Access Point Deployment Optimisation in Communication-based Train Control Systems

by

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Abstract

Through the use of new communication-based train control (CBTC) systems, modern metro railways have been able to provide a more efficient, more reliable and more eco-friendly transport services. The main advantages of the CBTC systems are achieved by utilising modern communication technologies. The performance of the communications network is dependent on a well-designed access point (AP) deployment, as this determines the overall communication capability and impacts the cost. In this thesis, a systematic methodology is proposed for formulating and solving AP deployment planning (ADP) problems in two scenarios: (i) a tunnel section area; and (ii) a real-world metro system. Different mathematical models are presented for modelling the ADP problem in these two scenarios. In addition to mathematical models, an exhaustive search and a customized search algorithm, which uses a multi-objective evolutionary algorithm based on decomposition (MOEA/D), are proposed for solving the ADP optimisation problems. The methodologies are applied to the scenarios mentioned above. To evaluate the optimisation results, the optimised AP deployments are tested on a simulation platform integrating a railway network simulator and a communication network simulator. The test result shows that with the optimised AP deployments the DCS can achieve a better performance while using fewer APs.

Keywords: Communication-based train control system, AP deployment planning, Multi-objective optimisation and Integrated simulation platform

This thesis is dedicated to my parents and my girlfriend,

for their endless love and selfless support.

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Contents

List of Figures

List of Tables

List of Abbreviations

ABA Agent-Based Approach

ACK Acknowledgement

ADP AP Deployment Planning

AP Access Point

ATO Automatic Train Operation

ATP Automatic Train Protection

ATS Automatic Train Supervision

BB Branch-and-Bound

BER Bit Error Rate

BFS Brute Force Search

BIP Binary Integer Programming

BPSK Binary Phase-shift Keying

BS Base Station

CBTC Communication-Based Train Control

CDMA Code-Division Multiple Access

CF Cost Function

CI Computer-based Interlocking

CSMA/CA Carrier-Sense Multiple Access with Collision Avoidance

CTCS Chinese Train Control System

CW Contention Window

DCS Data Communication System

DIFS Distributed Coordination Function Inter-Frame Space

DSSS Direct-sequence Spread Spectrum

DS-CDMA Direct-sequence CDMA

EA Evolutionary Algorithm

ETCS European Train Control System

FHSS Frequency-hopping Spread Spectrum

GA Genetic Algorithm

GoS Grade of Service

GRA Greedy Algorithm

GSM-R Global System for Mobile Communications for Railway

HML-I Hefei Metro Line I

IFS Inter-Frame Space

IRG Inner Receiver Grid

ISM Industrial, Scientific and Medical

IHS Iterative Heuristic Search

MA Movement Authority

MAC Media Access Control

MB Mobile Station

MOEA Multi-objective Optimisation Evolutionary Algorithm

MOEA/D Multi-objective Optimisation Evolutionary Algorithm based on Decomposition

MOP Multi-objective Optimisation Programming

NSD Normalized Service Delay

NSGA Non-dominated Sorting Genetic Algorithm

NSGA-II Non-dominated Sorting Genetic Algorithm-II

OFDM Orthogonal-Frequency Division Multiplexing

PAES Pareto Archived Evolutionary Strategy

PER Packet Error Rate

PESA Pareto Envelope-based Selection Algorithm

PESA-II Pareto Envelope-based Selection Algorithm-II

PF Pareto Front

PO Pareto Optimal

PS Pareto Set

PSO Particle Swarm Optimisation

QPSK Quadrature Phase-Shift Keying

RCR Reduction Estimation-Combinatorial Optimisation-Reduction

RW Random Walk

SA Simulated Annealing

SIFS Short Inter-frame Space

SIR Signal-to-Interference Ratio

SNR Signal-to-Noise Ratio

SNIR Signal-to-Noise-plus-Interference Ratio

SOP Single-objective Optimisation Programming

SPEA Strength Pareto Evolutionary Algorithm

SPEA-II Strength Pareto Evolutionary Algorithm-II

TBTC Track-Circuit Based Control

TS Tabu Search

TU Train Unit

VEGA Vector Evaluated Genetic Algorithm

VOBC Vehicle On-board Controller

VFSA Very Fast Simulated re-Annealing

WLAN Wireless Local Area Network

ZC Zone Controller

Publications During PhD Study

[1] **Wen, T.**, Lyu, X., Constantinou, C., Chen, L. and Roberts, C. (2015) Co-simulation testing of data communication system supporting CBTC, *in* 'The IEEE 18th International Conference on Intelligent Transportation Systems' pp. 2665–2670. Chapter 5 is based on this conference paper.

[2] **Wen, T.**, Constantinou, C., Chen, L., Tian, Z. and Roberts, C. (2017), 'Access point deployment optimization in CBTC data communication system', *IEEE Transactions on Intelligent Transportation Systems* **PP**(99), 1–11. Chapter 4 and 6 are based on this journal paper.

[3] **Wen, T.**, Constantinou, C., Chen, L., Li, Z. and Roberts, C. (2017), 'A practical access point deployment optimization method in communication-based train control systems', *IEEE Transactions on Intelligent Transportation Systems* (in revision). Chapter 4 and 7 are based this journal paper draft.

Chapter 1

Introduction

1.1 Research Background

With many major emerging economies experiencing huge economic growth and population expansion, the demand for safer, more efficient and comfortable public mass transport systems is urgent. Metro systems are a good choice for new mega-cities, as they meet the increasing need for low emissions and high capacity transport (Wen et al., 2015).

The digitalization of railway systems is reshaping the public perception of transit. Modern railways, incorporating emerging technologies, will make train travel more punctual, more comfortable, more enjoyable and more eco-friendly. All of the aforementioned perspectives of the digitalised railways rely on a secure, reliable, high capacity and continuous data communication system (DCS) to support the railway control systems. In the early years, railway systems tended to apply track-circuits to realise the communication between trains and the train control centre. These types of train control systems are known as track-circuit based train control (TBTC) systems. TBTC systems result in low detection resolution, which leads to long operational headways for trains, in the hope of ensuring there is no possibility of potential collisions.

In other words, track-circuit based technology gives rise to low operation efficiency in railways. To overcome the shortcomings of TBCT systems, an increasing number of metro systems tend to use new generation train control systems, which are best known as communication-based train control (CBTC) systems. By utilising modern wireless communication technology, CBTC systems can help railways to increase capacity (Farooq and Soler, 2017). Because less infrastructure is required, the cost of building and undertaking maintenance for CBTC systems is significantly lower than that of.

The CBTC systems are automatic railway signalling systems, they employ high-capacity bi-directional train to ground communication technology to guarantee that the wayside zone control (ZC) centre knows the accurate location and velocity of each running train in real-time; this also allows the running trains to receive movement authorities (MA) continuously (Zhu et al., 2014*a*). As a main subsystem of the CBTC system, the data communication system (DCS) is responsible for the two-way communication between the train and the ZC via wayside radio units (WRUs)(Aziminejad et al., 2015), which are also known as access points (AP) (Farooq et al., 2018) or base stations (BS) (Zhu et al., 2014*b*). A typical CBTC system in a section is shown in Figure 1.1. The track is divided into different zones and those are controlled by relevant ZCs. In each zone, a number of APs are allocated and connected with the relevant ZC via backbone networks. When a train is running within the radio coverage of an AP, the bi-directional train to ground communication will happen; when the train is leaving this coverage and running into the coverage of the next AP, a hand-over procedure will be triggered. To achieve continuous bi-directional data exchange, the AP deployment must be sufficiently overlapping.

However, an overly generous AP deployment either does not help, or even can have a negative impact on the system reliability of the DCS. There are several wireless communication means used in DCS, such as waveguide (Wang et al., 2013), leaky cable (Wang et al., 2016) and inductive loop (Guillaumin, 2001). However, due to there are more commercial off-the-shelf products available in the market, the most popular technology is the wireless local area networks (WLAN) (Aziminejad et al., 2015; Farooq and Soler, 2017; Pascoe and Eichorn, 2009), which is also known as Wi-Fi. The original Wi-Fi standard is known as the legacy IEEE 802.11 standard, which was released in

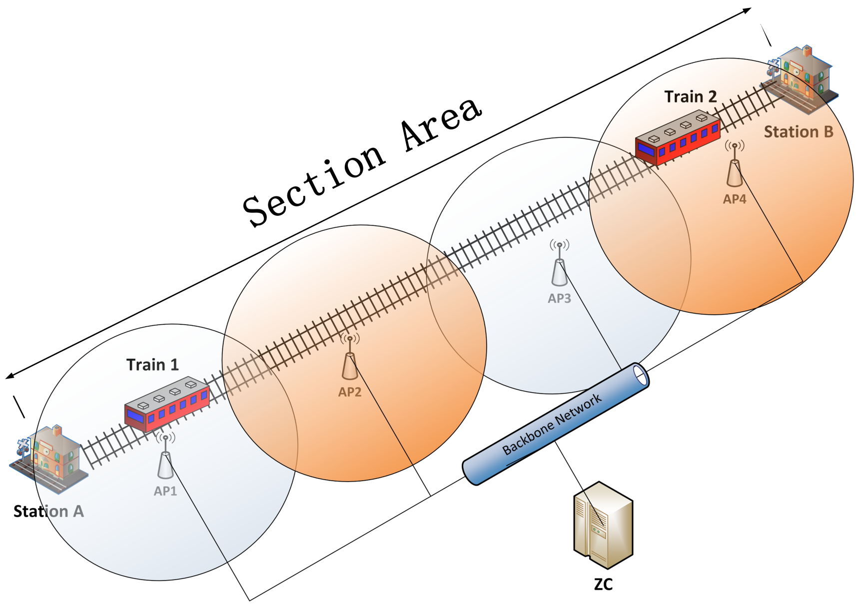


Figure 1.1: A diagram of the communication-based train control (CBTC) systems (Author)

1997, and was modified by several IEEE 802.11 amendments (Omar et al., 2016). In the majority of cases, WLAN-based DCS systems utilise the 2.4 GHz industrial, scientific and medical (ISM) band and the IEEE 802.11 family of protocol standards for the media access control (MAC) layer protocol, the working frequency of which is divided into a number of channels. Due to the limited spectrum, there are overlaps between neighbouring adjacent channels, which means that some of the APs may have to work on the overlapped channels. As a result, if adjacent APs are too close to each other, serious co-&adjacent-channel interference can happen (Campolo et al., 2016; Gokturk and Ferazoglu, 2014; Li et al., 2018), and the system cost increase. Therefore, to achieve a continuous and reliable bi-directional data exchange in DCS the AP deployment must be well planned.

1.2 Problem Statement

A well-planned AP deployment is important for CBTC systems, in terms of system reliability, capacity and equipment required.

As mentioned, for a DCS, the coverage of APs must be seamless and a proper overlap is necessary to ensure passing trains can carry out a successful hand-over between different AP coverage areas. From the point of view of coverage, a dense deployment of APs is therefore desirable; however, when an AP deployment is too dense this can result in a severe co-channel interference and can dramatically decrease the system reliability of the DCS. To balance the potential risks caused by co-channel interference and the requirement for seamless AP coverage, a well-planned WLAN-based wireless communication system is vital for the operational reliability of the CBTC system.

Another critical problem underlying any AP deployment methodology is how to manage the trade-off between capacity and seamless coverage, both of which are determined by the relative positioning of APs. There are a number of significant uncertainty factors in metro systems, including the environmental disturbance in tunnel and station (e.g. the presence of other trains in tunnel can alter the propagation significantly, the complex station structure can cause more serious multipath effects), dynamics between transceivers, *etc.*. These uncertainties can degrade the system capacity (achievable bit rates) and signal coverage (percentage of space and time where the minimum acceptable bit rate is achieved), which make an optimised AP deployment very difficult to achieve.

The deployment of APs is a very important planning issue not only because it determines the overall communication performance, in terms of reliability and capacity, but it can also significantly affect the cost of the train control systems. As stated in a report (Beijing National Railway Research and Design Institute of Signal and Communication Co., Ltd., 2006), in mainline railways, the cost of the wireless network takes 40% of the whole budget of building a train control system, which requires over 50,000 US dollars per kilometer to construct (He et al., 2015). However, what is surprising is that about 40% of the wireless network in mainline railways could be wasteful (He et al., 2015). Even though there is no revealed figures for metro systems, it is easy to imagine that there is an enormous potential in financial cost saving if a more reasonable AP deployment is employed in the DCS.

Conventionally, in designing the DCS, the method of determining the deployment of APs mainly relied on engineering experience based propagation modelling and radio surveys performed over a few some selected sample environments (Aziminejad et al., 2015). However, to achieve a seamless radio coverage, more conservative variables value are applied in modelling, which could lead to a less well-designed AP deployment and potentially affect the reliability and the system cost of the DCS. Moreover, a mass deployment of AP would render the existing methods impractical, as they employ highly time-consuming empirically-derived data analysis to realise each deployment.

There is no established method for optimizing the AP deployment in CBTC systems. None of the existing AP planning methods has been properly and originally designed for the environment of CBTC systems. The characteristics of metro lines, including a typical environment topography and strict requirements on dependability, have not been carefully taken into consideration in the existing AP deployment optimisation methods, which could lead to imperfect implementations. Furthermore, propagation simulators, packet level simulators and train simulators exist, but integrating them together and using them as a combined tool to undertake overall wireless control network optimisation is a new area of study. The main difficulties lie in:

1. Consolidating and expanding the range of radiowave propagation models required to reliably predict signal strengths in a comprehensive range of metro environments;
2. Using suitable metrics to precisely and efficiently measure the wireless data exchange performance in WLAN of CBTC systems;
3. Integrating the CBCT relevant radiowave propagation models and the system performance metrics to propose the cost function;
4. Adopting proper practicable search algorithms to find the optimised AP deployments within contradicting objectives, e.g. seamless coverage and channel interference;
5. Building an integrated simulation platform to quantitatively evaluate the overall CBTC system performance of the optimised deployments.

1.3 Objectives and Contributions of the Thesis

The objective of this thesis is to develop a theory of how to optimise the deployment of APs in DCS with an associated design methodology, and to address the practical challenges of implementing such a theory into real cases. This thesis will theoretically account for a comprehensive range of the constraints and uncertainties faced in wireless communication, without sacrificing implementation viability, as it will enable the DCS to have an optimised AP deployment and allow the system to achieve a better and more dependable performance.

The main contribution of this thesis is to propose an AP deployment optimisation method that is suitable in a railway context and an integrated simulation platform. The work proposed in this thesis should establish an new research area, that combines communication theory and railway engineering; meanwhile, it will establish a practical methodology and useful testing tool to help suppliers of CBTC systems improve their ability in planning the AP placement.

1.4 Thesis Outline

This thesis is structured into eight chapters, as shown in below:

The overall research motivations and background are addressed in chapter 1, in which the main problem in AP deployment planning(ADP) is presented.

Chapter 2 introduces the typical system structure of CBTC systems and presents a general literature review of the existing ADP methods proposed by other researchers worldwide.

Chapter 3 reviews some state-of-the-art optimisation programmings and algorithms.

Chapter 4 formulates the ADP optimisation problem in CBTC systems. The wireless communication challenges, objectives and cost function of the ADP optimisation problem are addressed.

Chapter 5 proposes a simulation platform integrated by a railway network simulator and a communication network simulator respectively.

