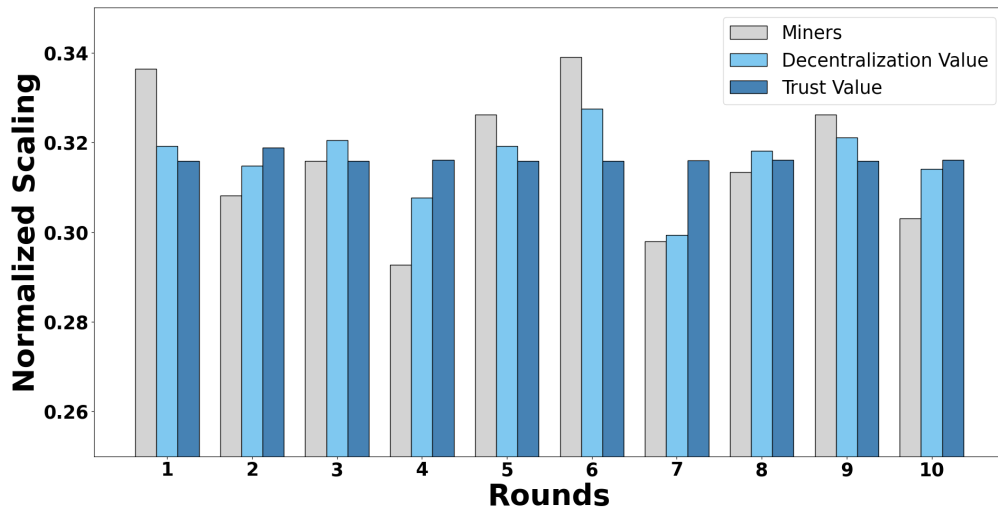
intensity of miners’ locations and the share of electricity generated from low-carbon resources in their countries play essential roles in the total carbon emissions. For example, a miner that uses high power generated from low-carbon resources and is located in a country with a low carbon intensity can produce low carbon emissions. In contrast, another miner that uses low power generated from brown resources and is located in a country with high carbon intensity can thus produce high carbon emissions. As seen in Figure 6.5A, miners in round 4 consume higher energy than those in round 3 but produce lower carbon emissions.

Many miners do not necessarily mean high energy consumption and carbon emissions in a blockchain-based system that uses the self-optimising model. For example, Figure 6.5A shows fewer miners in round 7 compared to round 8, but those miners’ energy consumption and carbon emissions are higher than the miners’ wastes in round 8. This is because of the differences in the number of mining devices for each miner and its location. Our model can select miners within a blockchain-based system that consume adequate power and are located in countries with low carbon intensities and high shares of electricity from green resources. As a result, the carbon emissions of the system are reduced.

It is worth mentioning that the high number of miners does not always lead to a high decentralisation or high trustworthiness (see Figures 6.4 and 6.5B). For example, a blockchain-based



(A)



(B)

Figure 6.5: The energy consumption, carbon emissions and the number of miners (A) and the decentralisation, trust and the number of miners for one experiment (B) for one experiment.

system can be centralised if only a few miners add new blocks even though many miners are in its network. This is because of the differences between the hashrate of miners. Figure 6.5B shows that miners in round 7 are higher than the miners in round 4, but the decentralisation and trustworthiness values in round 4 are higher than the values in round 7.

6.7 Conclusion

Despite the wide interest in Blockchain technology and its recognised potential, a critical debate has been raised in regard to its sustainability because of its excessive energy consumption and carbon

emissions as the cost of a trust provision. In this chapter, we have proposed a novel self-adaptive model for more sustainable blockchain-based systems. The model leverages MAPE-K and MOOM to dynamically trade-off between four objectives: energy consumption, carbon emission, decentralisation and trustworthiness of these systems. The solution optimises the environmental sustainability of blockchain-based systems at run-time by minimising miners' energy consumption and carbon emissions within these systems without compromising the core properties of blockchain technology. The experimental results show that energy consumption and carbon emissions can be more environmentally sustainable compared to the normal use of PoW and similar models. In addition, the results show that the model has the potential to maintain an adequate level of decentralisation and trustworthiness while balancing between the considered objectives. Finally, they show that there are strong positive correlations between each pair of objectives except decentralisation with other objectives. It also shows the relationships between the number of miners and each objective as strongly positive.

This work has paved the way for future research on enhancing the sustainability of blockchain-based systems. In the next chapter, we have discussed the possible opportunities for future studies.

Chapter Seven

CONCLUSION

7.1 Introduction

In this thesis, we present research into the field of computational sustainability that enhances the sustainability of blockchain-based systems by balancing the core properties of blockchain technology (i.e., decentralisation and trustworthiness) with energy consumption and carbon emissions of blockchain-based systems. This chapter provides an overall conclusion of the thesis. Section 7.2 discusses how we have addressed the research questions. In Section 7.3, we summarise the key findings and link the different chapters of the thesis. In addition, we discuss potential threats to the validity of this research in Section 7.4. This is followed by possible future directions discussed in Section 7.5. Finally, the closing remarks are presented in Section 7.6.

7.2 Addressing the Research Questions

As explained in Chapter 1, this thesis aims to optimise blockchain technology by balancing conflicting objectives. The thesis focuses on optimising the environmental sustainability of blockchain-based systems by balancing energy consumption, carbon emissions, decentralisation and trustworthiness using evolutionary algorithms. In this context, we propose novel models that address our research questions. This section shows how we have addressed the research questions of the thesis.

7.2.1 Research Question 1

RQ1: What is the state of the art in optimising the environmental sustainability of blockchain technology and its design? We conducted a systematic literature review that provides a better understanding of the state of the art in optimising the environmental sustainability of

blockchain-based systems. We found that the environmental sustainability of blockchain-based systems is affected by different factors connected to the design of this technology. Therefore, we classified these factors based on their relations with blockchain components, such as the architectural component of blockchain technology. Moreover, we consolidated the efforts in the literature to enhance the environmental sustainability of blockchain-based systems by providing a classification framework that categorises the methods and techniques that specifically optimise the energy consumption and carbon emissions of these systems, leading to more sustainable systems. Also, we investigated the weakness of these approaches. In addition, we discussed tools for measuring the environmental sustainability of blockchain-based systems, including energy consumption, carbon emissions and e-waste. Finally, we determined the gaps and future directions in developing environmentally sustainable blockchain-based systems based on the SLR findings.

7.2.2 Research Question 2

RQ2: How can the environmental sustainability of a blockchain-based system be optimised without compromising its inherent properties, such as decentralisation and trustworthiness? In Chapter 4, we formulated the problem of optimising the environmental sustainability of blockchain (i.e., energy and carbon emission minimisation) as an SBSE problem. We represented the problem of selecting miners for mining blocks in a blockchain-based system as a subset selection problem. We proposed a novel model composed of multiple fitness functions. The model was used to explore the complex search space by selecting a subset of miners that minimises energy consumption and carbon emissions without drastically impacting the core properties of blockchain technology (i.e., decentralisation and trustworthiness). We integrated our proposed fitness functions into five EAs to solve the problem of selecting blockchain miners. Several experiments were conducted to demonstrate the effectiveness and applicability of the model in enhancing the environmental sustainability of blockchain-based systems. The results showed that the environmental sustainability of blockchain-based systems could be enhanced with little reduction in competing objectives. The results also showed that the selected EAs outperformed the baseline algorithm. The proposed model was used to optimise the environmental sustainability of blockchain-based systems. However, it can potentially be used for optimising other objectives of these systems, such as security and scalability.

7.2.3 Research Question 3

RQ3: How can we evaluate the reputation of miners within blockchain-based systems, considering the dynamic of miners' behaviours, to support the environmental sustainability of these systems? We proposed a reputation model that influences how reputation is fundamentally managed within blockchain-based systems. We introduced several major characteristics and properties to design the reputation model for blockchain-based systems. This reputation model aimed to evaluate the reputation of miners within blockchain-based systems and then select trusted miners for mining new blocks. The model could boost the trustworthiness of blockchain-based systems, which may be reduced due to reducing the number of miners or when it compromises conflicting objectives. It could also minimise energy consumption and carbon emissions for blockchain-based systems when it overlies existing consensus algorithms to select miners based on their reputation values. The proposed reputation model assessed the reputation of individual miners by reflecting the miners' behaviour within a blockchain-based system that uses a traditional Proof of Work consensus algorithm. The model was evaluated analytically and compared to other existing trust and reputation models for evaluating the trust and reputation of miners. In addition, we performed experimental evaluations to represent the performance of our model and its accuracy in detecting malicious miners. We evaluated the effectiveness of the model regarding the energy consumption and carbon emissions of blockchain-based systems. The evaluation showed that our model fulfilled several desirable properties that should always be satisfied by reputation models for blockchain-based systems, whereas other models only sometimes met these requirements. Our experiments also demonstrated the model's effectiveness in detecting malicious miners. In terms of the energy consumption and carbon emissions of these systems, integrating the model with PoW succeeded in reducing energy consumption and carbon emissions compared to the standard PoW consensus algorithm. Our model can potentially be integrated with any consensus algorithm that uses a mining process. Also, it has the potential to enable environmentally sustainable blockchain-based systems mining without compromising the inherent trustworthiness of blockchain technology.

7.2.4 Research Question 4

RQ4: How can we dynamically enhance the environmental sustainability of blockchain-based systems while maintaining their decentralisation and trustworthiness, taking into account environmental changes and decision-makers' requirements? In Chapter 6, we proposed a novel self-adaptive model to optimise blockchain-based systems. The self-optimising model continuously monitored the deployed system and adaptively selected a set of miners, considering environmental changes and decision-makers' needs. The model aimed to trade off conflicting objectives regarding optimising the environmental sustainability of these systems. The model dynamically selected a subset of miners to perform sustainable mining processes without compromising the fundamental properties of blockchain technology. The objective was to minimise the energy consumption and carbon emissions of blockchain-based systems, while maximising the decentralisation and trustworthiness of the systems. We implemented simulations and evaluated the efficiency and effectiveness of the model. The results showed that our model was able to dynamically optimise the environmental sustainability of blockchain-based systems. It can minimise energy consumption and carbon emissions while maintaining a desirable level of decentralisation and trustworthiness of the decision-makers under different operating conditions compared to similar models, including the straightforward use of Proof of Work. Although the model was utilised for optimising four conflicting objectives (i.e., the energy consumption, carbon emissions, decentralisation and trustworthiness of blockchain-based systems), it can potentially be applied as a self-adaptive model for any other conflicting objectives of blockchain-based systems.

7.3 Summary of Contributions and Findings

Throughout this thesis, we have tackled the critical challenge of improving the environmental sustainability of blockchain-based systems. Our research contributions are summarised as follows:

1. **Environmental Sustainability SLR and Research Gap Identification.** In Chapter 3, we conducted a comprehensive SLR to explore the state-of-the-art methods and techniques aimed at enhancing the environmental sustainability of blockchain-based systems. The SLR provided a solid foundation for our research by identifying key research gaps in this domain. By understanding the existing limitations and challenges, we set the stage for our novel contributions to

address environmental sustainability issues in blockchain-based systems.

2. Multi-objective Optimisation Model (MOOM) for Environmental Sustainability.

In Chapter 4, we formulated the environmental sustainability problem of blockchain-based systems as an SBSE problem. To address this, we developed a robust MOOM that leverages EAs to optimise energy consumption and carbon emissions while simultaneously maximising decentralisation and trustworthiness. Our results demonstrated that our approach can enhance the environmental sustainability of blockchain-based systems without compromising other crucial objectives. However, we also identified limitations regarding the static nature of the model and the need for an improved reputation model for miners.

3. Dynamic Reputation Model for Enhancing Trustworthiness and Environmental Sustainability.

Chapter 5 focused on addressing the need for a reputation model for miners within blockchain-based systems. We proposed a novel dynamic reputation model that calculates miners' reputation based on their contributions to mining blocks. This model effectively enhances the trustworthiness and environmental sustainability of the systems by selecting reputable miners to mine new blocks. The experiments demonstrated the model's high accuracy in detecting malicious miners and its significant impact in reducing energy consumption and carbon emissions compared to traditional PoW consensus. However, we also acknowledged concerns about potential impacts on decentralisation.