Chapter 6 presents a methodology application for solving small-scale ADP problems. This methodology application is investigated in a tunnel section and the result is evaluated on the integrated simulation platform.

Chapter 7 conducts a methodology application for solving large-scale ADP optimisation problems. A case study is carried out in a real-world metro. The optimised AP deployment is compared with the original planned AP layout and achieves a better result.

Conclusions and future work are presented in chapter 8.

Chapter 2

Research Review

2.1 Introduction

In recent years, communication-based train control (CBTC) systems have been developed to meet the rapidly increasing demands of railway systems in terms of efficiency and safety. The main advantage of CBTC systems is brought about utilising modern wireless communication technology. A key component in this technology is a well-planned deployment of access points (AP), which is a significant factor in ensuring the reliability of CBTC systems. The objective of AP deployment planning (ADP) is to build an optimised AP deployment, in terms of seamless coverage, less co-channel interference, higher performance and lower life-cycle cost, in order to enable the railway control system to meet the strict requirements for safer train control and to support the demands of the railway traffic management.

This chapter is formulated in three parts. In the first part, the basic system structure and the functionalities of each subsystem in the CBTC system are introduced. In the second part, an overview of existing methods of ADP will be presented. In the third part, there is a discussion of the underlying weaknesses of the proposed ADP methods.

2.2 An Overview of Communication-based Train Control (CBTC) Systems

The aim of various types of train control systems is to prevent potential train collisions (Bailey, 2008), therefore, for the train control systems, one of the core tasks is to accurately detect the location of the trains (Pascoe and Eichorn, 2009). In conventional train control systems, track is divided into different sections, which are called block. Consecutive blocks are distinguished from one another by stop signals, the track circuits are installed in the running rails to detect the presence or absence of trains within a block. Once a train is in a block, the entire section will be occupied, the stop signal will prevent the drivers of others trains entering it (Farooq and Soler, 2017). However, as the block length is fixed, track-circuit based train control systems are not able to detect the exact location of the trains in a timely manner, therefore, this type of train control systems is referred as fixed block signalling (Pascoe and Eichorn, 2009).

As a successor of track-circuit based train control systems (TBTC), CBTC systems do not require track circuits to detect trains on the tracks (Diemunsch, 2013). By using modern wireless communication technologies, e.g., waveguide (Wang et al., 2013), leaky cable (Wang et al., 2016) and inductive loop (Guillaumin, 2001), CBTC systems detect the trains' location in a continuous way, which enables a more efficient railway operation. The CBTC system structure is formed by the wayside equipment, the trainborne equipment, data communication system (DCS), computer-based interlocking (CI), train operation control and train subsystems (IEEE Std. 1474.3, 2008), which is illustrated in Figure 2.1. In terms of functionalities, based on the definition of the IEEE standard 1474.1-2004, the CBTC system is a "continuous, automatic train control system utilizing high-resolution train location determination, independent from track circuits; continuous, high-capacity, bidirectional train-to-wayside data communications; and trainborne and wayside processors capable of implementing automatic train protection (ATP) functions, as well as optional automatic train operation (ATO) and automatic train supervision (ATS) functions (IEEE Std. 1474.1, 2004, abstract)." Apart from the APT, ATO and ATS, there is a data communication system (DCS) to undertake the continuous, high-capacity, bidirectional train-to-wayside data communications and a computer-based interlocking (CI) to control the wayside machines and signals in CBTC systems. In the following, the functionalities of each subsystems in the CBTC systems will be briefly introduced.

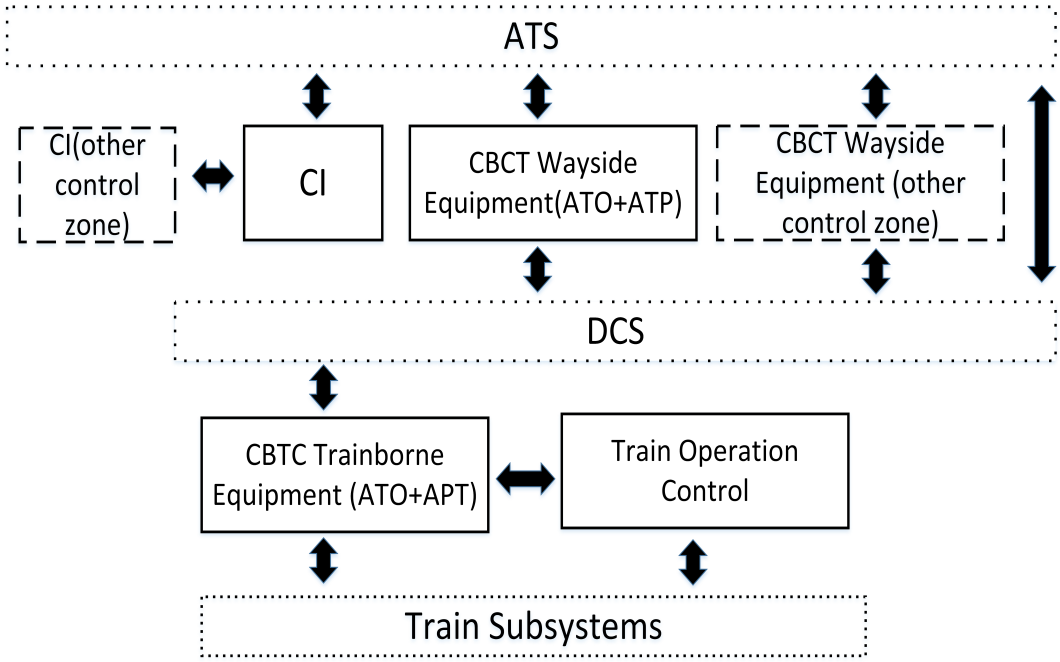


Figure 2.1: A typical CBTC system structure (Author)

2.2.1 Automatic Train Protection (ATP)

ATP is the most critical subsystem in the CBTC system. The main objective of the ATP is to protect the trains from potential hazards. If a train moves forward without receiving the movement authority (MA) given by the wayside zone controller (ZC) or runs faster then the permitted speed, an immediate brake application will be automatically triggered (Booth, 2012). The ATP system is distributed into two parts, namely the wayside part and onboard part:

Wayside ATP is a component of the ZC. The main job of the wayside ATP is to manage the data exchange with the corresponding trains, generate the MA based on the received train operation data and CI status, and then send the MA back to the relevant trains.

Onboard ATP is a part of the vehicle on-board controller (VOBC) (IEEE Std. 1474.1, 2004). As a critical subsystem, ATP helps to prevent collisions as a result of the driver's failure to observe a signal or speed restriction. Based on the received and prior stored data, such as MA, train location, speed limits, gradient, etc., the onboard ATP can produce a safety speed profile. The onboard ATP also monitors and regulates the train speed to stick with the safety speed profile, and applies emergency braking when it is necessary (Farooq and Soler, 2017).

2.2.2 Automatic Train Operation (ATO) and Automatic Train Supervision (ATS)

ATO system is designed to automatically and more efficiently control the train speed (Gu et al., 2014). There are 5 Grades of Automation (GoA) (Caramia et al., 2017), which are defined according to who is responsible for handling the functions of train operation, e.g., the driver, attendant or the system itself. For the highest level of automation, the train can be operated fully automatically without the interaction or even presence of a driver (Caramia et al., 2017). The detail of the GoA is shown in Table 2.1. ATO is a distributed

Table 2.1: The Grades of Automation in CBTC Systems (Author)

GoA	Operation Type	Motion Setting	Stopping Train	Door Closure	Operation in Distruption
0	Driver	Driver	Driver	Driver	Driver
1	ATP+Driver	Driver	Driver	Driver	Driver
2	ATP+ATO+Driver	Automatic	Automatic	Driver	Driver
3	Driverless	Automatic	Automatic	Attendant	Attendant
4	Driver Unattended	Automatic	Automatic	Automatic	Automatic

system that consists of wayside ATO and onboard ATO:

Wayside ATO is a component of the ZC. It provides the destination and departure time for each of the trains.

Onboard ATO works under the framework of VOBC. By referencing the safety speed profile generated by onboard ATP, the ATO will produce an operational speed profile and regulate the driving functions of the train under this speed profile automatically.

In addition to ATP and ATO, ATS is used in some CBTC systems. The main task for ATS is to supervise the status of trains, schedule or reschedule the routes, and manage the traffic by commanding the CI according to the scheduled timetable (Farooq and Soler, 2017). To ensure the preceding route is clear for train running, based on the route requirements, CI checks the status of wayside signal equipment and switch machines, sets them to designated position. After the route has been successfully scheduled, CI informs the ZC about the ends of safe routes (Bu et al., 2014).

2.2.3 Data Communication System (DCS)

The DCS is in charge of the bidirectional communication between the trainborne equipment and the wayside infrastructure. DCS consists of onboard networks, radio networks and wayside backbone networks (Bu et al., 2014; Zhang et al., 2009):

Onboard networks The main component of the onboard networks is the train unit (TU), which is a kind of wireless transceiver equipped with an external antenna used to communicate with the wayside APs in a wireless way. To have a reliable wireless communication performance during the hand-off procedure, the TU is installed in both the front and rear parts of the train, and it is connected to the associated VOBC via Ethernet.

Radio networks The objective of the radio networks is to build continuous connections between the trainborne equipment and the wayside infrastructure. There are two mainstream technologies applied in radio networks of radio-based train control systems, the earlier ones use an inductive loops (Guillaumin, 2001; Morar, 2012), and the more modern ones use a wireless local area network (WLAN) (Farooq and Soler, 2017). The high reliability and low cost of the inductive loop based radio networks have been service-proven for more than 30 years in train control systems, however, the drawback of this type of train control system is that only intermittent train-to-wayside data transmission can be achieved (Sullivan, 2005). The WLANs are managed by IEEE 802.11 protocols and operating in one of the three frequency bands designated as 900 MHz, 2.4 GHz and 5.8 GHz (Fitzmaurice, 2013). However, due to more off-the-shelf products are available in the commercial market, DCS are more likely to be working at 2.4 GHz (Fitzmaurice, 2013). In WLAN-based CBTC system, each of the APs has a radio coverage, which is indicatively shown in Figure 2.2 by using different colours. The radio coverage of APs must be properly overlapped to ensure that radio coverage is seamless. When a train runs in the radio coverage of an AP, wireless communication between the trainborne equipment and the wayside infrastructure can happen.

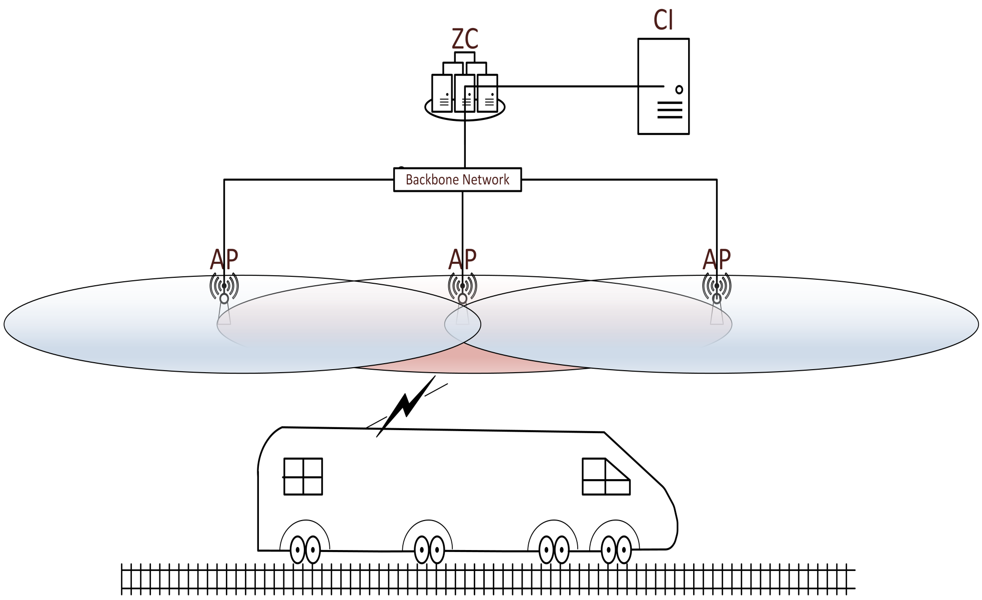


Figure 2.2: Radio coverage in a Typical CBTC system (Author)

Wayside backbone networks Wayside backbone networks are used to connect the wayside infrastructure, including APs, ZC, ATS and CI.

2.3 Literature Review of AP Deployment Planning (ADP) Strategies

Although AP deployment planning (ADP) is significant for a wireless communication network, the problem of ADP in the railway context has not been well studied, and only limited literature is available.

In (He et al., 2015), the deployment planning problem of base stations (BS)[1] in the global system for mobile communications for railway (GSM-R) used in railway control systems is raised, and an optimised BS deployment arrangement is proposed. In this paper, a standardized path-loss and shadowing fading model is applied for describing the radio wave propagation in a high-speed railway context and an extensive real-world measurement campaign was carried out to evaluate the accuracy of this proposed wireless channel model. It shows that, by using this improved channel model to define the BS interval, 40% of deployed BSs can be saved. As a result, the method proposed in this paper focuses on a macroscopic BS planning strategy, and only a suggested spacing between APs is provided. As a result, many other planning details, such as the exact location of each BS and the influence caused by co-channel interference, are not properly considered. So this method proposed can not be directly applied to plan the AP deployment in CBTC systems.

More research has been conducted towards the deployment planning problem of AP or BS in a non-railway context. In the early stages of their deployment, the locations of BSs were mainly selected depending on a regular pattern, which was fine tuned by engineers based on their engineering experience (Joseph, 2007). These experience based BS planning strategies demand extensive tuning in order to reach the performance requirements (Groe and Larson, 2000; Kim, 2000; McCullough, 2001). More recently, to achieve a more accurate and efficient planning procedure, more and more theoretically supported AP or BS deployment planning methods have been proposed.

[1]In cellular systems, the role of the access point is known as the base station

In Wong's thesis(Joseph, 2007; Wong, Mason, Neve and Sowerby, 2006; Wong et al., 2003; Wong, Neve and Sowerby, 2006), a unique framework for forming an automatic optimisation tool towards solving the BS deployment problem in code-division multiple access (CDMA) based systems is proposed, which contains various BS deployment models covering different indoor environment scenarios. The optimisation problem is formed via binary integer programming (BIP), and the objective of the optimisation is to minimise the number of BS used, taking into account the physical environment, whilst also maintaining the wireless communication quality. The results are sorted by a customised genetic algorithm (GA), branch-and-bound (B&B) method and generic GA respectively, which shows the customised GA can achieve a better performance.

However, there is no completion of the optimisation tool in Wong's work. Accordingly, in (Pujji, 2012; Pujji et al., 2009, 2013), Pujji and his colleagues extended this BS deployment planning framework by proposing a hybrid algorithm termed reduction estimation—combinatorial optimisation—reduction (RCR) approximation. In this improved framework, the grade of service (GoS) is introduced as a metric, and the objective of the optimisation is to find the minimal BS number required that can maintain a certain level of GoS. In this work, three factors, namely, call traffic variability, transceiver mobility and call switching technologies, and six detailed scenarios combining these three factors have been carefully considered. Additionally, the planning problem of AP deployment in multi-floored building environment is investigated.

Similarly, in (Amaldi, Capone and Malucelli, 2003; Amaldi et al., 2008; Amaldi, Capone, Malucelli and Signori, 2003), by using the BIP to formulate the problem, a BS deployment planning method focusing on 3G cellular networks is proposed. The objective of the optimisation is to find the trade-off of BS deployment between radio coverage and the number of BS used. Signal-to-interference ratio (SIR) and the received signal power level are considered as the criteria. The problem is solved by greedy algorithm (GRA) and further processed by applying a customised tabu search (TS).

In (Lee and Kang, 2000), by using BIP to formulate the problem and TS to solve the problem, another planning methodology applied in CDMA systems is proposed by Lee and Kang, whose objective is to optimize the trade-off between cost and capacity. In this work, two optimisation demands, namely, designing an optimised BS deployment and improving the BS deployment performance in an existing system, are investigated. The performance comparison of results shows that the TS is more suitable than GA for solving BS deployment planning problems.

In (Molina et al., 1999, 2000; Sharma et al., 2002), Molina, *et al.* presented a novel algorithm, named as combinatorial algorithm for total (CAT) optimisation, for solving the BS deployment planning problem. A number of possible BS locations are predefined. The objective of the optimisation is to deploy the minimized BSs to ensure the deployment can maintain an accepted radio coverage and capacity. CAT splits the possible BS locations into a number of small groups, and the solution will be a subset of these small groups. In addition to CAT, the problem is also solved by GRA and GA. A comparison of the results shows that CAT is more accurate and efficient. However, as the optimisation is carried on the basis of group combinations, the quality of solutions heavily relies on the group size.

In (Fruhwirth and Brisset, 2000), POPULAR (Planning fOr Pico-cellULar Radio), a package to find the optimal BS deployment, is presented for an indoor multi-floored environment. This is a constraint-based optimisation method, in which the radio coverage area of a test point is approximated by a polygon, and the signal attenuation is estimated by using ray-tracing. The intersection areas of multiple polygons are supposed to be the potential placements for BS. The objective is to minimize the number of BS required to cover all the polygons.

In (Cheung and Murch, 1998), the concept of QoS and outage probability are introduced as the optimisation criteria. The locations where BS can potentially be placed are predefined in a service area, and the optimised deployment of BS will be a subset of these predefined potential locations. Weight factors are assigned based on the traffic density at the location of each MS. The problem is formulated to minimize the weighted spatial outage probability in the service area. To solve the optimisation problem, simplex search (Murty, 2000) and Powell's conjugate direction method (Powell, 1964) are applied. The result shows that a big improvement is achieved by adopting the optimised

BS deployment.

In (Liang et al., 2012), a novel transmitter placing a scheme for indoor wireless networks is provided. The service area is divided into the inner receiver grid (IRG) to present the distribution of receivers, and the optimised locations of transmitters will be a subset of the IRG. This scheme is implemented in two phases: the first phase is to use the iterative heuristic search (IHS) to quantify the minimal number of transmitters required; the second phase is to apply a modified simplex algorithm to find the best coverage scenarios by using the minimized transmitter number. The result shows this novel scheme can provide a better coverage deployment than exhaustive search, manual placement and GA.

By taking the interference into consideration, Akl, *et al.* presented a CDMA system design optimisation model in (Akl et al., 1999, 2001). In this optimisation model, the sensitivity of capacity, BS locations, pilot-signal power and power compensation factor are incorporated as the optimisation constraints. The optimisation objective of this proposed design model is to maximize the system capacity. To mitigate the interference problem, a compensation factor is used to adjust the transmission power of each cell.

In many CBTC systems, WLAN is employed to carry out the train-to-wayside wireless communication (Farooq and Soler, 2017). When planning a small WLAN system, it is typical that APs are allocated only based on the estimated radio coverage radius of the AP and the predefined spacing interval (Hills, 2001), which is rough and unreliable. In order to mitigate the multipath impact on the wireless data exchange quality, many WLAN systems use orthogonal frequency-division multiplexing (OFDM), to explore the capability of the CDMA based AP or BS deployment planning methods in OFDM-based WLAN systems, some comparisons have been made in (Namik et al., 2012). By setting the same AP deployment in both an OFDM-based system and a direct-sequence CDMA (DS-CDMA) based system, a difference in radio coverage is found, which proves that the capability of CDMA-based AP deployment planning methods is not suitable for WLAN systems.

In (Rodrigues et al., 2000), the AP deployment planning problem in WLAN systems is discussed and an optimisation model is proposed. As the WLAN is working on an unlicensed frequency, in addition to the AP deployment, the channel assignment must also be considered. The objective of this proposed model is to maximise the coverage by adjusting the deployment of the APs. Meanwhile, to manage the potential interference, dedicated constraints are incorporated into this model to make sure that the working channels are sufficiently separated in the spectrum.

In (Lu et al., 2016), from the perspective of balancing the trade-off between cost-effectiveness and normalized service delay (NSD), an AP deployment planning strategy is proposed. NSD is defined as the service quality degradation caused by switching between the Wi-Fi networks and cellular networks. By identifying and analysing the conflict between the density of APs and vehicle traffic, the optimised trade-off is produced. The results will support the planning of Wi-Fi deployment in vehicle communication networks.

In (Zheng et al., 2012), two verification algorithms for checking $\alpha - coverage$ are provided. The $\alpha - coverage$ is defined as an intermittent coverage planning for Wi-Fi network users that can guarantee the worst-case is acceptable. By using this coverage, the required AP number can be significantly reduced. The problem is formulated by minimising the $\alpha_N - coverage$ and $\alpha_P - coverage$ respectively. To efficiently solve the problems, approximation algorithms, vertex multicut (Garga et al., 2004) and set covering (Vazirani, 2003), are introduced and applied. The results achieved by approximations are proven to be better than other heuristic algorithms.

In (Amaldi et al., 2004), the objective of maximising the system capacity in a WLAN is formulated by using the hyperbolic and quadratic function. The result is searched by a heuristic method that contains GRS phase and local search phase. The GRS is used for a prior search, then the final output is delivered by using local search. The optimisation result shows that the proposed heuristic can identify a near optimal AP deployment within a reasonable time.

In some literature, in order to further improve the optimisation efficacy so that the proposed optimisation strategies can be adopted in the real world, evolution-inspired searching algorithms are applied.

In (Kobayashi et al., 2000), an investigation of the optimal deployment of AP in an OFDM-featured WLAN is carried out. The objective of this optimisation is to minimise the average bit error rate (BER) of working transceivers when the input is specified, including the AP number, transmission power and the configuration of the indoor environment. Very fast simulated re-annealing (VFSA) is applied to solve the optimisation problem.

In (Du and Yang, 2016), the AP deployment optimisation problem is formulated through maximising the sum of the Euclidean distance between each fingerprint, which are selected from the predefined reference points. The fingerprints of each reference point are estimated by using a log-distance propagation model. In this planning method, a map with coordinates and graphics is pretested, which is inherently exploited in this constraint-based optimisation problem. The optimisation problem is solved by particle swarm optimisation (PSO) and random placement. A comparison between the result archived by PSO and random placement shows that PSO can produce better AP deployment solution in terms of reducing the maximum error distance.

To prove the GA is a good option for solving BS deployment planning optimisation problems, a result comparison is set out in (Krishnamachari and Wicker, 2000). In this paper, an optimisation problem is proposed, whose objective is formulated to maximise the radio coverage by using a minimised number of BS. By comparing the optimisation result achieved by random walk (RW), simulated annealing (SA), TS and GA, a conclusion is drawn that GA is particularly scalable in solving deployment optimisation problems, especially when doing large scale optimisation.

In (Weicker et al., 2003), the deployment problem is formulated by two objective functions, namely cost and interference. Three evolutionary based multi-objective optimisation algorithms, including strength Pareto evolutionary algorithm-II (SPEA-II), non-dominated sorting genetic algorithm-II (NSGA-II) and steady state evolutionary algorithm with Pareto tournaments (stEAPT), are adopted to solve this multi-objective programming problem. The work proposed in this paper shows that multi-objective optimisation evolutionary algorithms (MOEAs) are strong enough tools to tackle real-world problems.

When planning the AP deployment in a large WLAN system, to save the computational feasibility, a divide and conquer method is applied to make the work scalable. In (Gibney et al., 2011), to make the AP deployment planning problem in a large and complex WLAN scalable, an environment segmentation algorithm is proposed. The main concept of this algorithm is to divide the large problem into smaller ones and conquer these smaller problems in turn. For each of the smaller problems, a number of criteria are considered, such as resource utilisation, oversubscription, balance factor and signal-to-noise ratio (SNR) balance. The priority for each of the criteria is defined by a corresponding weight factor taking account of the user requirements. In this work, the agent-based approach (ABA) (Stuart and Peter, 2009) is adopted to solve the problem.

2.4 Limitations of the Existing ADP Strategies

In the previous section, a literature review of the existing research on AP deployment planning strategy is presented. The reviewed literature is summarised in Table 2.2. Although the question of how to plan the deployment of the BS or AP in a wireless communication system is well established in the existing literature, all of these proposed planning strategies are applicable to non-CBTC system environments, and no previous work takes into account the mobility and topographical constraints of CBTC systems.

The main limitations in existing ADP strategies can be grouped into the following aspects:

Non-railway Context CBTC systems are working in a very specific railway environment which contains many features and scenarios, such as viaducts, tunnels, cuttings, *etc*. However, most of the proposed deployment planning strategies have only been used in generic environments.

Inadequate Network Configuration There are quite a number of deployment planning strategies which are designed for cellular networks, including GSM, CDMA or 3G networks, which are not followed by the most DCS of CBTC systems, in which the wireless communication networks are provided by OFDM or spread-spectrum based WLANs.

Improper Application of Optimisation Algorithms When planning the deployment of WLAN in a real world environment with multiple objectives, the choice of algorithm is critical because an improper application of a searching algorithm can lead to a very big degradation in the optimisation result quality. Most of the existing research tends to use weight factors to set the priority for each of the objectives, which could be arbitrary and may lead to inaccurate optimisation results.

Aimed at addressing these limitations, in this thesis, a novel AP deployment planning strategy focusing on the CBTC environment will be proposed. In this strategy, the railway features will be carefully considered, the network will refer to the configuration of WLANs, and an efficient and accurate searching algorithm will be customised and applied to find the optimised result.

2.5 Summary

In this chapter, the typical structure of CBTC systems and the existing research on AP or BS deployment planning optimisation in wireless communication networks has been reviewed.

The CBTC system is a new generation of train control system, where the main advantage comes from adopting bidirectional wireless communication technology. A typical CBTC contains five subsystems, namely ATP, ATO, ATS, CI and DCS. ATP is the most significant subsystem within a CBTC system. The main task of ATP is to trigger the braking when emergencies happen so that trains are protected from collisions. In some

CBTC systems, to improve the system efficiency, ATO is applied to automatically operate the trains. ATS is a supervision system, which is used to manage the railway traffic commanding the CI. DCS is in charge of exchanging the data flow within each subsystem and with the trains.

The research on deployment planning is extensive. However, there are three drawbacks underlying the existing literature. Firstly, there is only limited research focusing on railway scenarios. Secondly, many CBTC systems are using OFDM or spread spectrum based WLANs (Farooq and Soler, 2017; Fitzmaurice, 2013), which are not consistent with most of the proposed planning strategies (e.g., CDMA). Most importantly, when the optimisation problem is formulated by multiple objective functions, the majority of the proposed strategies tend to use self-defined weighting factors to set the priority for each of the objectives, which could be arbitrary and may lead to inaccurate optimisation results.

Table 2.2: Literature List (Author)

Author	Year	Network	Context	Algorithm	Reference
He, *et al.*	2015	GSM-R	Railway		(He et al., 2015)
Wong, *et al.*	2006	CDMA	Indoor	B&B,GA	(Joseph, 2007; Wong, Mason, Neve and Sowerby, 2006; Wong et al., 2003; Wong, Neve and Sowerby, 2006)
Pujji, *et al.*	2009	CDMA	Indoor	Hybrid Algorithm—(RCR)	(Pujji, 2012; Pujji et al., 2009, 2013)
Amaldi, *et al.*	2003	Cellular	Outdoor	Tabu Search	(Amaldi et al., 2004; Amaldi, Capone and Malucelli, 2003; Amaldi et al., 2008; Amaldi, Capone, Malucelli and Signori, 2003)
Lee and Kang	2000	CDMA	Outdoor	Tabu Search	(Lee and Kang, 2000)
Molina, *et al.*	1999	W-CDMA	Outdoor	CAT	(Molina et al., 1999, 2000; Sharma et al., 2002)
Fruhwirth and Brisset	2000	Cellular	Indoor	B&B	(Fruhwirth and Brisset, 2000)
Cheung and Murch	1998	Cellular	Indoor	Simplex and Powell Algorithm	(Cheung and Murch, 1998)
Liang, *et al.*	2012	GSM	Indoor	IHS and Simplex Algorithm	(Liang et al., 2012)
Akl, *et al.*	1999	CDMA	Outdoor	B&B	(Akl et al., 1999, 2001)
Rodrigues, *et al.*	2000	WLAN	Indoor	Simplex Algorithm	(Rodrigues et al., 2000)
Kobayashit, *et al.*	2000	WLAN	Indoor	VFSA	(Kobayashi et al., 2000)
Du and Yang	2016	WLAN	Indoor	PSO	(Du and Yang, 2016)
Lu, *et al.*	2016	WLAN	Outdoor	B&B	(Lu et al., 2016)
Zheng, *et al.*	2012	WLAN	Outdoor	Approximations (VM and SC)	(Lu et al., 2016)
Krishnamachar, *et al.*	2000	GSM	Outdoor	SA, Random Walk, GA, Tabu Search,	(Krishnamachari and Wicker, 2000)
Weicker, *et al.*	2003	Cellular	Outdoor	SPEA2, NSGA-II, stEAPT	(Weicker et al., 2003)
Gibney, *et al.*	2011	WLAN	Indoor	ABA	(Gibney et al., 2011)

Chapter 3

Review of Optimisation Programmings and Algorithms

In the last chapter, some existing deployment planning methods have been investigated, where deployment optimisation problems can be divided into two groups, depending on whether the involved objective is single or multiple. When only one objective needs to be satisfied, this kind of optimisation problem is referred to as single-objective optimisation programming (SOP), which is the simplest of the optimisation problems. The aim of optimising the ADP in this thesis is to provide an optimised AP deployment that can simultaneously improve system safety, reliability, performance and minimise the system life-cycle cost. Obviously, there are multiple objectives involved in this ADP problem, so the optimisation of the ADP is referred to as multi-objective optimisation programming (MOP).

To have a clear understanding of MOP, in this chapter, the fundamentals of MOP and the popular approaches for solving MOPs are investigated. Generally, two main types of approach are used in solving MOPs, such as scalarization-based mathematical programming methods and nature-inspired metaheuristics (Fei et al., 2017). Mathematical programming is known as a classical method, it formulates a single-objective optimisation problem whose optimal solutions are equivalent to the solution of the MOP (Figueira et al., 2005). More often, MOPs are solved by nature-inspired metaheuristics, such as multi-objective evolutionary algorithm (MOEA) (Xia et al., 2014).