4. Self-Adaptive Model for Optimal Environmental Sustainability.

Building upon the concerns raised in Chapters 4 and 5, Chapter 6 addressed the static nature of the model and potential decentralisation impacts. We introduced a self-adaptive model that integrates self-adaptive architectures and multi-objective optimisation models. This dynamic approach utilises an EA to maintain decentralisation and trustworthiness while optimising energy consumption and carbon emissions based on environmental conditions and user requirements. By incorporating our reputation model, we mitigated potential decreases in trustworthiness due to minimised miner numbers. The results highlighted that this model presents a promising approach to achieving more environmentally sustainable blockchain-based systems without compromising decentralisation and trustworthiness, surpassing similar models in performance.

Our research significantly advances the field of environmentally sustainable blockchain-based

systems. By demonstrating the potential to reduce energy consumption and carbon emissions, we have contributed to promoting greener blockchain technology. Additionally, our dynamic reputation model enhances trustworthiness and security, further fostering environmental sustainability. Moreover, by considering dynamic environmental changes and user requirements, we have successfully developed a model that dynamically enhances the environmental sustainability of blockchain technology without compromising its core properties.

In conclusion, our thesis underscores the importance of prioritising environmental sustainability in blockchain technology. Our contributions will inspire further research and innovation, creating more sustainable and resilient blockchain-based systems for a greener and more trustworthy future. Our models' dynamic and self-adaptive nature holds immense promise in addressing environmental sustainability challenges in the rapidly evolving landscape of blockchain technology.

7.4 Threats to Validity

This section presents potential threats to the validity of this research. In the following sections, we discuss these threats with regard to our contributions.

7.4.1 Threats to Validity Related to the Literature Review

We can summarise the main challenges and limitations of the validity of our review with three points:

- **Missing Relevant Studies.** Our SLR may have missed some studies that have considered developing blockchain environmental sustainability as part of their works without mentioning this specifically in the abstract, introduction or conclusion. However, we designed our search protocol to include papers that list the research terms in all metadata, including keywords that the writers of the papers specify. Thus, we trust the quality of the digital databases to identify and index papers.

We have used a snowballing technique to reveal any potentially relevant material that the search query may miss. The objective is to acquire the best possible collection of primary studies and subsequent follow-ups on the topic. The snowballing technique, detailed in [312], was added to the search process to check cross-references in the chosen primary studies.

- **Bias in Selection of Studies.** Reviews can be affected by publication bias; however, the search protocol used by our SLR surveyed four well-known scientific databases, allowing us to source high-quality published research. Our protocol may not have identified some blockchain research because blockchain technology is still a new topic within computer science research and practice. Moreover, some industry research would not be available to us because they may have been conducted and published internally or as white papers. Nonetheless, we believe that using scientific databases with Google Scholar enables us to find more articles and gives us a higher chance of finding papers presented as white papers.
- **Inaccuracy in Data Extraction.** There are different reasons why inaccuracy may arise in the data collection phase, such as researchers' backgrounds, personalities and choice of how to present methodological approaches and findings. However, the strategy we have employed to minimise inaccuracies during data extraction is to ensure that all the extracted data have been checked twice. Hence, we are confident that we have kept inaccuracies to a minimum during data extraction.

7.4.2 Threats to Validity Related to Proposed Approaches

In this section, we consider potential threats to validity related to the proposed approaches as follows:

- **Approaches' Generality.** We have proposed static and dynamic models that can trade off four conflicting objectives of blockchain-based systems. We have utilised the models to balance these systems' energy consumption, carbon emissions, decentralisation and trustworthiness. Though the models have shown promising results, we cannot claim the applicability and generality of the models with other conflicting objectives. However, these models can guide researchers to apply these models to other conflicting objectives. Therefore, further research is needed to evaluate our model with other conflicting objectives. This can present new modalities, simplification, extension or customisation to the models.

7.4.3 Threats to Validity Related to Evaluation

The potential threats to the validity of our experiments and evaluation can be summarised as follows:

- **Simulation Environment.** In this thesis, we have conducted our experiments in a controlled environment via a simulator for blockchain-based systems that use Proof of Work. This can be one potential threat to validity. However, we have utilised a well-known simulator that simulates a common blockchain application, Bitcoin. In addition, using simulators can facilitate faster experimentation for diverse scenarios without expenses and costs. To mitigate the threat, we have used real-world data to conduct our experiments. Although we have carefully designed the simulation environment to emulate real-world systems, we recognise that further studies will be required to assess the effectiveness of our models in real-world scenarios.
- **Computational Overhead.** Some hidden computational overhead can be an external threat to the validity of this work, and it needs to be analysed and evaluated before applying the approaches in industry. This overhead may result from the Multi-Objective Optimisation Model, including searching for Pareto fronts. Also, it can come from the phases of the feedback loop, such as the computational overhead from monitoring miners within a blockchain-based system and analysing collected data. However, the computational overhead that has been observed in the simulated experiments is indicative of the expected overhead that may be encountered in a real-world context.
- **Energy Measurement.** Another threat to the validity of the evaluation derives from the fact that the work is evaluated using the energy consumption information of mining devices provided by their manufacturers. However, this information is considered the most accurately examined information. Although our evaluations are conducted with reasonable energy consumption information, we appreciate the further extension of the work to use the actual observed energy consumption of mining devices.

7.5 Future Directions

Several opportunities for future research can be derived from the work presented in this thesis. In this section, we discuss some potential future directions.

7.5.1 Optimising Blockchain-based Systems Using their Different Decentralisation Types

Blockchain technology decentralisation types can play essential roles in optimising blockchain-based systems. This thesis focused on the most critical decentralisation type, consensus decentralisation. It is considered the main factor affecting the environmental sustainability of these systems. We have demonstrated the efficiency of using this type to optimise sustainability without compromising the inherent properties of the technology. However, as discussed in Chapter 2, each kind of decentralisation can have an effect on the environmental sustainability of these systems. Therefore, we appreciate that further research needs to consider other types of decentralisation to optimise blockchain-based systems' environmental sustainability.

7.5.2 Optimising Blockchain-based Systems Using Renewable Energy

Renewable energy resources can enhance the environmental sustainability of blockchain-based systems. In this thesis, we optimised the environmental sustainability of blockchain-based systems by minimising energy consumption and carbon emissions. Energy consumption and carbon emissions are utilised as objectives of the Multi-Objective Optimisation Models proposed in Chapters 4 and 6. Although we have considered low-carbon energy for calculating the energy consumption of miners for the optimising models, future studies are needed to explore the use of renewable energy resources as a separate objective in optimising the environmental sustainability of the systems. In this context, using renewable energy resources can include several dimensions, such as mining blocks, verifying blocks, cooling strategies and the mixed use of brown and green energy.

7.5.3 Integrating Machine Learning Approaches with Blockchain-based Systems

Machine Learning (ML) is a branch of Artificial Intelligence (AI) that focuses on developing systems that learn via experiences. It has powerful data processing capabilities and can feasibly solve a wide range of problems. Integrating ML and blockchain technology can be a promising solution for many

issues of blockchain-based systems and could be usefully combined with our optimisation approaches. Therefore, one potential direction is to integrate ML approaches with feedback loops, such as MAPE-K, and use previous adaptation data to predict the behaviour of miners in mining new blocks in relation to energy consumption and carbon emissions.

7.5.4 Multi-Criteria Decision Making for Optimising Blockchain-based Systems

Multi-Criteria Decision Making (MCDM) is a way of organising and solving problems that involve multiple criteria for decision and planning. It is the research of finding and selecting options based on the decision-makers' preferences. In this thesis, we propose MOOMs to optimise the environmental sustainability of blockchain-based systems using EAs that provide Pareto fronts of optimal solutions. Therefore, it would be beneficial to extend our optimisation models to utilise MCDM techniques, such as TOPSIS, to rank or sort optimal solutions from a Pareto front and pick the optimal solution based on the decision-makers' preferences.

7.6 Closing Remarks

In conclusion, this thesis significantly contributes to the area of computational sustainability for one of the emerging technologies, blockchain technology. It makes novel contributions by optimising the environmental sustainability of blockchain technology. Also, it shows a new insight into managing reputation within blockchain-based systems to support the environmental sustainability of these systems.

The findings of this thesis can provide a better understanding of optimising the conflicting objectives of blockchain-based systems and designing them to be more sustainable. The experiments have indicated the effectiveness of the proposed optimisation models in enhancing the environmental sustainability of blockchain-based systems statically and dynamically without compromising the fundamental properties of this technology. We also present a novel model for assessing the reputation of miners within blockchain-based systems so as to support their environmental sustainability.

In this research journey, we have stated our vision in Chapter 1, which is “to design sustainable blockchain-based systems that can contribute to the Sustainable Development Agenda without

compromising the inherent properties of the technology”. Although achieving this vision could need several theses in this field, our work inspires future research in balancing the inherent decentralisation and trustworthiness of the technology and its environmental sustainability in terms of energy consumption and carbon emissions.

Appendix One

Systematic Literature Review Methods

This appendix provides an overview of the research methods and systematic processes we employ to conduct a review of the environmental sustainability of the design of blockchain-based systems. The procedures followed by this SLR are in line with the guidelines for undertaking SLRs [77], [78]. In more detail, we perform six stages in the current SLR, as shown in Figure A.1.

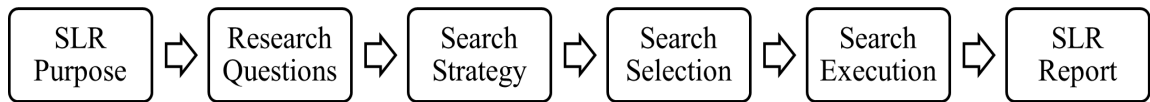


Figure A.1: SLR Processes

A.1 Goal and Research Questions

The purpose of our SLR is to conduct a review of the environmental sustainability of blockchain-based systems. It focuses on analysing the existing methods proposed as a way to promote the environmental sustainability of blockchain-based systems. As presented in Chapter 3, our SLR aims to answer the first question of the thesis introduced in Chapter 1: **RQ1: What is the state of the art in optimising the environmental sustainability of blockchain technology and its design?**

The review is focused on answering the following sub-questions:

- **RQ1.1:** What are the factors that need to be considered when systematically evaluating the environmental sustainability of blockchain-based systems?
- **RQ1.2:** What are the state-of-the-art methods and techniques for developing a more environmentally sustainable blockchain technology?
- **RQ1.3:** How can the current methods for improving the environmental sustainability of blockchain-based systems be categorised?

- **RQ1.4:** What are the challenges and weaknesses of these methods?
- **RQ1.5:** How is the environmental sustainability of blockchain technology measured?
- **RQ1.6:** What are the gaps in the current research regarding the development of environmentally sustainable blockchain designs?

A.2 Search Strategy

A.2.1 Data Sources

Since blockchain technology is a relatively new field of research, selecting the best sources for reviewing previous research is relatively complex. The search process was undertaken by employing the automatic search facility in a number of digital libraries/indexing systems: SpringerLink, ScienceDirect, IEEE Xplore, ACM Digital Library and Google Scholar. These electronic databases are recommended in [77], [313]. Additionally, they are regarded as the most substantial and complete scientific databases for literary reviews [314] and the most relevant and trusted source for computer science [315]. We chose to search for publications between 2008 and December 2022 because the term blockchain originated in 2008 with Satoshi Nakamoto, and the first application of blockchain, Bitcoin, launched in 2009.

A.2.2 Search Terms

The search terms aim to identify all studies relevant to blockchain-based systems that have associations with environmental sustainability. For each database trial, searches were undertaken to check how many papers would be returned and how relevant they would be. The purpose of a trial search is to test how feasible the search string is and make the appropriate adjustments. Based on the topic of the current review and its research questions, the terms for the search queries were defined in accordance with the practices recommended in [77], [78]. Variations of searches were conducted, where the search has been guided by the inclusion criteria described in Section A.3 and key terms, such as ‘Blockchain’, ‘Environmental Sustainability’, ‘Energy Consumption’ and ‘Consensus Algorithm’. In reference to consensus mechanisms, for instance, ‘Proof of Work’, the consideration of this term is intentional as it is regarded as the “genesis” of existing consensus mechanisms to date, and subse-

quent mechanisms usually explicitly leverage ‘Proof of Work’. Additionally, consensus algorithms are considered the focal constituent components for the computational cost of this technology and are major contributors to energy consumption and, therefore, important when considering environmental sustainability.

A Cross-references check, where we searched for papers with an explicit or implicit connection to the search, complements the basic searches primarily focused on environmental sustainability. Cross-reference checks have included papers that, for example, discuss energy consumption and/or carbon emissions, optimisations, monitoring, measuring energy consumption and/or environmental sustainability, proposing new efficient consensus algorithms etc. The objective is to acquire the best possible collection of primary studies and subsequent follow-ups on the topic. We employed the snowballing technique, as detailed in [312], to add to the search process, checking cross-references in the chosen primary studies to reveal any potentially relevant material that may be missed by the search query.

A.3 Selection of Primary Studies

While we were screening the results of the search, the relevance of each paper was determined by a close examination of the titles, abstracts, introductions and conclusions. If these elements did not offer sufficient information to decide on the article’s relevance, the entire paper was studied. The selection was undertaken in line with the inclusion/exclusion criteria set out in Table A.1. The references of the chosen primary studies were examined to see if any relevant studies had been missed and, if so, where they could be found; they were then subjected to the same primary study selection process.

A.4 Search Execution

We employed the search terms for the data sources in the search engines to search both full-text and metadata (i.e., title, keywords and abstract). The main researchers completed the search on 31st of January 2023, following the agreed search strategy; the process was supervised by two supervisors. During this practice, specific settings were created for each search engine because every digital library

Table A.1: Selection Criteria of Primary Studies

Inclusion Criteria
1. Full research and short papers published in conferences and journals
2. Published book chapters and books
3. Papers discussing aspects of the environmental sustainability of blockchain
4. Papers discussing the environmental sustainability of blockchain architecture
5. Papers discussing aspects influencing environmental sustainability of blockchain
6. Papers proposing methods for improving the sustainability of blockchain
7. Papers defining and characterising the methods to measure blockchain environmental sustainability
Exclusion Criteria
1. Abstract papers, tutorial papers, presentations or essays
2. Papers without an abstract
3. Papers published not in the English language
4. papers focusing on blockchain adoption
5. Papers proposing methods for utilising blockchain technology to improve the environmental sustainability of other systems
6. Papers on the application of blockchain without having a link to environmental sustainability

Table A.2: Number of Related Papers Collected for the Study

Database	Number of Related Papers
SpringerLink	8
ScienceDirect	27
IEEE Xplore	30
ACM Digital Library	12
Google Scholar	27 of the first 200 hits
Total	104

has its own way of working. This was an attempt to reduce the amount of rejection and duplication by customising the options for every search engine. In particular, when filters were available, they were used to ask the search engine to only return studies it had published itself or to only bring back English language results.

As a result of this stage, 104 out of 1575 papers were selected (see Table A.2). The papers were collected as a bibliography in BibTeX format, which creates a collection of bibliographies for the retrieved papers. After that, Mendeley, an open-source reference manager system that can be used for managing such databases, was employed to create a single bibliography file after the duplicates had been detected and removed.

References

- [1] C. T. Nguyen, D. T. Hoang, D. N. Nguyen, D. Niyato, H. T. Nguyen, and E. Dutkiewicz, “Proof-of-stake consensus mechanisms for future blockchain networks: Fundamentals, applications and opportunities,” *IEEE Access*, vol. 7, pp. 85 727–85 745, 2019.
- [2] D. L. K. Chuen, Ed., *Handbook of Digital Currency: Bitcoin, Innovation, Financial Instruments, and Big Data*. New York, NY, USA: Academic Press, 2015.
- [3] S. Nakamoto. “Bitcoin: A peer-to-peer electronic cash system.” (2008), [Online]. Available: <https://bitcoin.org/bitcoin.pdf>.
- [4] F. Casino, T. K. Dasaklis, and C. Patsakis, “A systematic literature review of blockchain-based applications: Current status, classification and open issues,” *Telematics and Informatics*, vol. 36, pp. 55–81, 2019.
- [5] R. Buyya, S. N. Srirama, G. Casale, *et al.*, “A manifesto for future generation cloud computing: Research directions for the next decade,” *ACM Comput. Surv.*, vol. 51, no. 5, 2018.
- [6] B. Moldan, S. Janoušková, and T. Háek, “How to understand and measure environmental sustainability: Indicators and targets,” *Ecological Indicators*, vol. 17, pp. 4–13, 2012.
- [7] A. O. Bada, A. Damianou, C. M. Angelopoulos, and V. Katos, “Towards a green blockchain: A review of consensus mechanisms and their energy consumption,” in *17th International Conference on Distributed Computing in Sensor Systems (DCOSS)*, 2021, pp. 503–511.
- [8] Z. Zheng, S. Xie, H.-N. Dai, X. Chen, and H. Wang, “Blockchain challenges and opportunities: A survey,” *International Journal of Web and Grid Services*, vol. 14, no. 4, pp. 352–375, 2018.
- [9] J. Truby, “Decarbonizing bitcoin: Law and policy choices for reducing the energy consumption of blockchain technologies and digital currencies,” *Energy Research and Social Science*, vol. 44, pp. 399–410, 2018.
- [10] A. De Vries, “Bitcoin’s energy consumption is underestimated: A market dynamics approach,” *Energy Research & Social Science*, vol. 70, p. 101 721, 2020.
- [11] Cambridge Centre for Alternative Finance. “Cambridge Bitcoin Electricity Consumption Index.” Accessed December 31, 2020. (2020), [Online]. Available: <https://www.cbeci.org>.

- [12] K. Peffers, T. Tuunanen, M. A. Rothenberger, and S. Chatterjee, “A design science research methodology for information systems research,” *Journal of Management Information Systems*, vol. 24, no. 3, pp. 45–77, 2007.
- [13] A. Gervais, G. O. Karame, K. Wüst, V. Glykantzis, H. Ritzdorf, and S. Capkun, “On the security and performance of proof of work blockchains,” in *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security (CCS '16)*, 2016, pp. 3–16.
- [14] C. Gomes, T. Dietterich, C. Barrett, *et al.*, “Computational sustainability: Computing for a better world and a sustainable future,” *Commun. ACM*, vol. 62, no. 9, pp. 56–65, 2019.
- [15] A. Alofi, M. A. Bokhari, R. Hendley, and R. Bahsoon, “Selecting miners within blockchain-based systems using evolutionary algorithms for energy optimisation,” in *Proceedings of the Genetic and Evolutionary Computation Conference Companion (GECCO '21)*, 2021, pp. 291–292.
- [16] A. Alofi, M. Bokhari, R. Bahsoon, and B. Hendley, “Optimizing the energy consumption of blockchain-based systems using evolutionary algorithms: A new problem formulation,” *IEEE Transactions on Sustainable Computing*, pp. 1–13, 2022.
- [17] A. Alofi, R. Bahsoon, and R. Hendley, “Minerrepu: A reputation model for miners in blockchain networks,” in *IEEE International Conference on Web Services (ICWS)*, 2021, pp. 724–733.
- [18] A. A. Monrat, O. Schelén, and K. Andersson, “A survey of blockchain from the perspectives of applications, challenges, and opportunities,” *IEEE Access*, vol. 7, pp. 117 134–117 151, 2019.
- [19] M. Nofer, P. Gomber, O. Hinz, and D. Schiereck, “Blockchain,” *Business & Information Systems Engineering*, vol. 59, pp. 183–187, 2017.
- [20] M. Andoni, V. Robu, D. Flynn, *et al.*, “Blockchain technology in the energy sector: A systematic review of challenges and opportunities,” *Renewable and Sustainable Energy Reviews*, vol. 100, pp. 143–174, 2019.
- [21] A. Kosba, A. Miller, E. Shi, Z. Wen, and C. Papamanthou, “Hawk: The blockchain model of cryptography and privacy-preserving smart contracts,” in *IEEE Symposium on Security and Privacy (SP)*, 2016, pp. 839–858.
- [22] B. W. Akins, J. L. Chapman, and J. M. Gordon, “A whole new world: Income tax considerations of the bitcoin economy,” *Pitt. Tax Rev.*, vol. 12, p. 25, 2014.
- [23] M. Sharples and J. Domingue, “The blockchain and kudos: A distributed system for educational record, reputation and reward,” in *European Conference on Technology Enhanced Learning*, 2016, pp. 490–496.

- [24] Y. Zhang and J. Wen, “An iot electric business model based on the protocol of bitcoin,” in *18th International Conference on Intelligence in Next Generation Networks*, 2015, pp. 184–191.
- [25] K. Christidis and M. Devetsikiotis, “Blockchains and smart contracts for the internet of things,” *IEEE Access*, vol. 4, pp. 2292–2303, 2016.
- [26] M. Crosby, Nachiappan, P. Pattanayak, S. Verma, and V. Kalyanaraman, “Blockchain technology: Beyond bitcoin,” *Applied Innovation*, vol. 2, pp. 6–19, 2016.
- [27] M. Pilkington, “11 blockchain technology: Principles and applications,” *Research handbook on digital transformations*, vol. 225, pp. 225–253, 2016.
- [28] Z. Zheng, S. Xie, H. Dai, X. Chen, and H. Wang, “An overview of blockchain technology: Architecture, consensus, and future trends,” in *IEEE International Congress on Big Data (BigData Congress)*, 2017, pp. 557–564.
- [29] T. M. Fernández-Caramés and P. Fraga-Lamas, “A review on the use of blockchain for the internet of things,” *IEEE Access*, vol. 6, pp. 32 979–33 001, 2018.
- [30] L. S. Sankar, M. Sindhu, and M. Sethumadhavan, “Survey of consensus protocols on blockchain applications,” in *4th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 2017, pp. 1–5.
- [31] D. Puthal, N. Malik, S. P. Mohanty, E. Kougianos, and G. Das, “Everything you wanted to know about the blockchain: Its promise, components, processes, and problems,” *IEEE Consumer Electronics Magazine*, vol. 7, no. 4, pp. 6–14, 2018.
- [32] K. Domdouzis, “Chapter 6 - sustainable cloud computing,” in *Green Information Technology*, Boston: Morgan Kaufmann, 2015, pp. 95–110.
- [33] J. A. García-Berna, J. M. Carrillo de Gea, B. Moros, J. L. Fernández-Alemán, J. Nicolás, and A. Toval, “Surveying the environmental and technical dimensions of sustainability in software development companies,” *Applied Sciences*, vol. 8, no. 11, 2018.
- [34] T. Kuhlman and J. Farrington, “What is sustainability?” *Sustainability*, vol. 2, no. 11, pp. 3436–3448, 2010.
- [35] C. Becker, R. Chitchyan, L. Duboc, *et al.*, “Sustainability design and software: The karlskrona manifesto,” in *IEEE/ACM 37th IEEE International Conference on Software Engineering (ICSE '15)*, 2015, pp. 467–476.
- [36] G. H. Brundtland, “Our common future—call for action,” *Environmental Conservation*, vol. 14, no. 4, pp. 291–294, 1987.
- [37] P. Bambazek, I. Groher, and N. Seyff, “Sustainability in agile software development: A survey study among practitioners,” in *2022 International Conference on ICT for Sustainability (ICT4S)*, 2022, pp. 13–23.
- [38] C. Calero and M. Piattini, “Introduction to green in software engineering,” in *Green in Software Engineering*, 2015, pp. 3–27.