3.1 Single-objective Optimisation Programming (SOP)

In mathematics, the SOP is defined as the problem of finding the optimal solution in its search space. The SOP can be expressed as (Bandyopadhyay and Saha, 2013):

$$\begin{cases} \text{min/max} & f(x) \\ \text{s. t.} & g_i(x) \le 0,\ i = 1,2,\ldots,p \\ & h_j(x) = 0,\ j = 1,2,\ldots,q \end{cases} \tag{3.1}$$

where $f(x)$ is the objective function, $x = (x_1,\ldots,x_n) \in S \subset R^n$ is an n dimensional vector of feasible decision variables, S is the feasible decision variable space, $g_i(x)$ and $h_j(x)$ are inequality and equality constraints respectively. The aim is to find a decision variable x^* in S such that $f(x^*) \le f(\bar{x})$, $\forall \bar{x} \in S$ (min) or $f(x^*) \ge f(\bar{x})$, $\forall \bar{x} \in S$ (max) .

3.2 Techniques for Solving SOP

The core aim of the SOP is to search out the optimal solution. The techniques for searching the optimal solution in SOP problems can be classified into three categories (Bandyopadhyay and Saha, 2013; Goldberg, 1989):

1. Numerical techniques.
2. Enumerative techniques.
3. Guided random searching techniques.

Numerical techniques use a selection of mathematical equations as the necessary and sufficient conditions that the solution must satisfy. Numerical techniques are local in scope and also assume the existence of derivatives (Bandyopadhyay and Saha, 2013), which means that these techniques have limited applicability in many real world applications. As a result, numerical techniques will be neglected in this thesis.

Enumerative techniques tend to evaluate each of the points in the search space in order to find the optimal solution. This kind of technique is straightforward and can guarantee to find the optimal solution, but it will be extremely computationally demanding in dealing with large-scale optimisation problems. Brute force search (BFS) is an example of an enumerative technique.

Guided random searching techniques are extended from enumerative techniques: The search is randomly carried out in the search space and guided by using predefined conditions. Guided random searching techniques are very useful in solving large-scale optimisation problems with high computational demand. Evolutionary algorithms, such as genetic algorithms (GA), are good examples of these techniques. However, the optimality of the solution is not guaranteed by this kind of technique, only a nearly optimal solution can be achieved.

3.2.1 Brute Force Search (BFS)

BFS is one of the enumerative techniques, which is straightforward and widely used in solving SOPs. BFS is directly based on the problem statement and searches all the feasible solutions in the search space. By using BFS, the optimal solution can be guaranteed. BFS can be classified into two types, namely selection sorting and exhaustive search (Knuth, 1998):

Selection sorting is a typical BFS method used to order group of individuals (Donald, 1998). It is assumed that there are *N* individuals which need to be arranged in declining (or ascending) order. At first, the algorithm scans all the individuals and finds the smallest one. Then the smallest individual is swapped with the first individual. After that, this process is repeated until all the individuals are sorted. A indicative example of the selection sorting is illustrated in Figure 3.1, where a group of *n* individuals are ordered in a declining order.

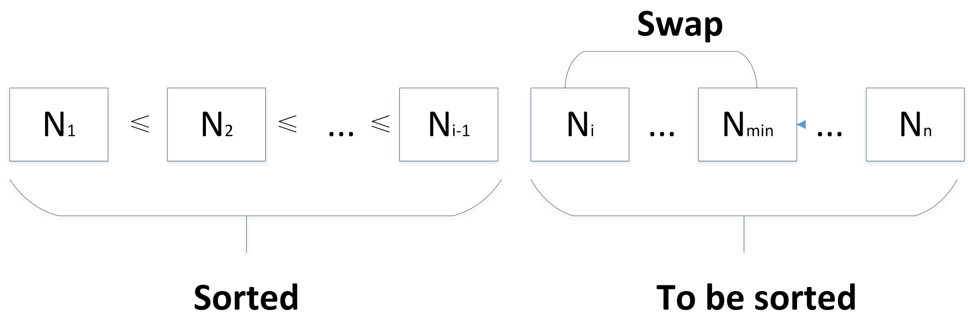


Figure 3.1: The flowchart of selection sorting (Author)

Exhaustive search is a kind of BFS used to search the solution that can fulfil certain characteristics. It exhaustively searches all the feasible solutions in the searching space, and then finds the most appropriate one. The flowchart of the exhaustive search is shown in Figure 3.2.

Even though BFS is very easy to implement and can guarantee the optimal solution, it is not very time efficient when searching a big space. As a result, instead of enumeration based search algorithms, evolutionary algorithms tend to be more popular in solving large-scale optimisation problems (Segredo et al., 2012).

3.2.2 Genetic Algorithm (GA)

GAs are an efficient, adaptive and robust optimisation process, which applies a guided random search on a very large, complex, and multimodal search space (Bandyopadhyay and Saha, 2013). The GA was first proposed by Holland in (Holland, 1975). GAs are inspired by mimicking evolutionary principles and chromosomal processing in natural genetics based on the concept of the Darwinian theory of natural selection (Kanthababu, 2013). Based on this theory, naturally, compared with weak and unfit species, the strong and fit species have a greater opportunity to produce their offspring through making

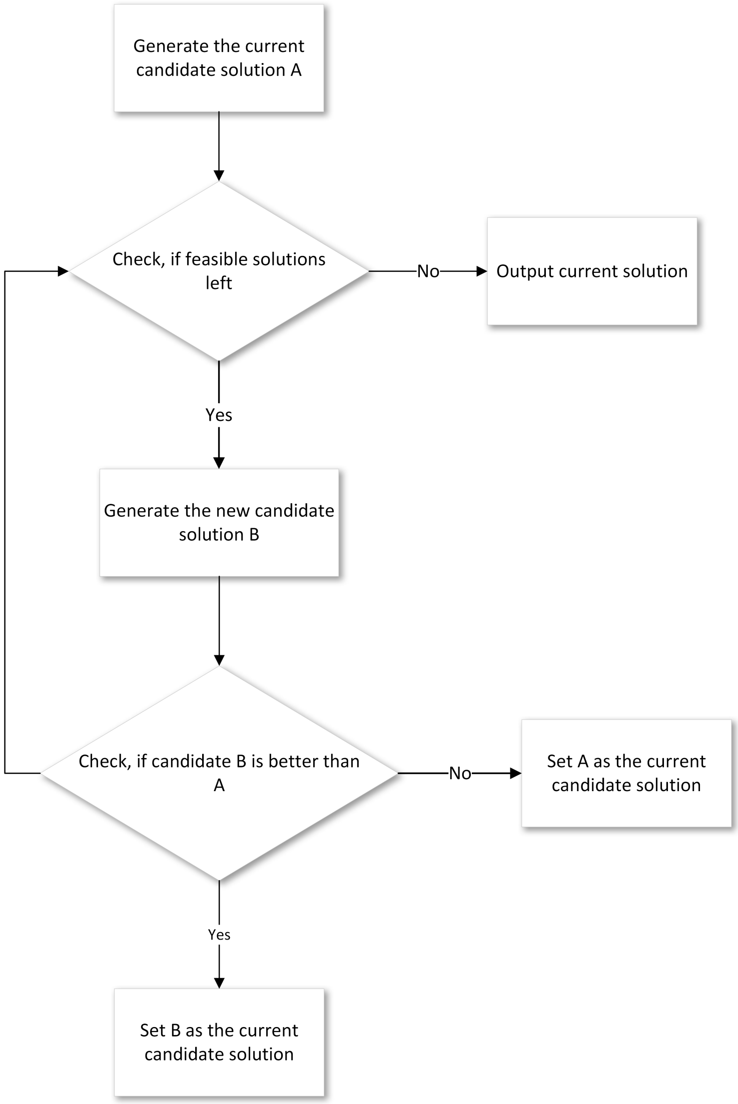


Figure 3.2: The flowchart of exhaustive search (Author)

crossover on their genes. In the long term, the species with the combined genes that come from strong ancestors will be dominant in the population. Over time, some positive mutations can randomly happen during the evolution, which may enable additional advantages to the offspring. On the other hand, the offspring which were involved with negative mutations will be eliminated in the following evolutionary processes.

The flowchart of a GA is shown in Figure 3.3. The initial population is randomly generated and the fitness is evaluated. Then, parents are selected based on the assigned fitness of each individual. There are a number of available selection methods, such as roulette wheel selection (Thomas, 1996), tournament selection (Blickle and Thiele,

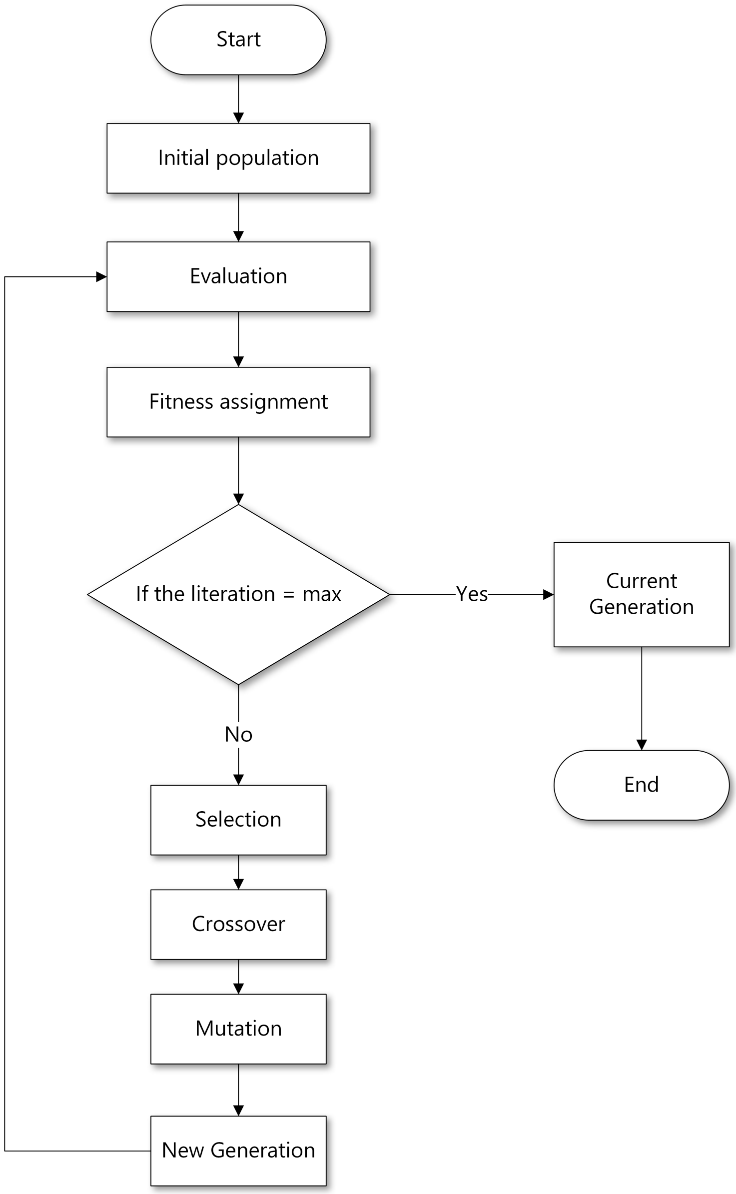


Figure 3.3: The flowchart of GA (Author)

1996) and rank-based wheel selection (Reeves and Rowe, 2002), which can be applied to meet the different demands of users. Finally, after crossover and mutation, the offspring will be generated as the new generation. The new generation will keep on being updated until the termination condition is reached.

3.3 Multi-objective Optimisation Programming (MOP)

In the real world, people need to make decisions every day. Sometimes, the decision can be made simply, as the decision maker only needs to consider a single objective; however, most of the time, due to there being more complexities involved, more criteria must be considered by the decision maker, which means that the optimisation problem, instead of using a single objective function, must be formulated by multiple objectives. ADP is a typical multi-objective optimisation programming (MOP) problem.

To achieve a good ADP, it needs to find a deployment solution that simultaneously satisfies multiple objective functions, such as maximal system reliability, the best data exchange quality, lowest system life-cycle cost, *etc.*, or best trade-off among these objectives. As a result, MOP can be inherently adapted for formulating this kind of problem (Tharmarasa et al., 2009).

A MOP consists of a number of objective functions to be either minimized or maximized, which can be mathematically expressed as (Deb, 2001):

$$\begin{cases} \text{min/max} \quad F(x) = (f_1(x), f_2(x_)), \ldots, f_m(x)) \\ \quad\text{s. t.} \quad g_i(x) \leq 0,\ i = 1, 2, \ldots, p \\ \qquad\qquad h_j(x) = 0,\ j = 1, 2, \ldots, q \end{cases} \tag{3.2}$$

where $x = (x_1, \ldots, x_n) \in S \subset R^n$ is an n dimensional vector of feasible decision variables, S is the n dimensional feasible decision variable space, $F(x) = (f_1(x), f_2(x), \ldots, f_m(x_)) \in Z \subset R^m$ is the m dimensional vector of objectives, Z is the m dimensional objective space. In most cases, as the objectives in Z contradict each other, there is no solution $x^* \in S$ that can minimise or maximise all the objective functions simultaneously, and a number of Pareto optimal solutions exist. To have a better understanding of MOP, some definitions are given (Gong et al., 2009):

Definition 3.3.1. Dominate: A solution x_A is said to dominate the other solution x_B, if and only if $\forall i = 1, 2, \ldots, m, f_i(x_A) \leq f_i(x_B) \wedge \exists j = 1, 2, \ldots, m, f_j(x_A) < f_j(x_B)$, which is denoted as $x_A \succ x_B$ or x_A dominates x_B.

Definition 3.3.2. Pareto optimal (PO): A solution x^* is Pareto optimal, if and only if $\neg\exists x \in S : x \succ x^*$

Definition 3.3.3. Pareto set (PS): Pareto set P^* is the set of all the PO, which is denoted as $P^* \triangleq \{x^* \mid \neg\exists x \in S : x \succ x^*\}$

Definition 3.3.4. Pareto front (PF): The set of all the Pareto optimal objective vectors is the PF^*, which is denoted as $PF^* \triangleq \{F(x^*) = (f_1(x^*), f_2(x^*), \ldots, f_m(x^*)) \mid x_* \in P^*\}$

3.4 Techniques for Solving MOP

Similar to the SOP problems, the core part of solving MOP problems is how to find the optimal solution. There are two main types of approach used in solving MOPs, one is the classical method, the other is MOEA. The main principle of classical methods is to scalarize the multiple objective functions into an overall one and find the exact optimal solution by using an enumeration based algorithm (e.g., BFS), or the nearly optimal solution by using a guided random search algorithm (e.g., GA). However, in most MOEAs, the searching process is population based, and a group of solutions from the population keep being updated in each iteration. There is no optimal solution guaranteed in MOEAs, the main goal is to find the Pareto optimal solutions using evolutionary algorithms.

3.4.1 Classical Method

As it is impossible to find a solution that perfectly fulfils all the objectives in MOP at the same time, the optimal solution will be the one that offers the least conflict in objectives. However, in some cases, the objectives have different emphases, so the solution needs to satisfy the objectives subject to different priorities. To find the optimal solution, classical methods scalarise the objective vectors into one overall objective. In the following sections, some classical methods are investigated.