- [39] B. Penzenstadler and H. Femmer, “A generic model for sustainability with process- and product-specific instances,” in *Proceedings of the 2013 Workshop on Green in/by Software Engineering (GIBSE '13)*, 2013, pp. 3–8.
- [40] J. P. Barton and D. G. Infield, “Energy storage and its use with intermittent renewable energy,” *IEEE Transactions on Energy Conversion*, vol. 19, no. 2, pp. 441–448, 2004.
- [41] B. Penzenstadler, V. Bauer, C. Calero, and X. Franch, “Sustainability in software engineering: A systematic literature review,” in *16th International Conference on Evaluation Assessment in Software Engineering (EASE 2012)*, 2012, pp. 32–41.
- [42] G. Chapron, “The environment needs cryptogovernance,” *Nature*, vol. 545, no. 7655, pp. 403–405, 2017.
- [43] S. Saberi, M. Kouhizadeh, J. Sarkis, and L. Shen, “Blockchain technology and its relationships to sustainable supply chain management,” *International Journal of Production Research*, vol. 57, no. 7, pp. 2117–2135, 2019.
- [44] A. de Vries, “Bitcoin’s growing energy problem,” *Joule*, vol. 2, no. 5, pp. 801–805, 2018.
- [45] C. Stoll, L. Klaaßen, and U. Gallersdörfer, “The carbon footprint of bitcoin,” *Joule*, vol. 3, no. 7, pp. 1647–1661, 2019.
- [46] H. Vranken, “Sustainability of bitcoin and blockchains,” *Current Opinion in Environmental Sustainability*, vol. 28, pp. 1–9, 2017.
- [47] C. Mora, R. L. Rollins, K. Taladay, *et al.*, “Bitcoin emissions alone could push global warming above 2°c,” *Nature Climate Change*, vol. 8, pp. 931–933, 2018.
- [48] A. Park and H. Li, “The effect of blockchain technology on supply chain sustainability performances,” *Sustainability*, vol. 13, no. 4, p. 1726, 2021.
- [49] P. Giungato, R. Rana, A. Tarabella, and C. Tricase, “Current trends in sustainability of bitcoins and related blockchain technology,” *Sustainability*, vol. 9, no. 12, 2017.
- [50] L. Liu and W. Shi, “Trust and reputation management,” *IEEE Internet Computing*, vol. 14, no. 5, pp. 10–13, 2010.
- [51] A. Jøsang, R. Ismail, and C. Boyd, “A survey of trust and reputation systems for online service provision,” *Decision Support Systems*, vol. 43, no. 2, pp. 618–644, 2007.
- [52] Y. Wang and J. Vassileva, “Trust and reputation model in peer-to-peer networks,” in *Proceedings Third International Conference on Peer-to-Peer Computing (P2P2003)*, 2003, pp. 150–157.
- [53] M. Momani and C. Subhash, “Survey of trust models in different network domains,” *International Journal of Ad Hoc, Sensor & Ubiquitous Computing*, vol. 1, no. 3, pp. 1–19, 2010.

- [54] A. Abdul-Rahman and S. Hailes, "Supporting trust in virtual communities," in *Proceedings of the 33rd annual Hawaii international conference on system sciences*, 2000, 9–pp.
- [55] D. Gambetta, "Can we trust trust?" *Trust: Making and Breaking Cooperative Relations, electronic edition, Department of Sociology, University of Oxford*, pp. 213–237, 2000.
- [56] L. Lamport, R. Shostak, and M. Pease, "The byzantine generals problem," *ACM Transactions on Programming Languages and Systems (TOPLAS)*, vol. 4, no. 3, pp. 382–401, 1982.
- [57] A. M. Antonopoulos, *Mastering Bitcoin: Programming the open blockchain*. " O'Reilly Media, Inc.", 2017.
- [58] S. Bajoudah, C. Dong, and P. Missier, "Toward a decentralized, trust-less marketplace for brokered iot data trading using blockchain," in *IEEE International Conference on Blockchain (Blockchain)*, 2019, pp. 339–346.
- [59] D. Madala, M. P. Jhanwar, and A. Chattopadhyay, "Certificate transparency using blockchain," in *IEEE International Conference on Data Mining Workshops (ICDMW)*, 2018, pp. 71–80.
- [60] B. K. Mohanta, S. S. Panda, U. Satapathy, D. Jena, and D. Gountia, "Trustworthy management in decentralized iot application using blockchain," in *10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, 2019, pp. 1–5.
- [61] A. Lahbib, K. Toumi, A. Laouiti, A. Laube, and S. Martin, "Blockchain based trust management mechanism for iot," in *IEEE Wireless Communications and Networking Conference (WCNC)*, 2019, pp. 1–8.
- [62] E. Bellini, Y. Iraqi, and E. Damiani, "Blockchain-based distributed trust and reputation management systems: A survey," *IEEE Access*, vol. 8, pp. 21 127–21 151, 2020.
- [63] I. Bashir, *Mastering Blockchain*. Packt Publishing Ltd, 2017.
- [64] S. P. Gochhayat, S. Shetty, R. Mukkamala, P. Foytik, G. A. Kamhoua, and L. Njilla, "Measuring decentrality in blockchain based systems," *IEEE Access*, vol. 8, pp. 178 372–178 390, 2020.
- [65] K. Wu, B. Peng, H. Xie, and Z. Huang, "An information entropy method to quantify the degrees of decentralization for blockchain systems," in *2019 IEEE 9th International Conference on Electronics Information and Emergency Communication (ICEIEC)*, 2019, pp. 1–6.
- [66] I. Eyal, "The miner's dilemma," in *2015 IEEE Symposium on Security and Privacy (SP)*, IEEE Computer Society, 2015, pp. 89–103.
- [67] X. Li, P. Jiang, T. Chen, X. Luo, and Q. Wen, "A survey on the security of blockchain systems," *Future Generation Computer Systems*, vol. 107, pp. 841–853, 2020.

- [68] R. van Pelt, S. Jansen, D. Baars, and S. Overbeek, “Defining blockchain governance: A framework for analysis and comparison,” *Information Systems Management*, vol. 38, no. 1, pp. 21–41, 2021.
- [69] S. Brienza, S. Cebeci, S. S. Masoumzadeh, H. Hlavacs, O. Ozkasap, and G. Anastasi, “A survey on energy efficiency in p2p systems: File distribution, content streaming, and epidemics,” *ACM Computing Surveys*, vol. 48, pp. 1–37, Dec. 2015.
- [70] A. Vázquez-Rodas and L. J. de la Cruz Llopis, “A centrality-based topology control protocol for wireless mesh networks,” *Ad Hoc Networks*, vol. 24, pp. 34–54, 2015.
- [71] L. Lao, Z. Li, S. Hou, B. Xiao, S. Guo, and Y. Yang, “A survey of iot applications in blockchain systems: Architecture, consensus, and traffic modeling,” *ACM Comput. Surv.*, vol. 53, no. 1, 2020.
- [72] J. Huang, D. He, M. S. Obaidat, P. Vijayakumar, M. Luo, and K.-K. R. Choo, “The application of the blockchain technology in voting systems: A review,” *ACM Comput. Surv.*, vol. 54, no. 3, 2021.
- [73] J. Xu, C. Wang, and X. Jia, “A survey of blockchain consensus protocols,” *ACM Comput. Surv.*, 2023.
- [74] S. J. Alsunaidi and F. A. Alhaidari, “A survey of consensus algorithms for blockchain technology,” in *2019 International Conference on Computer and Information Sciences (ICIS)*, 2019, pp. 1–6.
- [75] J. Zou, D. He, S. Zeadally, N. Kumar, H. Wang, and K. R. Choo, “Integrated blockchain and cloud computing systems: A systematic survey, solutions, and challenges,” *ACM Comput. Surv.*, vol. 54, no. 8, 2021.
- [76] E. J. De Aguiar, B. S. Façal, B. Krishnamachari, and J. Ueyama, “A survey of blockchain-based strategies for healthcare,” *ACM Comput. Surv.*, vol. 53, no. 2, 2020.
- [77] P. Brereton, B. A. Kitchenham, D. Budgen, M. Turner, and M. Khalil, “Lessons from applying the systematic literature review process within the software engineering domain,” *Journal of Systems and Software*, vol. 80, no. 4, pp. 571–583, 2007.
- [78] B. A. Kitchenham and S. Charters, “Guidelines for performing systematic literature reviews in software engineering,” Tech. Rep., 2007.
- [79] M. Conoscenti, A. Vetro, and J. C. De Martin, “Blockchain for the internet of things: A systematic literature review,” in *IEEE/ACS 13th International Conference of Computer Systems and Applications (AICCSA)*, 2016, pp. 1–6.
- [80] P. Sharma, R. Jindal, and M. D. Borah, “Blockchain technology for cloud storage: A systematic literature review,” *ACM Comput. Surv.*, vol. 53, no. 4, 2020.
- [81] Y. Wang, J. H. Han, and P. Beynon-Davies, “Understanding blockchain technology for future supply chains: A systematic literature review and research agenda,” *Supply Chain Management: An International Journal*, vol. 24, no. 1, 2019.

- [82] A. Tandon, A. Dhir, A. N. Islam, and M. Mäntymäki, “Blockchain in healthcare: A systematic literature review, synthesizing framework and future research agenda,” *Computers in Industry*, vol. 122, 2020.
- [83] F. R. Batubara, J. Ubacht, and M. Janssen, “Challenges of blockchain technology adoption for e-government: A systematic literature review,” in *Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age (dg.o '18)*, 2018.
- [84] I. Konstantinidis, G. Siaminos, C. Timplalexis, P. Zervas, V. Peristeras, and S. Decker, “Blockchain for business applications: A systematic literature review,” in *Business Information Systems*, 2018, pp. 384–399.
- [85] C. Shen and F. Pena-Mora, “Blockchain for cities—a systematic literature review,” *IEEE Access*, vol. 6, pp. 76 787–76 819, 2018.
- [86] O. Bermeo-Almeida, M. Cardenas-Rodriguez, T. Samaniego-Cobo, E. Ferruzola-Gómez, R. Cabezas-Cabezas, and W. Bazán-Vera, “Blockchain in agriculture: A systematic literature review,” in *Technologies and Innovation*, 2018, pp. 44–56.
- [87] E. H. Lund, L. Jaccheri, J. Li, O. Cico, and X. Bai, “Blockchain and sustainability: A systematic mapping study,” in *IEEE/ACM 2nd International Workshop on Emerging Trends in Software Engineering for Blockchain (WETSEB)*, 2019, pp. 16–23.
- [88] F. Eigelshoven, A. Ullrich, and B. Bender, “Public blockchain—a systematic literature review on the sustainability of consensus algorithms,” in *Proceedings of the 28th European Conference on Information Systems (ECIS)*, 2020.
- [89] Y. Xiao, N. Zhang, W. Lou, and Y. T. Hou, “A survey of distributed consensus protocols for blockchain networks,” *IEEE Communications Surveys Tutorials*, vol. 22, no. 2, pp. 1432–1465, 2020.
- [90] P. Giungato, R. Rana, A. Tarabella, and C. Tricase, “Current trends in sustainability of bitcoins and related blockchain technology,” *Sustainability*, vol. 9, no. 12, p. 2214, 2017.
- [91] R. L. Rana, P. Giungato, A. Tarabella, and C. Tricase, “Blockchain applications and sustainability issues,” *Amfiteatru Economic*, vol. 21, no. 13, pp. 861–870, 2019.
- [92] C. Schinckus, “The good, the bad and the ugly: An overview of the sustainability of blockchain technology,” *Energy Research and Social Science*, vol. 69, p. 101 614, 2020.
- [93] N. V. Apatova, O. V. Boychenko, O. L. Korolyov, I. V. Gavrikov, and T. K. Uza-kov, “Stability and sustainability of cryptotokens in the digital economy,” in *Distributed Computer and Communication Networks: Control, Computation, Communications*, 2020, pp. 484–496.
- [94] K. J. O’Dwyer and D. Malone, “Bitcoin mining and its energy footprint,” in *25th IET Irish Signals Systems Conference 2014 and 2014 China-Ireland International Con-*

ference on Information and Communications Technologies (ISSC 2014/CICT 2014), 2014, pp. 280–285.