3.4.1.1 Objective Weighting Method

The most straightforward way to solve a MOP problem is to combine its multiple objectives into one single-objective scalar function. In general, this kind of approach is referred to as the weighted-sum or scalarisation method, as this combination is based on a weight factor assignment (Massimiliano and Paolo, 2008). By combining multiple objectives into an overall objective function, the MOP can be addressed as:

$$\begin{cases} \text{min/max} \quad F(x) = \sum_{j=1}^{N} w_j f_j(x) \\ \qquad \text{s.t.} \quad x \in X, \ j = 1, 2, \ldots, N \end{cases} \tag{3.3}$$

where X is the feasible search space, $F(x)$ is the overall objective function, $f_1(x), f_2(x), \ldots, f_N(x)$ are objective functions, $w_1(x), w_2(x), \ldots, w_N(x)$ are weights for each of the objectives. In this method, the optimal solution depends on the weight factors. The advantage of this method is that the priorities of each objective can be directly reflected and the optimal solution is guaranteed. However, sometimes the weight factors for each objective are dependent on the professional knowledge in this field, and wrong weight factor settings lead to an inaccurate optimal solution.

3.4.1.2 Distance Functions Method

Instead of using weight factors, in this method, a demand-level vector is introduced and assigned to each of the objectives. The distance functions method formulates the MOP problem as:

$$\begin{cases} \text{min} \quad F(x) = [\sum_{j=1}^{N} |f_j(x) - y_j|^r]^{\frac{1}{r}} \\ \text{s.t.} \quad x \in X, \ j = 1, 2, \ldots, N \\ \qquad 1 \leq r \leq +\infty \end{cases} \tag{3.4}$$

where X is the feasible search space, $z = (y_1, y_2, \ldots, y_N)^T$ is the demand-level vector as the reference point for each objective. When $r = 1$, the distance function method is equivalent to the objective weighting method; when $r = +\infty$ and the demand-level vector is the utopian objective vector, all the Pareto optimal solutions can be discovered. The utopian objective vector is assumed to be slightly worse than the ideal objective vector. The ideal objective vector is defined as $z^* = [f_1^*(x), \ldots, f_N^*(x)]^T$, where the m_{th} component is

$$\begin{cases} \min & f_m(x) \\ \text{s.t.} & x \in X,\ m \in 1,2,\ldots,N \end{cases} \tag{3.5}$$

and the utopian objective vector will be $z^{**} = [f_1^{**}(x), \ldots, f_N^{**}(x)]^T$, in which $f_m^{**} = f_m^* - \varepsilon_m$, ε_m is slightly bigger than 0, $m \in 1,2,\ldots,N$. It is necessary to note that the optimal solution depends on a proper demand-level vector selection, an arbitrary demand-level vector setting will lead to producing a non-optimal solution.

3.4.1.3 Min-Max Formulation Method

The idea of this method is to minimise the deviation in each objective function from their individual optimum. For a minimization problem, the MOP is formulated as:

$$\begin{cases} \min & F(x) = \max[Z_j(x)] \\ & Z_j(x) = \dfrac{f_j - \bar{f}_j}{\bar{f}_j} \\ & x \in X,\ j = 1,2,\ldots,N \end{cases} \tag{3.6}$$

where X is the feasible search space,$\bar{f}_1, \ldots, \bar{f}_N$ are the optima for each objective function. By using this method, the conflicts among objectives can be minimised and the optimal solution for objectives with equal priority can be addressed. By assigning different weight factors, unequal priorities can be given to each objective.

3.4.1.4 ε-Constraints Method

In this method, one of the objective functions is optimised by using other objective functions as constraints. By incorporating the constrains, the model is expressed as:

$$\begin{cases} \min \ \ f_j(x) \\ f_i(x) \leq \varepsilon_i, \ \ \forall i \in \{1,\ldots,n\} \setminus \{j\} \\ x \in X \end{cases} \tag{3.7}$$

where $\varepsilon_i = (\varepsilon_1,\ldots,\varepsilon_{j-1},\varepsilon_{j+1},\varepsilon_n) \subset R^{n-1}$ is an $n-1$ dimensional constraint vector. For objective $f_j(x)$ with $j = 1,\ldots,n$, if there exists a constraint vector, the optimal solution x^* to $f_j(x)$ will be a strict Pareto optimum, otherwise, x^* will be a weak Pareto optimum. By changing the constraint vector setting, the efficient optimal solutions of MOP are obtained (Massimiliano and Paolo, 2008; Mavrotas, 2009).

3.4.2 Limitations of Classical Method

Classical methods were previously widely used in formulating MOP problems. Most of the classical methods are preference-based, which could potentially result in an inaccurate optimum. For example, in the objective weighting method, the estimation of weight factors is a kind of preference input, which is based on prior known information. If this information is not comprehensive or there is a lack of professional knowledge, the estimation could be misguided and, as a result, the solution will not be an optimal solution.

To overcome this shortfall underlying classical methods, in the following section, multi-objective evolutionary algorithms (MOEA) will be introduced and reviewed. Instead of adding the preference at the beginning, based on evolutionary algorithms and population selection, MOEAs will generate a number of Pareto optimal solutions first, and then the decision maker can choose the optimal solution on the basis of preference.

3.4.3 Multi-objective Evolutionary Algorithms (MOEA)

The history of solving the MOP based on evolution can be dated back to 1967 when Rosenberg first proposed this idea in his Ph.D. thesis (Rosenberg, 1967). However, this was not successfully realised. In 1975, Holland proposed the GA, and then, in 1985, Schaffer presented the vector evaluated genetic algorithm (VEGA) (Schaffer, 1985), which is the first time that the MOP is solved by using evolutionary algorithms (EA). In 1989, (Goldberg, 1989) was published, in which the Pareto theory was integrated with a GA. This book is significant for the subsequent research that applies EAs in solving MOPs.

As a kind of evolution-inspired algorithms, a good example of EAs is the GA. However, GA can only be directly applied to solve optimisation problems with a single scalar objective function and it cannot inherently be adopted to solve MOP problems. To make use of GA in solving MOP problems, some necessary associations between the solutions and any objective functions must be properly built. There are two different approaches in building these associations, one is to treat the MOP as a whole by using a fitness assignment scheme, the other is to make decomposition for the MOP.

Some popular MOEAs will be introduced and reviewed, including VEGA, Strength Pareto Evolutionary Algorithm (SPEA and SPEA-II), Pareto Archived Evolutionary Strategy (PAES), Pareto Envelope-based Selection Algorithm (PESA and PESA-II) Nondominated Sorting Genetic Algorithm (NSGA and NSGA-II) and Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D). More details are given in the following sections.

3.4.3.1 Vector Evaluation Genetic Algorithm (VEGA)

As mentioned, VEGA (Schaffer, 1985) was proposed in 1985. The flowchart of VEGA is shown in Figure 3.4. Firstly, individuals are selected from the last generation population on a proportion basis and grouped into subpopulations in as a formula of of the performance in each objective, which is the first time that a vector fitness assignment scheme has been used in MOP optimisation problems. Then, to minimise the positional bias in each generation, the population is shuffled. Finally, by means of crossover and mutation, a new generation of the population is produced.

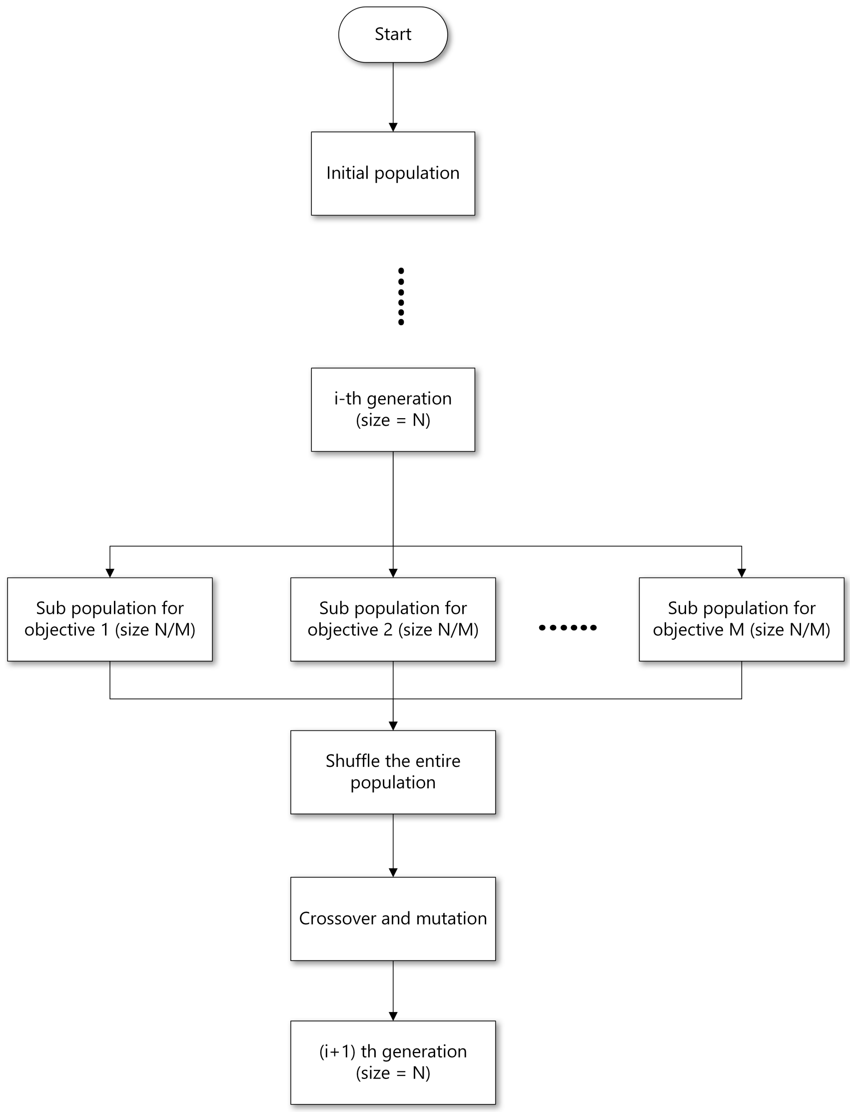


Figure 3.4: The flowchart of VEGA (Author)

3.4.3.2 Strength Pareto Evolutionary Algorithm (SPEA and SPEA-II)

In 1999, the SPEA was proposed (Zitzler and Thiele, 1999). In SPEA, the nondominated solutions in the population are stored in a Pareto set archive with continuous updating.

The fitness of each individual solution is indicated by strength, which is the number of dominated members in the population divided by the population size plus one. For the individuals in the Pareto set archive, the fitness value is presented by the strength; for the individuals in the population, the fitness value is calculated by summing the fitness value of all the members in the archive that dominate it, plus one. SPEA adopts a clustering procedure to maintain the size of the Pareto set archive. Tournament selection is used to select individuals into the mating pool from both of the populations and the Pareto set archive. To keep the diversity of the newly generated population, the individuals from the Pareto set archive have higher priority to be selected. The offspring generated from the mating pool will replace the old population. A flowchart of SPEA (Chitra Chinnasamy, 2011) is shown in Figure 3.5.

However, SPEA has underlying weaknesses in three areas, namely fitness assignment, density estimation and archive truncation. To overcome these weaknesses, a new version of SPEA, SPEA-II was proposed in (Zitzler et al., 2001). In assigning the fitness, differing from SPEA, the fitness value in SPEA-II takes both the dominating and dominated solutions and the relevant density information into account. The fitness value is amount of raw fitness plus density. The raw fitness of each individual, in both the population and the archive, is represented by the strength; the density estimation takes the inverse of the distance to the k_{th} nearest neighbour. For removing extra members from the archive, an environmental selection based truncation process is used, which helps the archived nondominated solutions to have a good spread.

The flowchart of SPEA-II is shown in Figure 3.6. First, the fitness value is assigned to all the individuals in the population and the Pareto set archive. Then the environmental selection is implemented to generate new members to update the Pareto set archive. During this process, a truncation operator may work to remove the extra member in the archive if it is out of size. Finally, by using binary tournament selection, parents are selected into the mating pool to produce a new population to replace the old population.

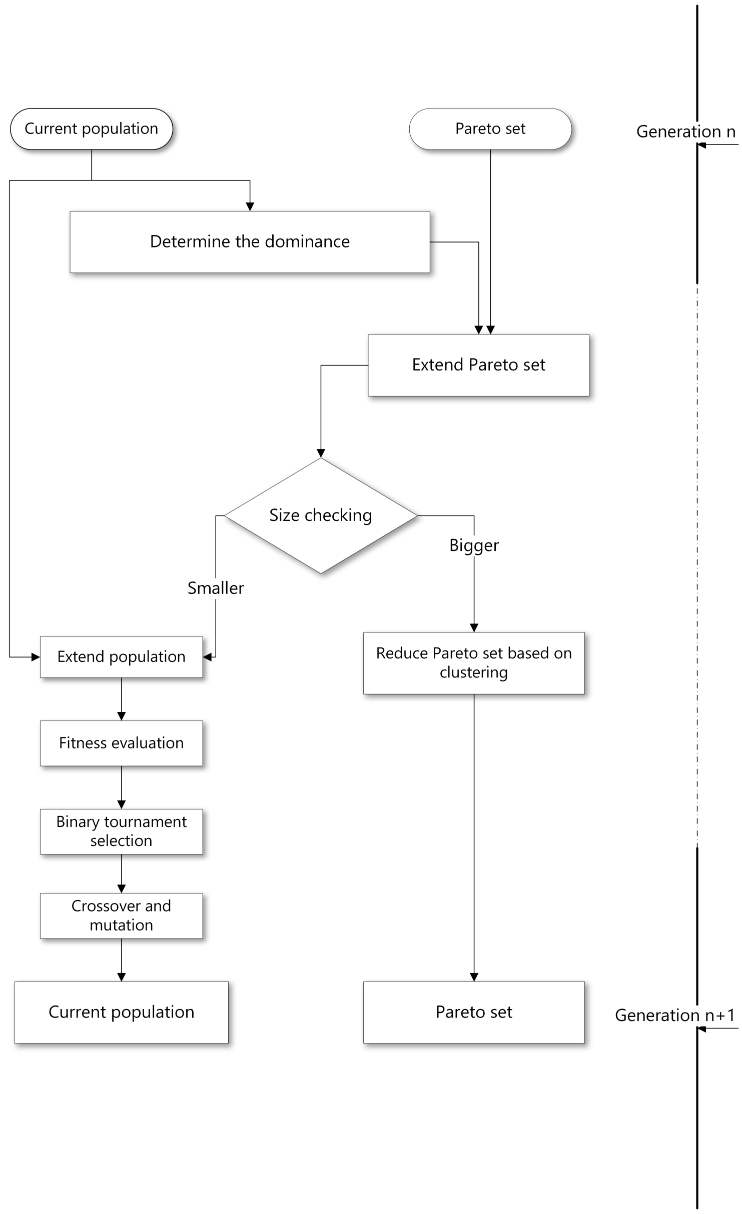


Figure 3.5: The flowchart of SPEA (Author)

3.4.3.3 Pareto Archived Evolution Strategy (PAES)

PAES uses a simple $(1+1)$ evolution strategy to carry out local search (Knowles and Corne, 2000). In this strategy, one current solution and one candidate solution are used to update the result in each iteration. The flowchart of this strategy is shown in Figure 3.7.

At the beginning, individuals are randomly generated, evaluated and added into an archive as the current solution. Then, the current solution produces a new solution candidate via

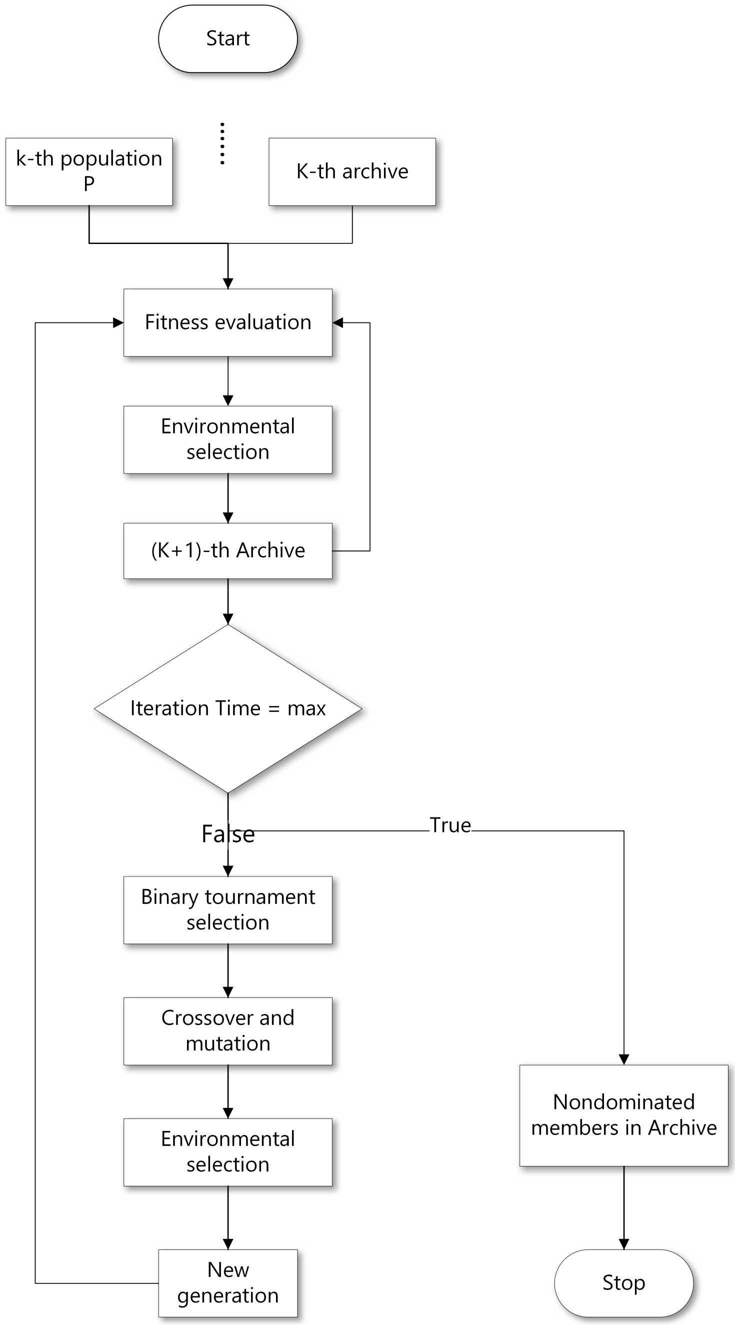


Figure 3.6: The flowchart of SPEA-II (Author)

mutation, if the new candidate is nondominated by neither its ancestor nor others in the previously founded solutions in the archive, it will become the current solution and be added to the archive, otherwise, it will be discarded. To keep the population diversity, based on the evaluation range of each objective, some grids are created, PAES puts every individual into one of the grids, the number of solutions that resides in a grid indicates the degree of crowding. The maximum size of the archive is predefined and when a candidate

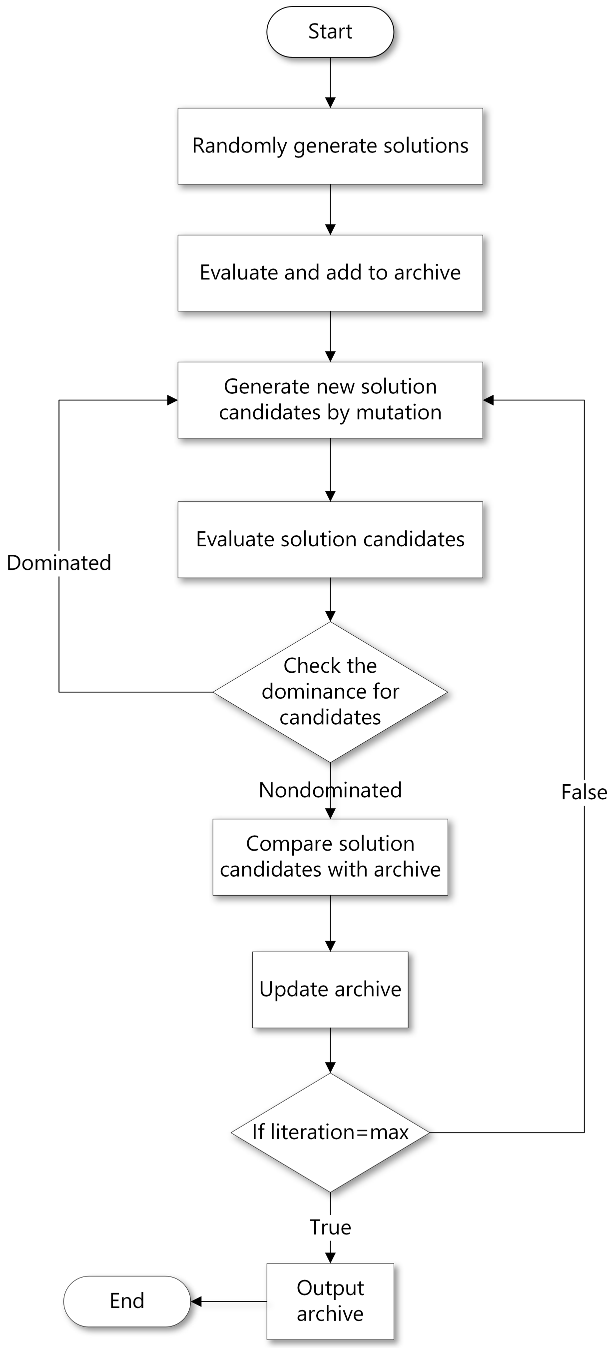


Figure 3.7: The flowchart of PAES (Author)

solution joins a full archive, one of the archived solutions in the most crowded grid will be replaced (Knowles and Corne, 1999).

3.4.3.4 Pareto Envelope-Based Selection Algorithm (PESA and PESA-II)

Inspired by the thought of grid, Corne *et al.* proposed a new algorithm, PEAS (Corne et al., 2000). This algorithm generates two population groups, which are called internal population (IP) and external population (EP) respectively. To maintain the diversity of EP, based on the evaluation range of each objective, the hyper-grid based scheme, and crowding strategy are used.

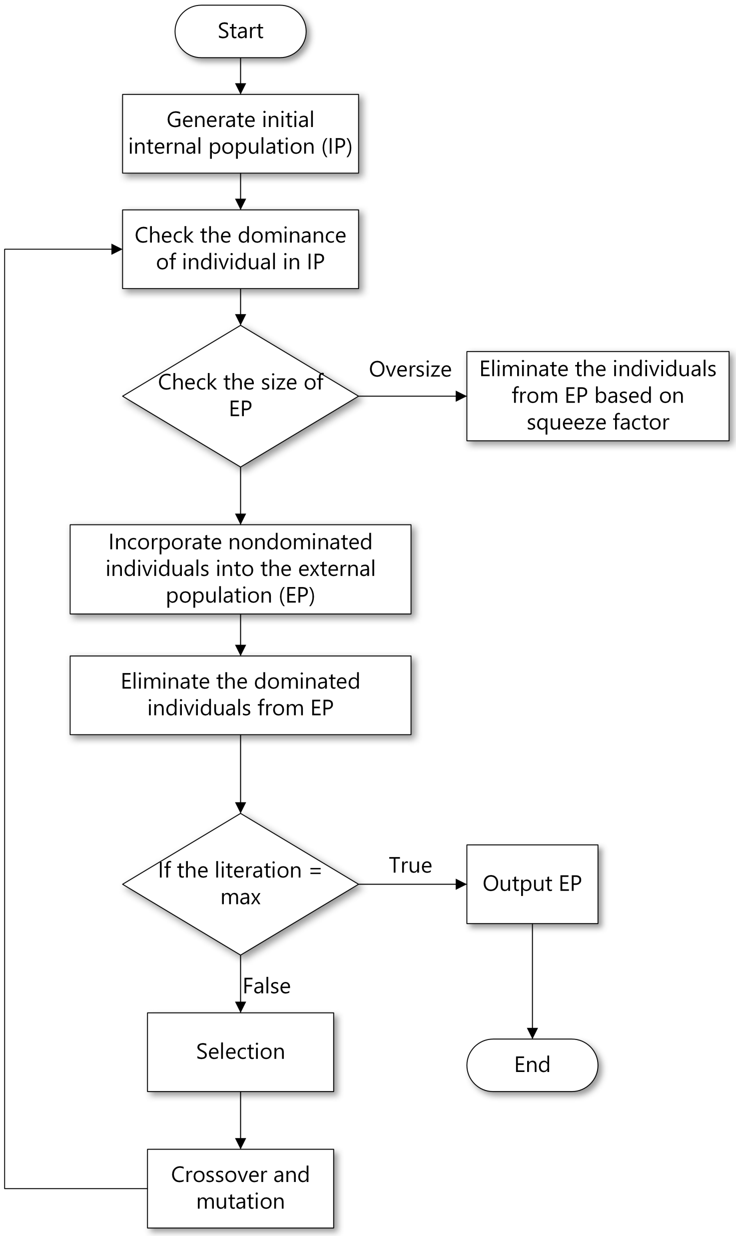


Figure 3.8: The flowchart of PESA (Author)

The flowchart of PESA is shown in Figure 3.8. At first, the initial population in IP is generated, and an empty EP is created. Then, the nondominated members of IP will be incorporated into EP, and the dominated members in EP will be removed. If the EP is oversized, one current member of EP will be eliminated based on a crowding strategy. In this strategy, the number of solutions located in the same hyper-grid is counted and referred to as a squeeze factor. In each iteration, parents will be picked out from the EP based on the crowding strategy and produce offspring for IP by using a GA.

In 2001, PESA-II was proposed, which is seen as a revision of the PESA. In PESA-II, a region-based selection method is used to provide a better spread of Pareto Front, which can improve the optimisation performance of the algorithm.

3.4.3.5 Nondominated Sorting Genetic Algorithm (NSGA and NSGA-II)

In (Srinivas and Deb, 1994), the NSGA was proposed. The flowchart of NSGA is shown in Figure 3.9. Firstly, each of the nondominated solutions is assigned a uniform large dummy fitness value and these form the first nondominated front. To keep the diversity in the population, the phenotypic distance based sharing function value of each solution in the first front is added as the niche count, and the original dummy fitness of each solution in the first front is divided by this count in order to produce a new shared fitness value. Then, these nondominated individuals in the first nondominated front will be ignored for a while, and the dominance of the rest of the population is identified to form the second nondominated front. These nondominated solutions in the second front are assigned a new dummy fitness that is smaller than the minimum shared dummy fitness value in the previous nondominated front. Classifications will be carried until the entire population is classified into different nondominated fronts. After that, reproduction will be carried out using a GA until the maximum iteration number arrives. The selection in this reproduction is based on the shared dummy value.

In (Deb et al., 2002), a new version of NSGA is proposed. NSGA-II is a more efficient algorithm. There are three main innovations in NSGA-II, namely, fast nondominated

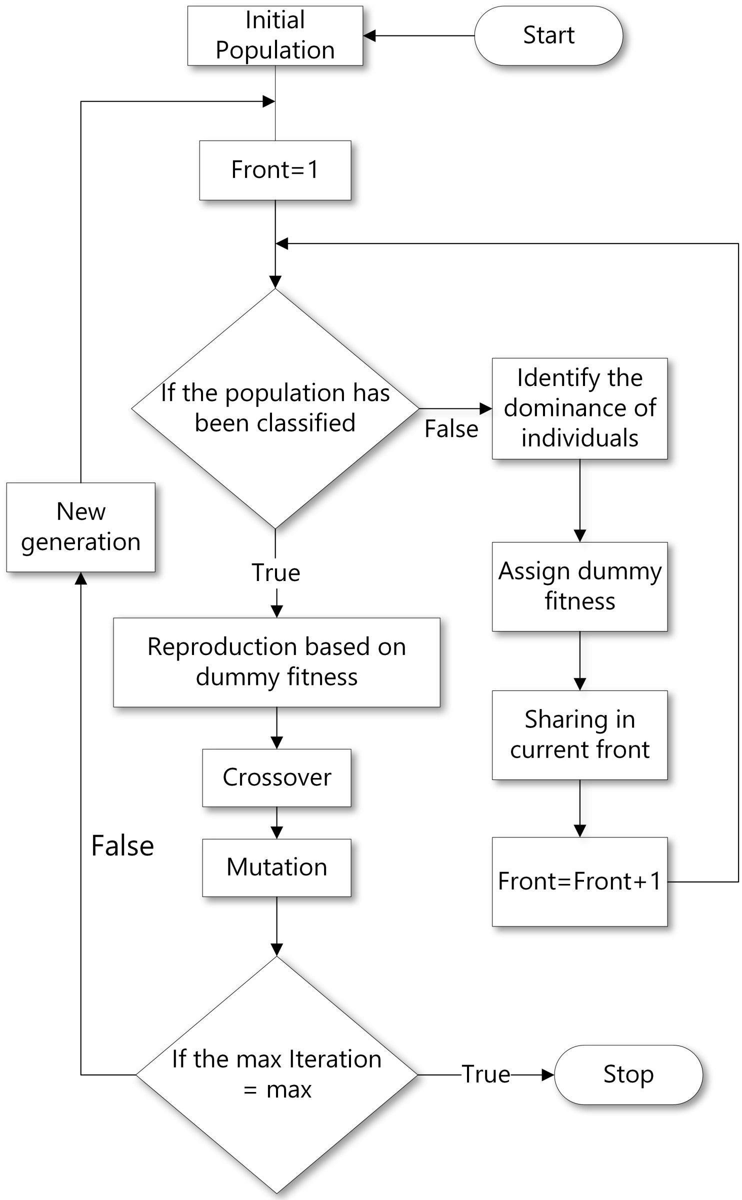


Figure 3.9: The flowchart of NSGA (Author)

sorting operator, crowding distance calculation operator and crowded comparison operator. The flowchart of the NSGA-II is shown in Figure 3.10. At the beginning, an initial population is generated. Then, by using the fast nondominated sorting operator, all the individuals are classified into different fronts. In each front, the individuals will be calculated with the relevant crowding distance. After that, by using the binary tournament selection and crowded comparison operator, the parents are selected to produce the offspring using a GA. Finally, the new generation will be selected from the union of the old generation and the offspring in the ascending order of front and crowding distance.