- [95] J. Li, N. Li, J. Peng, H. Cui, and Z. Wu, “Energy consumption of cryptocurrency mining: A study of electricity consumption in mining cryptocurrencies,” *Energy*, vol. 168, pp. 160–168, 2019.
- [96] J. Sedlmeir, H. U. Buhl, G. Fridgen, and R. Keller, “The energy consumption of blockchain technology: Beyond myth,” *Business & Information Systems Engineering*, pp. 1–10, 2020.
- [97] R. K. Jana, I. Ghosh, and M. W. Wallin, “Taming energy and electronic waste generation in bitcoin mining: Insights from facebook prophet and deep neural network,” *Technological Forecasting and Social Change*, vol. 178, p. 121 584, 2022.
- [98] M. Bedford Taylor, “Bitcoin and the age of bespoke silicon,” in *International Conference on Compilers, Architecture and Synthesis for Embedded Systems (CASES)*, 2013, pp. 1–10.
- [99] É. Delliere and C. Grange, “Understanding and measuring the ecological sustainability of the blockchain technology,” in *Proceedings of the 39th International Conference on Information Systems (ICIS)*, 2018.
- [100] S. Köhler and M. Pizzol, “Life cycle assessment of bitcoin mining,” *Environmental Science & Technology*, vol. 53, no. 23, pp. 13 598–13 606, 2019.
- [101] G. Hileman and M. Rauchs, “Global cryptocurrency benchmarking study,” Cambridge, MA, USA: Cambridge Centre for Alternative Finance, 2017.
- [102] S. Liaskos and B. Wang, “Towards a model for comprehending and reasoning about pow-based blockchain network sustainability,” in *Proceedings of the 33rd Annual ACM Symposium on Applied Computing (SAC ’18)*, 2018, pp. 383–387.
- [103] S. Erdogan, M. Y. Ahmed, and S. A. Sarkodie, “Analyzing asymmetric effects of cryptocurrency demand on environmental sustainability,” *Environmental Science and Pollution Research*, vol. 29, pp. 31 723–31 733, 2022.
- [104] M. Ball, A. Rosen, M. Sabin, and P. N. Vasudevan. “Proofs of useful work.” (2017), [Online]. Available: <https://eprint.iacr.org/2018/559>.
- [105] A. Shoker, “Brief announcement: Sustainable blockchains through proof of exercise,” in *Proceedings of the 2018 ACM Symposium on Principles of Distributed Computing (PODC ’18)*, 2018, pp. 269–271.
- [106] A. de Vries, U. Gellersdörfer, L. Klaaßen, and C. Stoll, “Revisiting bitcoin’s carbon footprint,” *Joule*, vol. 6, no. 3, pp. 498–502, 2022.
- [107] N. Lei, E. Masanet, and J. Koomey, “Best practices for analyzing the direct energy use of blockchain technology systems: Review and policy recommendations,” *Energy Policy*, vol. 156, p. 112 422, 2021.

- [108] M. Kouhizadeh and J. Sarkis, “Blockchain practices, potentials, and perspectives in greening supply chains,” *Sustainability*, vol. 10, no. 10, p. 3652, 2018.
- [109] E. Mengelkamp, B. Notheisen, C. Beer, D. Dauer, and C. Weinhardt, “A blockchain-based smart grid: Towards sustainable local energy markets,” *Computer Science-Research and Development*, vol. 33, no. 1-2, pp. 207–214, 2018.
- [110] V. Nehra, A. K. Sharma, and R. K. Tripathi, “Chapter 5 - blockchain implementation for internet of things applications,” in *Handbook of Research on Blockchain Technology*, Academic Press, 2020, pp. 113–132.
- [111] A. de Vries, “Bitcoin boom: What rising prices mean for the network’s energy consumption,” *Joule*, vol. 5, no. 3, pp. 509–513, 2021.
- [112] O. Fadeyi, O. Krejcar, P. Maresova, K. Kuca, P. Brida, and A. Selamat, “Opinions on sustainability of smart cities in the context of energy challenges posed by cryptocurrency mining,” *Sustainability*, vol. 12, no. 1, 2020.
- [113] L. Kristoufek, “Bitcoin and its mining on the equilibrium path,” *Energy Economics*, vol. 85, p. 104588, 2020.
- [114] B. A. Jones, A. L. Goodkind, and R. P. Berrens, “Economic estimation of bitcoin mining’s climate damages demonstrates closer resemblance to digital crude than digital gold,” *Scientific Reports*, vol. 12, pp. 1–10, 2022.
- [115] E. Atkins, L. Follis, B. D. Neimark, and V. Thomas, “Uneven development, crypto-regionalism, and the (un-)tethering of nature in quebec,” *Geoforum*, vol. 122, pp. 63–73, 2021.
- [116] J. Truby, R. D. Brown, A. Dahdal, and I. Ibrahim, “Blockchain, climate damage, and death: Policy interventions to reduce the carbon emissions, mortality, and net-zero implications of non-fungible tokens and bitcoin,” *Energy Research & Social Science*, vol. 88, p. 102499, 2022.
- [117] L. Cocco, A. Pinna, and M. Marchesi, “Banking on blockchain: Costs savings thanks to the blockchain technology,” *Future Internet*, vol. 9, no. 3, 2017.
- [118] D. Das and A. Dutta, “Bitcoin’s energy consumption: Is it the achilles heel to miner’s revenue?” *Economics Letters*, vol. 186, p. 108530, 2020.
- [119] E. Kabaklarlı, “Green fintech: Sustainability of bitcoin,” *Digital Finance*, vol. 4, pp. 265–273, 2022.
- [120] E. G. Teo, “Chapter 9 - emergence, growth, and sustainability of bitcoin: The network economics perspective,” in Academic Press, 2015, pp. 191–200.
- [121] S. King and S. Nadal. “Ppcoin: Peer-to-peer crypto-currency with proof-of-stake.” (2012), [Online]. Available: <https://www.peercoin.net/whitepapers/peercoin-paper.pdf>.

- [122] G. Wood, “Ethereum: A secure decentralised generalised transaction ledger,” *Ethereum project yellow paper*, vol. 151, pp. 1–32, 2014.
- [123] U. Mukhopadhyay, A. Skjellum, O. Hambolu, J. Oakley, L. Yu, and R. Brooks, “A brief survey of cryptocurrency systems,” in *14th Annual Conference on Privacy, Security and Trust (PST)*, 2016, pp. 745–752.
- [124] M. Saad, Z. Qin, K. Ren, D. Nyang, and D. Mohaisen, “E-pos: Making proof-of-stake decentralized and fair,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 32, no. 8, pp. 1961–1973, 2021.
- [125] D. Larimer, “Delegated proof-of-stake (dpos),” BitShares Organization, 2014.
- [126] L. Ren. “Proof of stake velocity: Building the social currency of the digital age.” (2014), [Online]. Available: <https://www.reddcoin.com/reddpaper>.
- [127] F. Tschorsch and B. Scheuermann, “Bitcoin and beyond: A technical survey on decentralized digital currencies,” *IEEE Communications Surveys & Tutorials*, vol. 18, no. 3, pp. 2084–2123, 2016.
- [128] I. Bentov, C. Lee, A. Mizrahi, and M. Rosenfeld, “Proof of activity: Extending bitcoin’s proof of work via proof of stake,” *SIGMETRICS Perform. Eval. Rev.*, vol. 42, no. 3, pp. 34–37, 2014.
- [129] NEM. “Nem technical reference.” (2018), [Online]. Available: https://nem.io/wp-content/themes/nem/files/NEM_techRef.pdf.
- [130] P. Siano, G. D. Marco, A. Rolán, and V. Loia, “A survey and evaluation of the potentials of distributed ledger technology for peer-to-peer transactive energy exchanges in local energy markets,” *IEEE Systems Journal*, vol. 13, no. 3, pp. 3454–3466, 2019.
- [131] M. Moniruzzaman, A. Yassine, and R. Benlamri, “Blockchain-based mechanisms for local energy trading in smart grids,” in *IEEE 16th International Conference on Smart Cities: Improving Quality of Life Using ICT and IoT and AI (HONET-ICT)*, 2019, pp. 110–114.
- [132] H. A. Abdelsalam, A. K. Srivastava, and A. Eldosouky, “Blockchain-based privacy preserving and energy saving mechanism for electricity prosumers,” *IEEE Transactions on Sustainable Energy*, vol. 13, no. 1, pp. 302–314, 2022.
- [133] Y. P. Tsang, K. L. Choy, C. H. Wu, G. T. S. Ho, and H. Y. Lam, “Blockchain-driven iot for food traceability with an integrated consensus mechanism,” *IEEE Access*, vol. 7, pp. 129 000–129 017, 2019.
- [134] X. Fu, H. Wang, P. Shi, and H. Mi, “Popf: A consensus algorithm for jledger,” in *IEEE Symposium on Service-Oriented System Engineering (SOSE)*, 2018, pp. 204–209.
- [135] Y. Zhang, L. Zhang, Y. Liu, and X. Luo, “Proof of service power: A blockchain consensus for cloud manufacturing,” *Journal of Manufacturing Systems*, vol. 59, pp. 1–11, 2021.

- [136] M. Raikwar and D. Gligoroski, “The meshwork ledger, its consensus and reward mechanisms,” in *2021 International Conference on COMMunication Systems & NETWORKS (COMSNETS)*, 2021, pp. 290–298.
- [137] I. Corporation. “Proof-of-elapsed-time (poet).” (2015), [Online]. Available: <https://sawtooth.hyperledger.org/docs/core/nightly/0-8/architecture/poet.html>.
- [138] M. Milutinovic, W. He, H. Wu, and M. Kanwal, “Proof of luck: An efficient blockchain consensus protocol,” in *Proceedings of the 1st Workshop on System Software for Trusted Execution*, 2016, pp. 1–6.
- [139] S. Dziembowski, S. Faust, V. Kolmogorov, and K. Pietrzak, “Proofs of space,” in *Proceedings of the Conference on Advances in Cryptology (CRYPTO 2015)*, 2015, pp. 585–605.
- [140] T. Moran and I. Orlov. “Simple proofs of space-time and rational proofs of storage.” (2016), [Online]. Available: <https://eprint.iacr.org/2016/035>.
- [141] A. Miller, A. Juels, E. Shi, B. Parno, and J. Katz, “Permacoin: Repurposing bitcoin work for data preservation,” in *IEEE Symposium on Security and Privacy*, 2014, pp. 475–490.
- [142] A. Juels and B. S. Kaliski, “Pors: Proofs of retrievability for large files,” in *Proceedings of the 14th ACM Conference on Computer and Communications Security (CCS ’07)*, 2007, pp. 584–597.
- [143] S. King. “Primecoin: Cryptocurrency with prime number proof-of-work.” (2013), [Online]. Available: <https://primecoin.io/bin/primecoin-paper.pdf>.
- [144] P. Daian, I. Eyal, A. Juels, and E. G. Sirer, “(short paper) piecework: Generalized outsourcing control for proofs of work,” in *Financial Cryptography and Data Security*, 2017, pp. 182–190.
- [145] F. Bravo-Marquez, S. Reeves, and M. Ugarte, “Proof-of-learning: A blockchain consensus mechanism based on machine learning competitions,” in *IEEE International Conference on Decentralized Applications and Infrastructures (DAPPCON)*, 2019, pp. 119–124.
- [146] C. Chenli, B. Li, Y. Shi, and T. Jung, “Energy-recycling blockchain with proof-of-deep-learning,” in *IEEE International Conference on Blockchain and Cryptocurrency (ICBC)*, 2019, pp. 19–23.
- [147] Y. Liu, F. R. Yu, X. Li, H. Ji, and V. C. M. Leung, “Blockchain and machine learning for communications and networking systems,” *IEEE Communications Surveys Tutorials*, vol. 22, no. 2, pp. 1392–1431, 2020.
- [148] X. Qu, S. Wang, Q. Hu, and X. Cheng, “Proof of federated learning: A novel energy-recycling consensus algorithm,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 32, no. 8, pp. 2074–2085, 2021.

- [149] Y. Wang, H. Peng, Z. Su, T. H. Luan, A. Benslimane, and Y. Wu, “A platform-free proof of federated learning consensus mechanism for sustainable blockchains,” *IEEE Journal on Selected Areas in Communications*, vol. 40, no. 12, pp. 3305–3324, 2022.
- [150] Y. Lu, X. Huang, Y. Dai, S. Maharjan, and Y. Zhang, “Blockchain and federated learning for privacy-preserved data sharing in industrial iot,” *IEEE Transactions on Industrial Informatics*, vol. 16, no. 6, pp. 4177–4186, 2020.
- [151] W. A. Syafruddin, S. Dadkhah, and M. Köppen, “Blockchain scheme based on evolutionary proof of work,” in *IEEE Congress on Evolutionary Computation (CEC)*, 2019, pp. 771–776.
- [152] F. Zhao, X. Guo, and W. K. V. Chan, “Individual green certificates on blockchain: A simulation approach,” *Sustainability*, vol. 12, no. 9, p. 3942, 2020.
- [153] N. Shibata, “Proof-of-search: Combining blockchain consensus formation with solving optimization problems,” *IEEE Access*, vol. 7, pp. 172 994–173 006, 2019.
- [154] U. Klarman, M. Flores, and A. Kuzmanovic, “Mining the web with webcoin,” in *Proceedings of the 14th International Conference on Emerging Networking EXperiments and Technologies (CoNEXT '18)*, 2018, pp. 165–177.
- [155] A. Baldominos and Y. Saez, “Coin. ai: A proof-of-useful-work scheme for blockchain-based distributed deep learning,” *Entropy*, vol. 21, no. 8, p. 723, 2019.
- [156] H. Y. Yuen, F. Wu, W. Cai, H. C. Chan, Q. Yan, and V. C. Leung, “Proof-of-play: A novel consensus model for blockchain-based peer-to-peer gaming system,” in *Proceedings of the 2019 ACM International Symposium on Blockchain and Secure Critical Infrastructure (BSCI '19)*, 2019, pp. 19–28.
- [157] L. Bahri and S. Girdzijauskas, “When trust saves energy: A reference framework for proof of trust (pot) blockchains,” in *Companion Proceedings of the The Web Conference (WWW '18)*, 2018, pp. 1165–1169.
- [158] J. Zou, B. Ye, L. Qu, Y. Wang, M. A. Orgun, and L. Li, “A proof-of-trust consensus protocol for enhancing accountability in crowdsourcing services,” *IEEE Transactions on Services Computing*, vol. 12, no. 3, pp. 429–445, 2019.
- [159] Q. Zhuang, Y. Liu, L. Chen, and Z. Ai, “Proof of reputation: A reputation-based consensus protocol for blockchain based systems,” in *Proceedings of the 2019 International Electronics Communication Conference (IECC '19)*, 2019, pp. 131–138.
- [160] T. Xue, Y. Yuan, Z. Ahmed, K. Moniz, G. Cao, and C. Wang, “Proof of contribution: A modification of proof of work to increase mining efficiency,” in *IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC)*, vol. 01, 2018, pp. 636–644.
- [161] D. Puthal, S. P. Mohanty, P. Nanda, E. Kougianos, and G. Das, “Proof-of-authentication for scalable blockchain in resource-constrained distributed systems,” in *IEEE International Conference on Consumer Electronics (ICCE)*, 2019, pp. 1–5.