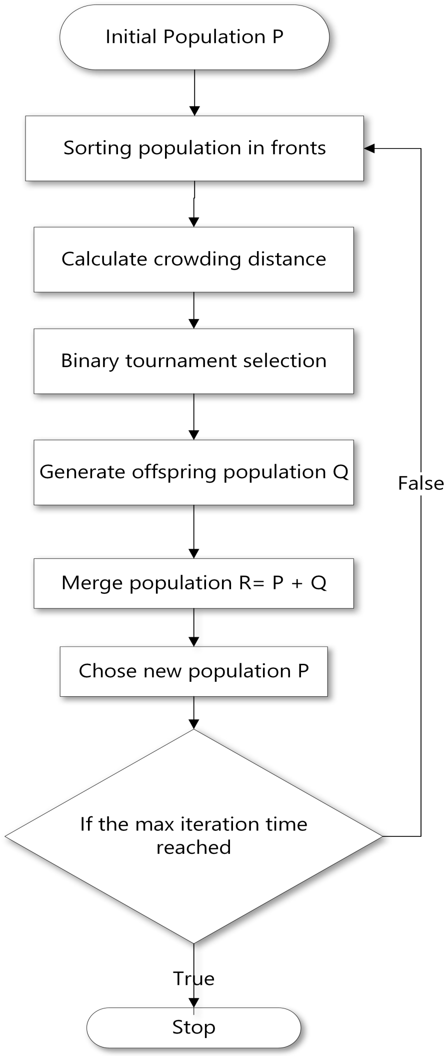


Figure 3.10: The flowchart of NSGA-II(Author)

3.4.3.6 Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D)

All these previous proposed state-of-the-art MOEAs take the MOP optimisation problem as a whole, with fitness assignment being used for associating each individual solution with any objective function based scalar optimisation problem. Instead of using fitness assignment, MOEA/D uses decomposition to build the association between scalar optimisation problems and individual solutions. MOEA/D decomposes the MOP into a number of subproblems by assigning uniformly spread weight vectors and solves these subproblems at the same time by substituting a population of solutions. The neighbourhood relation among these subproblems is defined by using Euclidean distance, the optimisation for each subproblem only makes use of the information within its neighbours (Zhang and Li, 2007).

There are a number of available decomposition approaches. Among these approaches, the Chebyshev approach and weighted sum approach are widely used (Miettinen, 1999):

1. Chebyshev Approach

$$\begin{cases} \min & g^{te}(x|\lambda,\ z^*) = \max\{\lambda_j |f_j(x) - z_j^*\} \\ & z^* = \min\{f_j(x)\} \\ \text{s. t.} & x \in X,\ \ \lambda_j \geq 0 \end{cases} \tag{3.8}$$

   where $f_j(x)$ is an objective function, $z = (z_i, \ldots, z_m)^T$ is the reference point vector, and $\lambda = (\lambda_1, \ldots, \lambda_m)^T$ is a weight vector. By altering λ, variant Pareto optimal solutions can be achieved.

2. Weighted Sum Approach: The approach can be mathematically expressed as

$$\begin{cases} \min & g^{ws}(x|\lambda) = \sum_{j=1}^{m} \lambda_j f_j(x) \\ & \sum_{j=1}^{m} \lambda_j = 1 \\ \text{s. t.} & x \in X,\ \ \lambda_j \geq 0 \end{cases} \tag{3.9}$$

   where $\lambda = (\lambda_1, \ldots, \lambda_m)^T$ is a weight vector. By changing the λ, different Pareto optimal solutions can be generated.

The flowchart of the MOEA/D using the Thecebycheff decomposition approach is shown in Figure 3.11. At the initial stage, an empty EP is set up in order to store the nondominated solutions, and the neighbourhood of each subproblem is sorted based on the Euclidean distances between any two weight vectors, and stored in an archive. After that, an initial population will be generated and evaluated, and the reference point vector is initialised. It is worth mentioning that the element of the reference point vector could be replaced if a better one is found in any iteration. At each generation, in each scalar optimisation subproblem, the new solution will be generated by using only the information from its neighbourhood. If the newly generated solution is the optimal so far and not dominated by any member of EP, this solution will be added to the EP, and any dominated member in EP will be eliminated.

Compared with other MOEAs, by integrating the concept of mathematical programming with MOP, a good spread of Pareto set can be achieved and the evolutionary algorithm can be inherently adapted to solve the problem. Furthermore, by introducing the relationship of neighborhood, the diversity and computational efficiency of MOEA/D can be well maintained.

3.4.4 Comparison of the MOEAs

In the previous section, a number of state-of-the-art MOEAs are introduced and reviewed. In most of the MOEAs, by implementing solution diversification and population-based elite preservation, MOEAs can have a better performance in solving MOPs than classical methods. To have a comprehensive understanding of MOEAs, by referring to (Konak et al., 2006), a comparison of MOEAs, including Vector Evaluation Genetic Algorithm (VEGA), Strength Pareto Evolutionary Algorithm (SPEA and SPEA-II), Pareto Archived Evolution Strategy (PAES), Pareto Archived Evolution Strategy (PESA and PESA-II), Nondominated Sorting Genetic Algorithm (NSGA and NSGA-II) and Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D), is concluded by the author and shown in Table 3.1

In MOEAs, the core objective is how to select better parents to produce offspring through the use of evolutionary algorithms. In most of the reviewed MOEAs, this selection is based on an ordering rule that is defined by domination and fitness assignment. However, in some MOEAs, instead of using the ordering rule, the

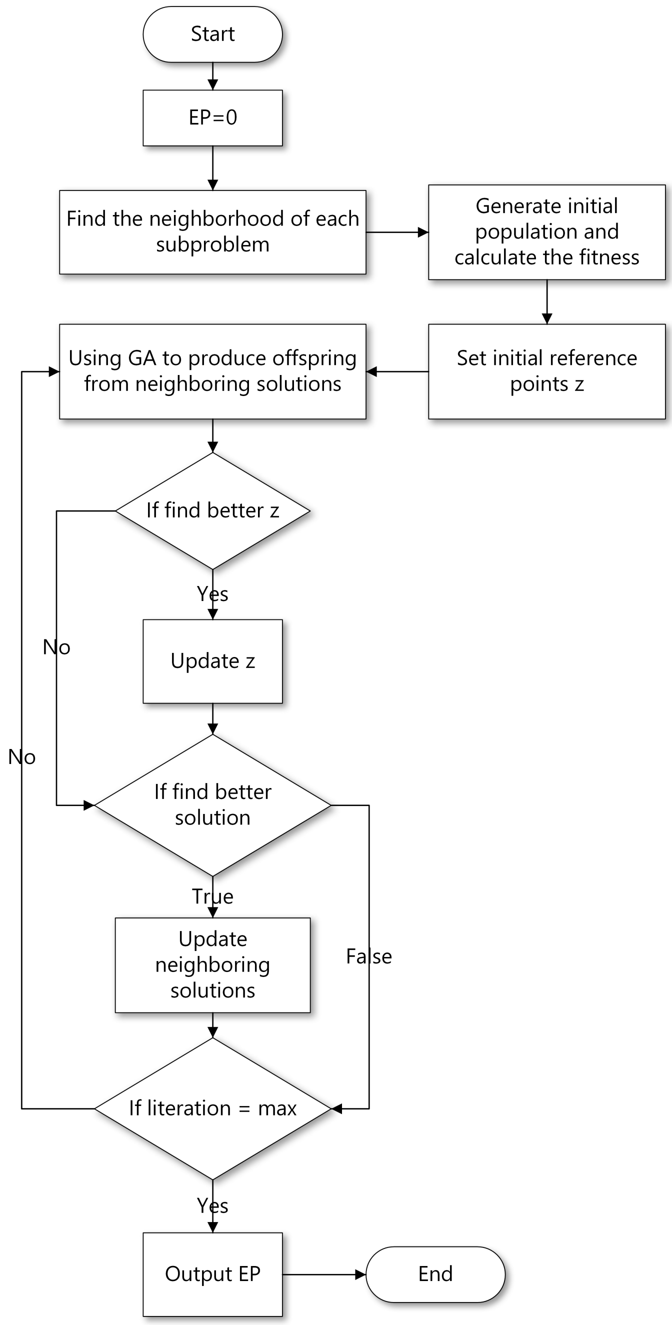


Figure 3.11: The flowchart of MOEA/D (Author)

optimisation is decomposed into a number of scalar optimisation subproblems and, as a result, the conventional selection approaches can be easily adopted in it. In addition to the selection, how to preserve the extreme solutions and keep the diversity in the Pareto front is also very critical for MOEAs. For ordering rule based MOEAs, the fitness assignment and diversity maintenance must be very carefully implemented, otherwise, the addressed Pareto optimal solutions will not provide a good spread.

Table 3.1: The Comparison of MOEAs (Author)

No.	MOEAs	Advantages	Disadvantages
1	VEGA	Easy to implement	Non-convex Pareto front
2	SPEA	Well tested and no parameter for clustering	Clustering is complex
3	SPEA-II	Good Pareto optimal diversity maintained	High computational cost
4	PAES	Easy to implement and low computational cost	Performance depends on the size of grid
5	PESA	Easy to implement and low computational cost	Performance depends on the size of grid
6	PESA-II	Easy to implement	Non-convex Pareto front
7	NSGA	Fast convergence	Need to define the sharing factor and high computational cost
8	NSGA-II	Less presenter required and well tested	Crowding strategy only work in objective space
9	MOEA/D	Easy to use scalar optimisation and high computational efficiency	Need to define the neighborhood size

However, in decomposition based MOEAs, since the MOP is decomposed into a number of scalar optimisation subproblems, the solution diversity can be naturally maintained. Furthermore, as they only make use of the information within the neighborhood, the computational cost can be managed (Zhang and Li, 2007).

Chapter 4

Formulation of the ADP Optimisation Problem in CBTC Systems

4.1 Introduction

In the previous chapter, a review of the algorithms for solving multi-objective optimisation programming (MOP) problems was presented. In this chapter, a mathematical model for formulating the AP deployment planning (ADP) optimisation problem in WLAN-based DCS is proposed.

The chapter begins with an investigation of the challenges underlying building a reliable wireless connection in DCS. Then, the optimisation problem formulations of the ADP are presented. Finally, how to apply the right algorithm to solve the different types of optimisation problem is addressed.

4.2 Challenges for the Wireless Communication in CBTC Systems

Due to the nature of electromagnetic wave propagation, there are a number of factors that can challenge the received wireless signal quality in both underground and overground environments e.g., area path-loss, multipath propagation shadow fading, co-&adjacent channel interference, latency caused by handoff, *etc.* (Erceg and K.V.S.Hari, 2001). In this section, a brief overview is presented of the wireless communication challenges which can significantly threaten the reliability of the wireless connection in the DCS of a CBTC environment.

4.2.1 Handoff Procedure and Latency

Due to the technical features of WLANs, when a train is moving near the boundary of adjacent AP coverage, a handoff procedure will be triggered, where the connection between the associating AP and the trainborne equipment is lost and a new connection between the approaching AP and the trainborne equipment will be established. During a journey of a train, handoffs happen frequently, for example, in Hefei Metro Line I in China, the 25 km long track has around 150 APs working in one direction, which means 150 handoffs are received (Hefei Metro, 2012).

Because the handoff procedure can change the communication quality rapidly, the procedure is a big threat to the operational safety of CBTC systems. A typical handoff procedure model followed by a majority of WLAN-enabled systems (Mishra et al., 2003) is shown in Figure 3.4. To ensure the WLAN-enabled systems have high reliability, in IEEE 802.11 protocols, carrier-sense multiple access with collision avoidance (CSMA/CA) is widely used in the media access control (MAC) layer (Guang et al., 2008). The CSMA/CA method uses inter-frame space (IFS) and a contention window (CW), which is based on a binary exponential back-off timer, to control the media access. For setting different priorities, different types of IFS are entered prior to the transmitted packet and, if the transmission fails and a retransmit is triggered, a back-off timer will be entered prior to attempting to retransmit. The back-off timer is randomly chosen from 0 to the minimum CW size and, if the retransmissions continues to fail, the CW size will be exponentially increased until it reaches a maximum CW size.

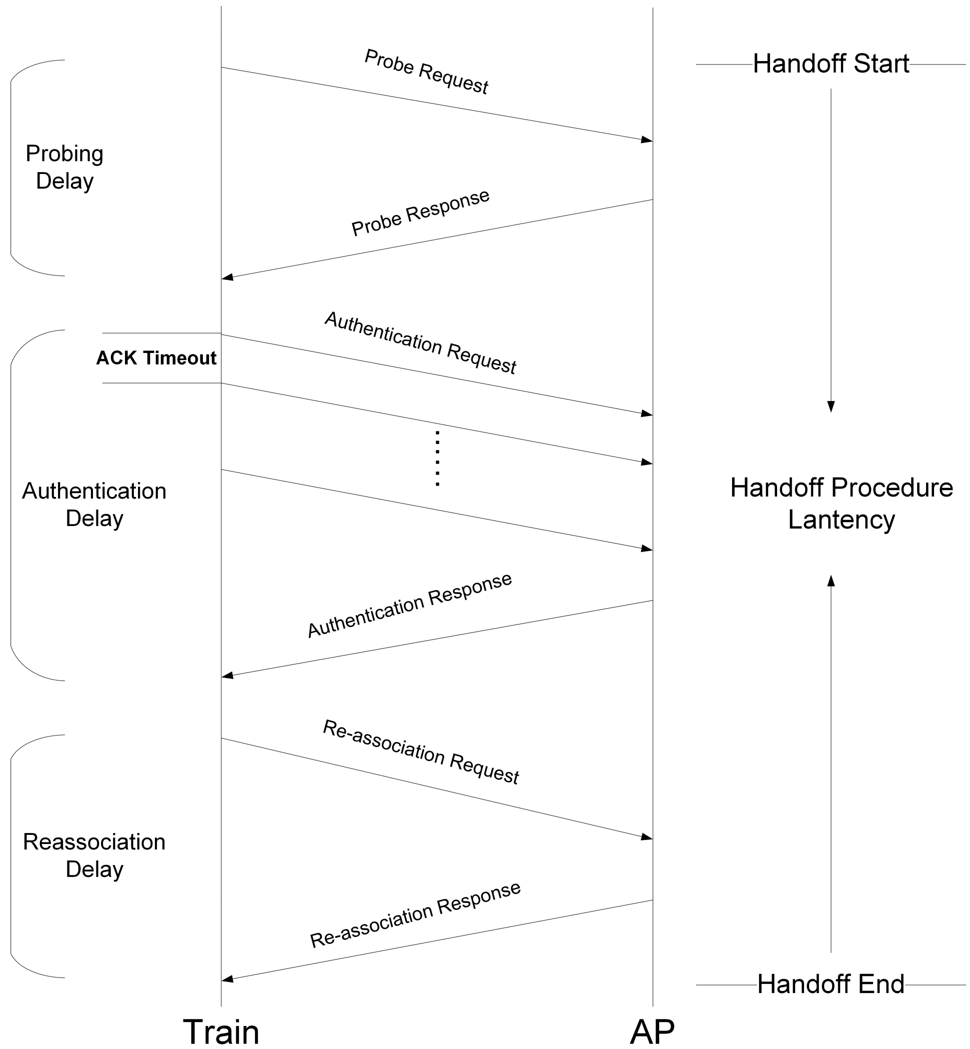


Figure 4.1: A typical handoff procedure of IEEE 802.11 protocol (Mishra et al., 2003)

Handoff procedures can result in a high packet loss. There are two different types of packet loss, which are caused by packet collisions and errors respectively. However, by taking the metro system environment into account, packet collisions only rarely happen, so the errors will mainly arise from the main packet loss (Zhu et al., 2009). Due to the mechanism of WLAN-enabled systems, when a transmitter does not receive an acknowledgement (ACK) within a timeout interval, the packet will be assumed as lost and retransmission will be triggered. After n retransmissions, the MAC layer delay T_{MAC} in an 802.11 WLAN-enabled system can be expressed as (Zhu et al., 2009):

$$\begin{aligned} T_{MAC}(n) = & T_{DIFS} + T_{data} + T_{SIFS} + T_{ack} + T_{DIFS} \\ & + T_{backoff}(1) + T_{data} + T_{SIFS} + T_{ack} + T_{DIFS} \\ & + T_{backoff}(2) + \ldots + T_{data} + T_{SIFS} + T_{ack} + T_{DIFS} \\ & \vdots \\ & + T_{backoff}(n) + T_{data} + T_{SIFS} + T_{propagation} \end{aligned} \tag{4.1}$$

where T_{ack} is the timeout time for receiving an ACK frame; T_{SIFS} and T_{DIFS} are the short inter-frame space (SIFS) and distributed coordination function inter-frame space (DIFS) respectively. These two types of inter-frame spaces can give different priorities for different transmitted packets; $T_{backoff}(n)$ is the backoff time after n packet retransmissions happened; $T_{propagation}$ is the propagation time for the transmitted packet from the transmitter to the receiver; T_{data} is the time consumed for generating the transmitted packet, which depends on the packet length and the data link rate.