- [162] Y. Wang, Z. Su, J. Li, *et al.*, “Blockchain-based secure and cooperative private charging pile sharing services for vehicular networks,” *IEEE Transactions on Vehicular Technology*, vol. 71, no. 2, pp. 1857–1874, 2022.
- [163] J. Feng, X. Zhao, K. Chen, F. Zhao, and G. Zhang, “Towards random-honest miners selection and multi-blocks creation: Proof-of-negotiation consensus mechanism in blockchain networks,” *Future Generation Computer Systems*, vol. 105, pp. 248–258, 2020.
- [164] M. Castro and B. Liskov, “Practical byzantine fault tolerance,” in *Proceedings of the 3rd Symposium on Operating Systems Design and Implementation (OSDI’99)*, 1999, pp. 173–186.
- [165] C. Cachin, “Architecture of the hyperledger blockchain fabric,” in *Workshop on distributed cryptocurrencies and consensus ledgers*, vol. 310, 2016, p. 4.
- [166] NEO. “Neo white paper.” (2018), [Online]. Available: <https://docs.neo.org/docs/en-us/basic/whitepaper.html>.
- [167] D. Schwartz, N. Youngs, and A. Britto. “The ripple protocol consensus algorithm.” (2014), [Online]. Available: <https://cryptoguide.ch/cryptocurrency/ripple/whitepaper.pdf>.
- [168] D. Mazieres, “The stellar consensus protocol: A federated model for internet-level consensus,” 2015. [Online]. Available: <https://www.stellar.org/papers/stellar-consensus-protocol>.
- [169] J. Kwon. “Tendermint: Consensus without mining.” (2014), [Online]. Available: <https://tendermint.com/static/docs/tendermint.pdf>.
- [170] C. Dwork, N. Lynch, and L. Stockmeyer, “Consensus in the presence of partial synchrony,” *Journal of the ACM*, vol. 35, no. 2, pp. 288–323, 1988.
- [171] K. Li, H. Li, H. Hou, K. Li, and Y. Chen, “Proof of vote: A high-performance consensus protocol based on vote mechanism consortium blockchain,” in *IEEE 19th International Conference on High Performance Computing and Communications; IEEE 15th International Conference on Smart City; IEEE 3rd International Conference on Data Science and Systems (HPCC/SmartCity/DSS)*, 2017, pp. 466–473.
- [172] S. Solat, “Rdv: An alternative to proof-of-work and a real decentralized consensus for blockchain,” in *Proceedings of the 1st Workshop on Blockchain-Enabled Networked Sensor Systems (BlockSys’18)*, 2018, pp. 25–31.
- [173] M. Vanhoef, C. Matte, M. Cunche, L. S. Cardoso, and F. Piessens, “Why mac address randomization is not enough: An analysis of wi-fi network discovery mechanisms,” in *Proceedings of the 11th ACM on Asia Conference on Computer and Communications Security*, 2016, pp. 413–424.
- [174] L. Luo and J. Zhou, “Blocktour: A blockchain-based smart tourism platform,” *Computer Communications*, vol. 175, pp. 186–192, 2021.

- [175] P. Z. Jonathan L. Gross Jay Yellen, Ed., *Handbook of Graph Theory*, 2nd. Boca Raton, FL, USA: Chapman and Hall/CRC, 2013.
- [176] L. Luu, V. Narayanan, C. Zheng, K. Baweja, S. Gilbert, and P. Saxena, “A secure sharding protocol for open blockchains,” in *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security (CCS '16)*, 2016, pp. 17–30.
- [177] Y. Sompolinsky and A. Zohar, “Secure high-rate transaction processing in bitcoin,” in *Financial Cryptography and Data Security*, 2015, pp. 507–527.
- [178] S. Popov. “The tangle.” (2018), [Online]. Available: <https://www.iota.org/foundation/research-papers>.
- [179] W. F. Silvano and R. Marcelino, “Iota tangle: A cryptocurrency to communicate internet-of-things data,” *Future Generation Computer Systems*, vol. 112, pp. 307–319, 2020.
- [180] L. Baird. “The swirls hashgraph consensus algorithm: Fair, fast, byzantine fault tolerance.” (2016), [Online]. Available: <https://www.swirls.com/whitepapers/>.
- [181] T. Koens and E. Poll, “What blockchain alternative do you need?” In *Data Privacy Management, Cryptocurrencies and Blockchain Technology*, 2018, pp. 113–129.
- [182] K. Wüst and A. Gervais, “Do you need a blockchain?” In *2018 Crypto Valley Conference on Blockchain Technology (CVCBT)*, 2018, pp. 45–54.
- [183] S. Liaskos, B. Wang, and N. Alimohammadi, “Blockchain networks as adaptive systems,” in *IEEE/ACM 14th International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS)*, 2019, pp. 139–145.
- [184] I.-H. Chuang, S.-H. Chiang, W.-C. Chao, S.-H. Huang, B.-L. Zeng, and Y.-H. Kuo, “A hierarchical blockchain-based data service platform in mec environments,” in *Proceedings of the 2020 The 2nd International Conference on Blockchain Technology (ICBCT'20)*, 2020, pp. 95–99.
- [185] R. Bezuidenhout, W. Nel, and A. Burger, “Nonlinear proof-of-work: Improving the energy efficiency of bitcoin mining,” *Journal of Construction Project Management and Innovation*, vol. 10, no. 1, pp. 20–32, 2020.
- [186] N. Lasla, L. Al-Sahan, M. Abdallah, and M. Younis, “Green-pow: An energy-efficient blockchain proof-of-work consensus algorithm,” *Computer Networks*, vol. 214, p. 109 118, 2022.
- [187] P. Jacquet and B. Mans, “Blockchain moderated by empty blocks to reduce the energetic impact of crypto-moneys,” *Computer Communications*, vol. 152, pp. 126–136, 2020.
- [188] S. Sharkey and H. Tewari, “Alt-pow: An alternative proof-of-work mechanism,” in *IEEE International Conference on Decentralized Applications and Infrastructures (DAPP-CON)*, 2019, pp. 11–18.

- [189] L. Yu, X.-f. Zhao, Y. Jin, H.-y. Cai, B. Wei, and B. Hu, “Low powered blockchain consensus protocols based on consistent hash,” *Frontiers of Information Technology & Electronic Engineering*, vol. 20, no. 10, pp. 1361–1377, 2019.
- [190] A. de Vries, “Renewable energy will not solve bitcoin’s sustainability problem,” *Joule*, vol. 3, no. 4, pp. 893–898, 2019.
- [191] A. A. Sori, M. Golsorkhtabaramiri, and A. A. Sori, “Green efficiency for quality models in the field of cryptocurrency; iota green efficiency,” in *2021 IEEE Green Technologies Conference (GreenTech)*, 2021, pp. 357–363.
- [192] L. Dittmar and A. Praktiknjo, “Could bitcoin emissions push global warming above 2°C?” *Nature Climate Change*, vol. 9, pp. 656–657, 2019.
- [193] N. Houy, “Rational mining limits bitcoin emissions,” *Nature Climate Change*, vol. 9, pp. 655–655, 2019.
- [194] E. Masanet, A. Shehabi, N. Lei, H. Vranken, J. Koomey, and J. Malmudin, “Implausible projections overestimate near-term bitcoin CO₂ emissions,” *Nature Climate Change*, vol. 9, pp. 653–654, 2019.
- [195] T. Mullen and P. D. Finn, “Towards an evaluation metric for carbon-emitting energy provenance of bitcoin transactions,” in *Proceedings of the Fourth ACM International Symposium on Blockchain and Secure Critical Infrastructure (BSCI ’22)*, 2022, pp. 11–21.
- [196] A. de Vries and C. Stoll, “Bitcoin’s growing e-waste problem,” *Resources, Conservation and Recycling*, vol. 175, p. 105901, 2021.
- [197] J. C. Corbett, J. Dean, M. Epstein, *et al.*, “Spanner: Google’s globally distributed database,” *ACM Trans. Comput. Syst.*, vol. 31, no. 3, 2013.
- [198] A. Hafid, A. S. Hafid, and M. Samih, “Scaling blockchains: A comprehensive survey,” *IEEE Access*, vol. 8, pp. 125244–125262, 2020.
- [199] D. Meshkov, A. Chepurnoy, and M. Jansen, “Short paper: Revisiting difficulty control for blockchain systems,” in *Data Privacy Management, Cryptocurrencies and Blockchain Technology*, 2017, pp. 429–436.
- [200] F. Lin, Z. Zheng, Z. Huang, C. Tang, H. Peng, and Z. Chen, “A sustainable reward mechanism for block mining in POW-based blockchain,” in *5th International Conference on Information, Cybernetics, and Computational Social Systems (ICCSS)*, 2018, pp. 156–161.
- [201] W. Wong and C. I. Ming, “A review on metaheuristic algorithms: Recent trends, benchmarking and applications,” in *2019 7th International Conference on Smart Computing & Communications (ICSCC)*, 2019, pp. 1–5.

- [202] M. T. M. Emmerich and A. H. Deutz, “A tutorial on multiobjective optimization: Fundamentals and evolutionary methods,” *Natural Computing*, vol. 17, no. 3, pp. 585–609, 2018.
- [203] Y. Qu, Z. Ma, A. Clausen, and B. N. Jørgensen, “A comprehensive review on evolutionary algorithm solving multi-objective problems,” in *2021 22nd IEEE International Conference on Industrial Technology (ICIT)*, vol. 1, 2021, pp. 825–831.
- [204] X. Fan, W. Sayers, S. Zhang, Z. Han, L. Ren, and H. Chizari, “Review and classification of bio-inspired algorithms and their applications,” *Journal of Bionic Engineering*, vol. 17, no. 3, pp. 611–631, 2020.
- [205] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: Nsga-ii,” *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.
- [206] E. Zitzler, M. Laumanns, and L. Thiele, “Spea2: Improving the strength pareto evolutionary algorithm,” *TIK-report*, vol. 103, 2001.
- [207] J. Knowles and D. Corne, “The pareto archived evolution strategy: A new baseline algorithm for pareto multiobjective optimisation,” in *Proceedings of the 1999 Congress on Evolutionary Computation-CEC99*, vol. 1, 1999, pp. 98–105.
- [208] E. Zitzler and L. Thiele, “Multiobjective evolutionary algorithms: A comparative case study and the strength pareto approach,” *IEEE Transactions on Evolutionary Computation*, vol. 3, no. 4, pp. 257–271, 1999.
- [209] E. Zitzler and S. Künzli, “Indicator-based selection in multiobjective search,” in *Parallel Problem Solving from Nature - PPSN VIII*, 2004, pp. 832–842.
- [210] K. Deb and H. Jain, “An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part i: Solving problems with box constraints,” *IEEE Transactions on Evolutionary Computation*, vol. 18, no. 4, pp. 577–601, 2014.
- [211] C. A. C. Coello, G. B. Lamont, and D. A. Van Veldhuizen, *Evolutionary algorithms for solving multi-objective problems*, 2nd ed. New York, NY, USA: Springer, 2007.
- [212] X. Gu, M. Li, L. Shen, *et al.*, “Multiobjective evolutionary optimization for prototype-based fuzzy classifiers,” *IEEE Transactions on Fuzzy Systems*, vol. 31, no. 5, pp. 1703–1715, 2023.
- [213] Y. Xue, M. Li, and X. Liu, “An effective and efficient evolutionary algorithm for many-objective optimization,” *Information Sciences*, vol. 617, pp. 211–233, 2022.
- [214] S. S. Meghwani and M. Thakur, “Adaptively weighted decomposition based multi-objective evolutionary algorithm,” *Applied Intelligence*, vol. 51, no. 6, pp. 3801–3823, 2021.

- [215] M. Hort and F. Sarro, “The effect of offspring population size on nsga-ii: A preliminary study,” in *Proceedings of the Genetic and Evolutionary Computation Conference Companion (GECCO '21)*, 2021, pp. 179–180.
- [216] Z. Li and X. Li, “A multi-objective binary-encoding differential evolution algorithm for proactive scheduling of agile earth observation satellites,” *Advances in Space Research*, vol. 63, no. 10, pp. 3258–3269, 2019.
- [217] P. Back, A. Suominen, P. Malo, O. Tahvonen, J. Blank, and K. Deb, “Towards sustainable forest management strategies with moeas,” in *Proceedings of the 2020 Genetic and Evolutionary Computation Conference (GECCO '20)*, 2020, pp. 1046–1054.
- [218] H. Noguchi, T. Harada, and R. Thawonmas, “Parallel differential evolution applied to interleaving generation with precedence evaluation of tentative solutions,” in *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO '21)*, 2021, pp. 706–713.
- [219] J. E. Fieldsend and K. Alyahya, “Visualising the landscape of multi-objective problems using local optima networks,” in *Proceedings of the Genetic and Evolutionary Computation Conference Companion (GECCO '19)*, 2019, pp. 1421–1429.
- [220] J. T. de Souza, C. L. Maia, F. G. de Freitas, and D. P. Coutinho, “The human competitiveness of search based software engineering,” in *2nd International Symposium on Search Based Software Engineering*, 2010, pp. 143–152.
- [221] W. Ren, J. Hu, T. Zhu, Y. Ren, and K.-K. R. Choo, “A flexible method to defend against computationally resourceful miners in blockchain proof of work,” *Information Sciences*, vol. 507, pp. 161–171, 2020.
- [222] S. Kim, “Impacts of mobility on performance of blockchain in vanet,” *IEEE Access*, vol. 7, pp. 68 646–68 655, 2019.
- [223] X. Zheng, Y. Zhu, and X. Si, “A survey on challenges and progresses in blockchain technologies: A performance and security perspective,” *Applied Sciences*, vol. 9, no. 22, 2019.
- [224] S. M. H. Bamakan, A. Motavali, and A. Babaei Bondarti, “A survey of blockchain consensus algorithms performance evaluation criteria,” *Expert Systems with Applications*, vol. 154, p. 113 385, 2020.
- [225] M. Mezmaiz, N. Melab, Y. Kessaci, *et al.*, “A parallel bi-objective hybrid metaheuristic for energy-aware scheduling for cloud computing systems,” *Journal of Parallel and Distributed Computing*, vol. 71, no. 11, pp. 1497–1508, 2011. [Online]. Available: <https://doi.org/10.1016/j.jpdc.2011.04.007>.
- [226] X.-F. Liu, Z.-H. Zhan, K.-J. Du, and W.-N. Chen, “Energy aware virtual machine placement scheduling in cloud computing based on ant colony optimization approach,” in *Proceedings of the 2014 Annual Conference on Genetic and Evolutionary Computation (GECCO '14)*, 2014, pp. 41–48.

- [227] J.-W. Lee and J.-J. Lee, “Ant-colony-based scheduling algorithm for energy-efficient coverage of wsn,” *IEEE Sensors Journal*, vol. 12, no. 10, pp. 3036–3046, 2012.
- [228] I. Ahmad, S. Ranka, and S. U. Khan, “Using game theory for scheduling tasks on multi-core processors for simultaneous optimization of performance and energy,” in *2008 IEEE International Symposium on Parallel and Distributed Processing*, 2008, pp. 1–6.
- [229] E. V. Dinesh Subramaniam and V. Krishnasamy, “Energy aware smartphone tasks offloading to the cloud using gray wolf optimization,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 3, pp. 3979–3987, 2021.
- [230] Y. Chen, N. Zhang, Y. Zhang, X. Chen, W. Wu, and X. Shen, “Energy efficient dynamic offloading in mobile edge computing for internet of things,” *IEEE Transactions on Cloud Computing*, vol. 9, no. 3, pp. 1050–1060, 2021.
- [231] M. Askarizade Haghghi, M. Maeen, and M. Haghparast, “An energy-efficient dynamic resource management approach based on clustering and meta-heuristic algorithms in cloud computing iaas platforms,” *Wireless Personal Communications*, vol. 104, no. 4, pp. 1367–1391, 2019.
- [232] S. A. Sert, H. Bagci, and A. Yazici, “Mofca: Multi-objective fuzzy clustering algorithm for wireless sensor networks,” *Applied Soft Computing*, vol. 30, pp. 151–165, 2015.
- [233] J. Gillett, S. Rahnamayan, M. Makrehchi, and A. A. Bidgoli, “A pareto front-based metric to identify major bitcoin networks influencers,” in *Proceedings of the 2020 Genetic and Evolutionary Computation Conference Companion (GECCO ’20)*, 2020, pp. 1395–1401.
- [234] H. Shi, S. Wang, and Y. Xiao, “Queuing without patience: A novel transaction selection mechanism in blockchain for iot enhancement,” *IEEE Internet of Things Journal*, vol. 7, no. 9, pp. 7941–7948, 2020.
- [235] B. R. Bruce, J. Petke, M. Harman, and E. T. Barr, “Approximate oracles and synergy in software energy search spaces,” *IEEE Transactions on Software Engineering*, vol. 45, no. 11, pp. 1150–1169, 2019.
- [236] M. A. Bokhari, B. Alexander, and M. Wagner, “In-vivo and offline optimisation of energy use in the presence of small energy signals: A case study on a popular android library,” in *Proceedings of the 15th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MobiQuitous ’18)*, 2018, pp. 207–215.
- [237] M. Linares-Vásquez, G. Bavota, C. E. B. Cárdenas, R. Oliveto, M. Di Penta, and D. Poshyvanyk, “Optimizing energy consumption of guis in android apps: A multi-objective approach,” in *Proceedings of the 2015 10th Joint Meeting on Foundations of Software Engineering (ESEC/FSE 2015)*, 2015, pp. 143–154.
- [238] R. Morales, R. Saborido, F. Khomh, F. Chicano, and G. Antoniol, “Earmo: An energy-aware refactoring approach for mobile apps,” *IEEE Transactions on Software Engineering*, vol. 44, no. 12, pp. 1176–1206, 2018.

- [239] B. R. Bruce, J. M. Aitken, and J. Petke, “Deep parameter optimisation for face detection using the viola-jones algorithm in OpenCV,” in *Search Based Software Engineering*, F. Sarro and K. Deb, Eds., 2016, pp. 238–243.
- [240] S. Sidiroglou-Douskos, S. Misailovic, H. Hoffmann, and M. Rinard, “Managing performance vs. accuracy trade-offs with loop perforation,” in *Proceedings of the 19th ACM SIGSOFT Symposium and the 13th European Conference on Foundations of Software Engineering (ESEC/FSE ’11)*, 2011, pp. 124–134.
- [241] P. Hewitt, *Conceptual Physics*, 13th ed. Boston, MA, USA: Pearson, 2021.
- [242] C. E. Shannon, “A mathematical theory of communication,” *The Bell System Technical Journal*, vol. 27, no. 3, pp. 379–423, 1948.
- [243] D. Mingxiao, M. Xiaofeng, Z. Zhe, W. Xiangwei, and C. Qijun, “A review on consensus algorithm of blockchain,” in *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2017, pp. 2567–2572.
- [244] I. Eyal and E. G. Sirer, “Majority is not enough: Bitcoin mining is vulnerable,” in *Financial Cryptography and Data Security*, 2014, pp. 436–454.
- [245] C. Audet, J. Bignon, D. Cartier, S. Le Digabel, and L. Salomon, “Performance indicators in multiobjective optimization,” *European Journal of Operational Research*, 2020.
- [246] M. Li and X. Yao, “Quality evaluation of solution sets in multiobjective optimisation: A survey,” *ACM Comput. Surv.*, vol. 52, no. 2, pp. 1–38, 2019.
- [247] M. Li, T. Chen, and X. Yao, “How to evaluate solutions in pareto-based search-based software engineering: A critical review and methodological guidance,” *IEEE Transactions on Software Engineering*, vol. 48, no. 5, pp. 1771–1799, 2022.
- [248] M. Li, S. Yang, and X. Liu, “A performance comparison indicator for pareto front approximations in many-objective optimization,” in *Proceedings of the 2015 Annual Conference on Genetic and Evolutionary Computation (GECCO ’15)*, 2015, pp. 703–710.
- [249] S. Rostami, F. Neri, and K. Gyaurski, “On algorithmic descriptions and software implementations for multi-objective optimisation: A comparative study,” *SN Computer Science*, vol. 1, no. 5, pp. 247–270, 2020.
- [250] K. Shang, H. Ishibuchi, L. He, and L. M. Pang, “A survey on the hypervolume indicator in evolutionary multiobjective optimization,” *IEEE Transactions on Evolutionary Computation*, vol. 25, no. 1, pp. 1–20, 2021.
- [251] F. Wilcoxon, “Individual comparisons by ranking methods,” *Biometrics Bull*, vol. 1, no. 6, pp. 80–83, 1945.
- [252] S. S. Shapiro and M. B. Wilk, “An analysis of variance test for normality (complete samples),” *Biometrika*, vol. 52, no. 3/4, pp. 591–611, 1965.

- [253] A. Vargha and H. D. Delaney, “A critique and improvement of the cl common language effect size statistics of mcgraw and wong,” *Journal of Educational and Behavioral Statistics*, vol. 25, no. 2, pp. 101–132, 2000.
- [254] G. Fournier and F. Petrillo, “Architecting blockchain systems: A systematic literature review,” in *Proceedings of the IEEE/ACM 42nd International Conference on Software Engineering Workshops (ICSEW ’20)*, 2020, pp. 664–670.
- [255] Carbon Footprint Ltd. “Country specific electricity grid greenhouse gas emissions factors.” Accessed November 02, 2020. (2020), [Online]. Available: https://www.carbonfootprint.com/international_electricity_factors.html.
- [256] M. S. Mahbub, M. Wagner, and L. Crema, “Multi-objective optimisation with multiple preferred regions,” in *Australasian Conference on Artificial Life and Computational Intelligence*, 2017, pp. 241–253.
- [257] U. Bhowan, M. Zhang, and M. Johnston, “Multi-objective genetic programming for classification with unbalanced data,” in *Australasian Joint Conference on Artificial Intelligence*, 2009, pp. 370–380.
- [258] E. Osaba, R. Carballedo, F. Diaz, E. Onieva, I. De La Iglesia, and A. Perallos, “Crossover versus mutation: A comparative analysis of the evolutionary strategy of genetic algorithms applied to combinatorial optimization problems,” *The Scientific World Journal*, vol. 2014, 2014.
- [259] J. H. Drake, A. Starkey, G. Owusu, and E. K. Burke, “Multiobjective evolutionary algorithms for strategic deployment of resources in operational units,” *European Journal of Operational Research*, vol. 282, no. 2, pp. 729–740, 2020.
- [260] Y.-H. Zhang, Y.-J. Gong, T.-L. Gu, and J. Zhang, “Ensemble mating selection in evolutionary many-objective search,” *Applied Soft Computing*, vol. 76, pp. 294–312, 2019.
- [261] W. Li, E. Özcan, R. John, J. H. Drake, A. Neumann, and M. Wagner, “A modified indicator-based evolutionary algorithm (mibea),” in *2017 IEEE Congress on Evolutionary Computation (CEC)*, 2017, pp. 1047–1054.
- [262] E. J. Hughes, “Fitness assignment methods for many-objective problems,” in *Multiobjective Problem Solving from Nature: From Concepts to Applications*, J. Knowles, D. Corne, and K. Deb, Eds. 2008, pp. 307–329.
- [263] B. Changaival, G. Danoy, D. Kliazovich, *et al.*, “Toward real-world vehicle placement optimization in round-trip carsharing,” in *Proceedings of the 2019 Genetic and Evolutionary Computation Conference (GECCO ’19)*, 2019, pp. 1138–1146.
- [264] V. Dedeoglu, R. Jurdak, G. D. Putra, A. Dorri, and S. S. Kanhere, “A trust architecture for blockchain in iot,” in *Proceedings of the 16th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MobiQuitous ’19)*, 2019, pp. 190–199.

- [265] A. Prabhakar and T. Anjali, "Tcon - a lightweight trust-dependent consensus framework for blockchain," in *11th International Conference on Communication Systems Networks (COMSNETS)*, 2019, pp. 1–6.
- [266] J. Kang, Z. Xiong, D. Niyato, D. Ye, D. I. Kim, and J. Zhao, "Toward secure blockchain-enabled internet of vehicles: Optimizing consensus management using reputation and contract theory," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 3, pp. 2906–2920, 2019.
- [267] T.-H. Kim, R. Goyat, M. K. Rai, *et al.*, "A novel trust evaluation process for secure localization using a decentralized blockchain in wireless sensor networks," *IEEE Access*, vol. 7, pp. 184 133–184 144, 2019.
- [268] F. Gai, B. Wang, W. Deng, and W. Peng, "Proof of reputation: A reputation-based consensus protocol for peer-to-peer network," in *Database Systems for Advanced Applications*, 2018, pp. 666–681.
- [269] E. K. Wang, Z. Liang, C.-M. Chen, S. Kumari, and M. K. Khan, "Porx: A reputation incentive scheme for blockchain consensus of iiot," *Future Generation Computer Systems*, vol. 102, pp. 140–151, 2020.
- [270] J. Yu, D. Kozhaya, J. Decouchant, and P. Esteves-Verissimo, "Repucoin: Your reputation is your power," *IEEE Transactions on Computers*, vol. 68, no. 8, pp. 1225–1237, 2019.
- [271] J. Bou Abdo, R. El Sibai, K. Kambhampaty, and J. Demerjian, "Permissionless reputation-based consensus algorithm for blockchain," *Internet Technology Letters*, vol. 3, no. 3, e151, 2020.
- [272] T. Do, T. Nguyen, and H. Pham, "Delegated proof of reputation: A novel blockchain consensus," in *Proceedings of the 1st International Electronics Communication Conference (IECC '19)*, 2019, pp. 90–98.
- [273] S. Vavilis, M. Petković, and N. Zannone, "A reference model for reputation systems," *Decision Support Systems*, vol. 61, pp. 147–154, 2014.
- [274] J. Wang and J. Liu, "The comparison of distributed p2p trust models based on quantitative parameters in the file downloading scenarios," *Journal of Electrical and Computer Engineering*, vol. 2016, 2016.
- [275] J.-H. Cho, K. Chan, and S. Adali, "A survey on trust modeling," *ACM Computing Surveys*, vol. 48, no. 2, 2015.
- [276] E. Koutrouli and A. Tsalgatidou, "Reputation systems evaluation survey," *ACM Computing Surveys*, vol. 48, no. 3, 2015.
- [277] K. Hoffman, D. Zage, and C. Nita-Rotaru, "A survey of attack and defense techniques for reputation systems," *ACM Computing Surveys*, vol. 42, no. 1, 2009.

- [278] A. Gervais, H. Ritzdorf, G. O. Karame, and S. Capkun, “Tampering with the delivery of blocks and transactions in bitcoin,” in *Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security (CCS ’15)*, 2015, pp. 692–705.
- [279] P. Horn, “Autonomic computing: Ibm’s perspective on the state of information technology,” 2001.
- [280] P. Arcaini, E. Riccobene, and P. Scandurra, “Modeling and analyzing mape-k feedback loops for self-adaptation,” in *IEEE 10th International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS)*, 2015, pp. 13–23.
- [281] E. Henrichs, V. Lesch, M. Straesser, S. Kounev, and C. Krupitzer, “A literature review on optimization techniques for adaptation planning in adaptive systems: State of the art and research directions,” *Information and Software Technology*, vol. 149, p. 106 940, 2022.
- [282] Y. Brun, G. Di Marzo Serugendo, C. Gacek, *et al.*, “Engineering self-adaptive systems through feedback loops,” in *Software Engineering for Self-Adaptive Systems*. 2009, pp. 48–70.
- [283] M. Salehie and L. Tahvildari, “Towards a goal-driven approach to action selection in self-adaptive software,” *Software: Practice and Experience*, vol. 42, no. 2, pp. 211–233, 2012.
- [284] ———, “Self-adaptive software: Landscape and research challenges,” *ACM Trans. Auton. Adapt. Syst.*, vol. 4, no. 2, 2009.
- [285] J. Kramer and J. Magee, “Self-managed systems: An architectural challenge,” in *Future of Software Engineering (FOSE ’07)*, 2007, pp. 259–268.
- [286] S. Dobson, S. Denazis, A. Fernández, *et al.*, “A survey of autonomic communications,” *ACM Trans. Auton. Adapt. Syst.*, vol. 1, no. 2, pp. 223–259, 2006.
- [287] S. Tomforde, H. Prothmann, J. Branke, *et al.*, “Observation and control of organic systems,” in *Organic Computing — A Paradigm Shift for Complex Systems*. 2011, pp. 325–338.
- [288] T. Chen, K. Li, R. Bahsoon, and X. Yao, “Femosaa: Feature-guided and knee-driven multi-objective optimization for self-adaptive software,” *ACM Trans. Softw. Eng. Methodol.*, vol. 27, no. 2, 2018.
- [289] S. Zhang, L. Ni, W. Xie, G. Li, and H. Sun, “Research on self-adaptive consensus method based on blockchain,” in *2022 IEEE 14th International Conference on Advanced Infocomm Technology (ICAIT)*, 2022, pp. 292–297.
- [290] M. Rasolroveicy and M. Fokaefs, “Dynamic reconfiguration of consensus protocol for iot data registry on blockchain,” in *Proceedings of the 30th Annual International Conference on Computer Science and Software Engineering (CASCON ’20)*, IBM Corp., 2020, pp. 227–236.

- [291] G. Leduc, S. Kubler, and J.-P. Georges, “Sabine: Self-adaptive blockchain consensus,” in *2022 9th International Conference on Future Internet of Things and Cloud (FiCloud)*, 2022, pp. 234–240.
- [292] D. Zhou, N. Ruan, and W. Jia, “A robust throughput scheme for bitcoin network without block reward,” in *2019 IEEE 21st International Conference on High Performance Computing and Communications; IEEE 17th International Conference on Smart City; IEEE 5th International Conference on Data Science and Systems (HPCC/SmartCity/DSS)*, 2019, pp. 706–713.
- [293] N. Ruan, D. Zhou, and W. Jia, “Ursa: Robust performance for nakamoto consensus with self-adaptive throughput,” *ACM Trans. Internet Technol.*, vol. 20, no. 4, 2020.
- [294] F. D. Macías-Escrivá, R. Haber, R. del Toro, and V. Hernandez, “Self-adaptive systems: A survey of current approaches, research challenges and applications,” *Expert Systems with Applications*, vol. 40, no. 18, pp. 7267–7279, 2013.
- [295] L. Jia, K. Wang, X. Wang, L. Yu, Z. Li, and Y. Sun, “Themis: An equal, unpredictable, and scalable consensus for consortium blockchain,” in *2022 IEEE 42nd International Conference on Distributed Computing Systems (ICDCS)*, 2022, pp. 235–245.
- [296] D. Weyns, “Software engineering of self-adaptive systems,” in *Handbook of Software Engineering*, S. Cha, R. N. Taylor, and K. Kang, Eds. 2019, pp. 399–443.
- [297] F. Alkhabbas, M. Alsadi, S. Alawadi, F. M. Awaysheh, V. R. Kebande, and M. T. Moghaddam, “Assert: A blockchain-based architectural approach for engineering secure self-adaptive iot systems,” *Sensors*, vol. 22, no. 18, 2022.
- [298] I. Singh and S.-W. Lee, “Comparative requirements analysis for the feasibility of blockchain for secure cloud,” in *Requirements Engineering for Internet of Things*, 2018, pp. 57–72.
- [299] W. Feng, Y. Li, X. Yang, Z. Yan, and L. Chen, “Blockchain-based data transmission control for tactical data link,” *Digital Communications and Networks*, vol. 7, no. 3, pp. 285–294, 2021.
- [300] Z. Shahbazi and Y.-C. Byun, “Towards a secure thermal-energy aware routing protocol in wireless body area network based on blockchain technology,” *Sensors*, vol. 20, no. 12, 2020.
- [301] S. Ahmadjee, C. Mera-Gómez, and R. Bahsoon, “Assessing smart contracts security technical debts,” in *2021 IEEE/ACM International Conference on Technical Debt (TechDebt)*, 2021, pp. 6–15.
- [302] D. Kraft, “Difficulty control for blockchain-based consensus systems,” *Peer-to-Peer Networking and Applications*, vol. 9, no. 2, pp. 397–413, 2016.
- [303] D. Fullmer and A. S. Morse, “Analysis of difficulty control in bitcoin and proof-of-work blockchains,” in *IEEE Conference on Decision and Control (CDC)*, 2018, pp. 5988–5992.

- [304] N. Singh and M. Vardhan, “Multi-objective optimization of block size based on cpu power and network bandwidth for blockchain applications,” in *Proceedings of the Fourth International Conference on Microelectronics, Computing and Communication Systems*, V. Nath and J. K. Mandal, Eds., 2021, pp. 69–78.
- [305] ———, “Computing optimal block size for blockchain based applications with contradictory objectives,” *Procedia Computer Science*, vol. 171, pp. 1389–1398, 2020.
- [306] H. Ritchie, M. Roser, and P. Rosado, “Co₂ and greenhouse gas emissions,” *Our World in Data*, 2020, <https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions>.
- [307] D. Weyns, S. Malek, and J. Andersson, “Forms: Unifying reference model for formal specification of distributed self-adaptive systems,” *ACM Trans. Auton. Adapt. Syst.*, vol. 7, no. 1, pp. 1–61, 2012.
- [308] Q. Lin, C. Li, X. Zhao, and X. Chen, “Measuring decentralization in bitcoin and ethereum using multiple metrics and granularities,” in *IEEE 37th International Conference on Data Engineering Workshops (ICDEW)*, 2021, pp. 80–87.
- [309] B. O’neill, *Elementary differential geometry*, 2nd ed. Elsevier, 2006.
- [310] C. Qian, Y. Yu, K. Tang, Y. Jin, X. Yao, and Z.-H. Zhou, “On the effectiveness of sampling for evolutionary optimization in noisy environments,” *Evolutionary Computation*, vol. 26, no. 2, pp. 237–267, 2018.
- [311] C. Qian, Y. Yu, and Z.-H. Zhou, “Analyzing evolutionary optimization in noisy environments,” *Evolutionary Computation*, vol. 26, no. 1, pp. 1–41, 2018.
- [312] C. Wohlin, “Guidelines for snowballing in systematic literature studies and a replication in software engineering,” in *Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering (EASE ’14)*, 2014, pp. 1–10.
- [313] K. Petersen, R. Feldt, S. Mujtaba, and M. Mattsson, “Systematic mapping studies in software engineering,” in *Proceedings of the 12th International Conference on Evaluation and Assessment in Software Engineering (EASE)*, 2008, pp. 68–77.
- [314] T. Dyba, T. Dingsoyr, and G. K. Hanssen, “Applying systematic reviews to diverse study types: An experience report,” in *First International Symposium on Empirical Software Engineering and Measurement (ESEM 2007)*, 2007, pp. 225–234.
- [315] M. Salama, R. Bahsoon, and N. Bencomo, “Chapter 11 - managing trade-offs in self-adaptive software architectures: A systematic mapping study,” in *Managing Trade-Offs in Adaptable Software Architectures*, Morgan Kaufmann, 2017, pp. 249–297.