Figure 4.1 shows a successful handoff procedure, which has a handoff latency that can be divided into three delays, i.e., probing, authentication and reassociation. In probing, the train onboard antenna scans the potential APs in range to establish a connection; most of the latency occurs in the probing process (Mishra et al., 2003). It is assumed that each packet in the authentication process and reassociation process has the same chance of being delayed, as a result, the handoff procedure latency $T_{latency}$ after n retransmissions can be expressed as:

$$T_{latency} = 4 \times T_{MAC}(n) + T_{processing} + T_{probing} \tag{4.2}$$

where $T_{processing}$ is the hardware response time of a transceiver before it starts to perform its function, $T_{probing}$ is the latency caused in the probing process. In a DCS system, to guarantee the continuity of the packet transmission, a very strict maximum handoff procedure latency must be applied.

4.2.2 Large-scale Fading and Interference

A key part of any wireless communication system is the wireless channel where the radio wave is employed to carry the signals or data (Yun and Iskander, 2015). As a result, understanding the challenge factors underlying radio wave propagation is a fundamental step of formulating the optimisation problems of ADP. There are two types of channel models, namely empirical channel models and deterministic channel models (Catedra and Perez, 1999). Generally, radio wave propagation can be deterministically described by Maxwell equations (Fleisch, 2008), waveguide models (Smith, 2002) and ray tracing channel models (Yun and Iskander, 2015). However, in solving real-world problems which consist of a countless number of elements and many types of materials with different electromagnetic properties, precisely implemented deterministic channel models will lead to extremely complex mathematical formulations (Hrovat et al., 2014). Different from deterministic channel models, empirical channel models describe the radio wave propagation based on observations and measurements alone, which can also achieve a good prediction result. To describe the propagation of radiowaves more precisely, some stochastic fading models are combined with empirical channel models. In order to the accurate prediction result at a moderate computational cost, empirical channel models are widely used when considering practical railway systems.

Generally, the wireless channel can be characterized by five elements, namely path-loss (including shadowing effects), multipath delay spread, small-scale fading, Doppler spread and co-channel as well as adjacent channel interference (Erceg and K.V.S.Hari, 2001). However, not all of these elements need tp be carefully accounted for in CBTC systems. For instance, due to the OFDM and spread sequence-based (e.g., direct-sequence spread spectrum (DSSS) and frequency-hopping spread spectrum (FHSS)) modulations used in the WLANs (Changqing et al., 2009; Fitzmaurice, 2013) and the relatively low operation speed of trains (the average speed of London Underground is around 50 km/h, which is the fastest metro system in Europe (ERRAC and UITP, 2009)), the effects caused by multipath delay spread and Doppler spread can be neglected. As a result, in this thesis, only path-loss (including shadowing) and co-channel interference are counted.

4.2.2.1 Propagation Path-loss and Shadowing Fading

Path-loss is the reduction in power of the radiowave as it travels in space. Path-loss has a positive correlation between distance and the degree of attenuation, which means that the further the signal travels, the more serious the decrease in signal power. This process can be empirically expressed as (Goldsmith, 2005):

$$\bar{P}_r(d)[\text{dBm}] = P_t[\text{dBm}] + G_{tx} + G_{rx} - 10n\log_{10}(\frac{d}{d_0}) + 10\log_{10}K \tag{4.3}$$

where P_t is the transmitted power; $\bar{P}_r$ is the received mean power; G_{tx} and G_{rx} are the transmitting gain and receiving gain respectively; n is the path-loss exponent, which is variable in different propagation environments; K is a dimensionless constant which is the path-loss gain at a reference distance (Erceg et al., 1999); d_0 is a reference distance for the far field of an antenna.

Fading can be caused by many factors. For example, multipath propagation can cause multipath fading, and large obstructions, including hills, ceilings and walls, can cause shadowing fading. Most DCS in CBTC systems use OFDM-based WLAN, a multi-carrier modulation scheme which employs a guard time interval enabling error free operation in multiple path environments with delay spreads roughly less than or equal to the guard interval, so here only shadow fading is accounted for. The shadowing effect can be seen as a deviation of the path-loss which statistically obeys a log-normal distribution with a varied mean value and standard deviation (Büyükçorak et al., 2015; Salo et al., 2005). The corresponding log-normal distribution can be expressed as:

$$P(x)[\text{dB}] = \frac{1}{\sqrt{2\pi}\sigma}\exp[\frac{-(x-m_0)^2}{2\sigma^2}] \tag{4.4}$$

where σ is the signal strength standard deviation in dB; m_0 is the mean power of the received signal in dBm. By combining the path-loss and shadowing fading together, at the propagation attenuation distance d, the exact received power P_r in logarithmic units is

(Goldsmith, 2005):

$$P_r(d)[\text{dBm}] = P_t[\text{dBm}] + G_{tx} + G_{rx} - 10n\log_{10}(\frac{d}{d_0}) + 10\log_{10}K - x \quad (4.5)$$

where x_{dB} is the shadowing.

4.2.2.2 Interference within APs

Apart from path-loss and shadow fading, another vital challenge for building a reliable wireless connection in DCS is the interference.

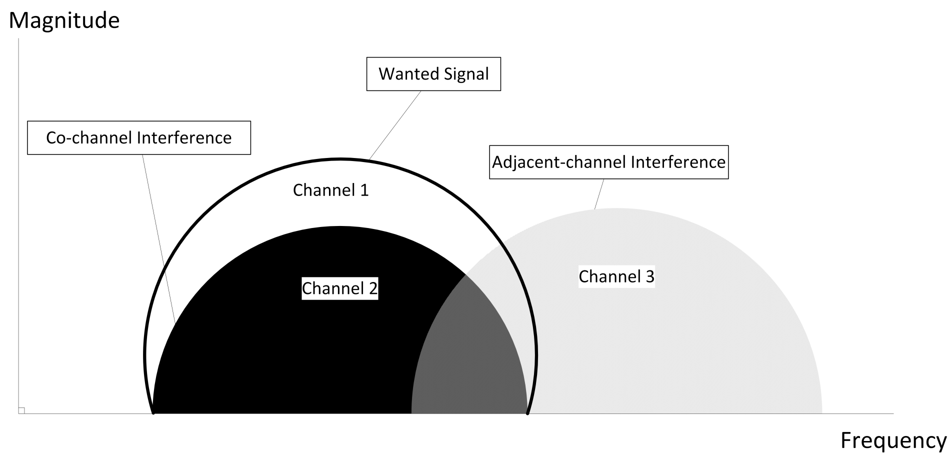


Figure 4.2: Co & adjacent-channel interference (Author)

In WLANs, due to the limited spectrum, the neighbouring APs may need to share or partly share the same frequency, which will result in co & adjacent channel interference. As shown in Figure 4.2, the Channel 1 carries the wanted signal, the Channel 2 and Channel 3 carry the co-channel interference and the adjacent-channel interference respectively. As proposed in (Chieochan et al., 2010), proper channel assignment can help to mitigate the degree of co-channel interference. However, it is very difficult to eliminate this kind of interference, as the reuse radius is limited. The signal-to-noise-plus-interference ratio (SNIR) is used as the metric to measure how serious the interference is. The SNIR is expressed as (Goldsmith, 2005):

$$\text{SNIR[dB]} = 10\log_{10}[E_b/(N_0+I_0)] + 10\log_{10}(f_b/B) \tag{4.6}$$

where $E_b/(N_0+I_0)$ is the energy per bit to noise plus co-channel interference power spectral density ratio; f_b is the the channel data rate; B is the channel bandwidth.

In planning WLANs, SNIR is a very important variable that should be considered carefully. A SNIR which is too low can lead to a high BER, which will decrease the reliability of communication in DCS. The theoretical BER is a function of $E_b/(N_0+I_0)$, which depends on the type of the digital modulation employed. For example, the BER of the binary phase-shift keying (BPSK) or quadrature phase-shift keying (QPSK) modulated WLANs is expressed as (John Proakis, 2007):

$$\text{BER} = \frac{1}{2}\text{erfc}\left(\sqrt{\frac{E_b}{N_0+I_0}}\right) \tag{4.7}$$

However, for the binary frequency-shift keying (BFSK) modulated WLANs, the BER is expressed as (Giordano and Levesque, 2015):

$$\text{BER} = \frac{1}{2}\text{erfc}\left(\sqrt{\frac{E_b}{2\times(N_0+I_0)}}\right) \tag{4.8}$$

It is worth mentioning that in different WLAN scenarios the dominating factors in SNIR vary between the interference and the noise, therefore, signal-to-noise ratio (SNR) and signal-to-interference ratio (SIR) are used as the metrics in noise-limited and interference-limited systems respectively, only E_b/N_0 or E_b/I_0 needs to be considered.

In CBTC systems, the system required BER is between 10^{-3} to 10^{-6} (Briso, 2007; Weatherburn and Arjinian, 2016*a*). To avoid the occurrence of a high BER, the level of interference must be under a certain level, which depends on the system requirement. The most effective way to decrease the co-channel interference level is to increase the channel reuse radius, but this can result in a reduced AP wireless coverage.

4.2.2.3 Outage Probability

Owing to shadow fading, the power density of any signal is randomly attenuated due to propagation in the metro environment, which makes it impossible to know the exact power of the signal at a certain distance deterministically. However, to meet the DCS system requirement of wireless communication, the received power strength of the desired signal must exceed the minimum receiver sensitivity, and the SNIR must be higher than the protection ratio; otherwise, the performance of the train-to-wayside wireless communication will be below the minimum safety level mandated by DCS, which is called outage. Even though there is no way to predict the exact received signal power or SNIR, stochastic functions can be used to measure the outage probability.

At the receiver, when receiving the desired signal, all of the undesired co-channel signals give rise to interference, but normally just a few of the nearest signals can influence the SNIR significantly. In this thesis, it is assumed that there are only two dominant interferers which can affect the communication performance significantly; these are generated by the two nearby APs.

As discussed in section 4.2.2.1, when the desired signal and interferences are transmitted through a fading channel and suffer random variation due to obstacles, this is called shadow fading. The power variability of the desired signal $P(x_0)$, $P(y_1)$ and $P(y_2)$ due to shadowing obeys a log-normal distribution, which can be expressed as (K. W. Sowbery, 1989):

$$P(x_0) = \frac{1}{\sqrt{2\pi}\sigma_0}\exp[\frac{-(x_0-m_0)^2}{2\sigma_0^2}] \tag{4.9}$$

$$P(y_1) = \frac{1}{\sqrt{2\pi}\sigma_1}\exp[\frac{-(y_1-m_1)^2}{2\sigma_1^2}] \tag{4.10}$$

$$P(y_2) = \frac{1}{\sqrt{2\pi}\sigma_2}\exp[\frac{-(y_2-m_2)^2}{2\sigma_2^2}] \tag{4.11}$$

where x_0, y_1 and y_2 are expressed in logarithmic units; σ_0, σ_1 and σ_2 are the deviations in dB of the desired signal and two major interfering signals respectively; m_0, m_1 and m_2 are the received signal mean power of the desired signal and two major interfering signals respectively, which can be calculated by equation (4.5).

The method to calculate the exact outage probability in the presence of two dominant interferers under shadow fading environment was proposed in 1989 (K. W. Sowbery, 1989). From there we can get

$$P_{out}^2 = P_{out}^1 + P_{add}^2 \tag{4.12}$$

and

$$P_{out}^1 = P_{out}^0 + P_{add}^1 \tag{4.13}$$

where P_{out}^2, P_{out}^1 and P_{out}^0 are the exact outage probabilities in the presences of two, one and no interferers respectively, P_{add}^2 and P_{add}^1 are the increased magnitude of outage probabilities caused by the extra interference. To calculate the P_{out}^2, it is necessary to compute P_{out}^1 and P_{add}^1 in advance.

$$P_{out}^1 = 1 - \int_{S_m}^{\infty} P(x) \int_{-\infty}^{x-R} P(y_1) dy_1 dx \tag{4.14}$$

where P_{out}^1 is the outage probability in the presence of a single interferer, R is the protection ratio in dB (Goldsmith, 2005), S_m is the minimum required signal power in dBm. Let:

$$u = \frac{y_1 - m_1}{\sqrt{2}\sigma_1}, so\ du = \frac{dy_1}{\sqrt{2}\sigma_1} \tag{4.15}$$

then this gives:

$$\int_{-\infty}^{x-R} P(y_1) dy_1 = \frac{1}{\sqrt{\pi}} \int_{-\infty}^{b} \exp(-u^2) du \tag{4.16}$$

where:

$$b = \frac{x - (m_1 + R)}{\sqrt{2}\sigma_1} \tag{4.17}$$

So equation (4.16) can be rewritten as:

$$\int_{-\infty}^{x-R} P(y_1) dy_1 = 1 - \frac{1}{2} \mathrm{erfc}[\frac{x - (m_1 + R)}{\sqrt{2}\sigma_1}] \tag{4.18}$$

Substituting equation (4.18) into equation (4.14) gives:

$$P_{add}^1 = \frac{1}{2} \int_{S_m}^{\infty} \exp[\frac{-(x - m_0)^2}{2\sigma_0^2}] \mathrm{erfc}[\frac{x - (m_1 - R)}{\sqrt{2}\sigma_1}] dx \tag{4.19}$$

and P^0_{out} is the outage probability in the absence of interference given by:

$$P^0_{out} = \frac{1}{2}\operatorname{erfc}[\frac{m_0 - S_m}{\sqrt{2}\sigma_0}] = \frac{1}{2}\operatorname{erfc}[\frac{\alpha}{\sqrt{2}\sigma_0}] \tag{4.20}$$

where $\alpha = m_0 - S_m$, which is the margin by which the desired signal power exceeds the minimum required signal power.

P^1_{add} can be simplified by making the following variable transformation:

$$u_1 = \frac{x - m_0}{\sqrt{2}\sigma_0}, so\ du_1 = \frac{dx}{\sqrt{2}\sigma_0} \tag{4.21}$$

and consequently,

$$P^1_{add} = \frac{1}{2\sqrt{\pi}} \int_{\frac{-\alpha}{\sqrt{2}\sigma_0}}^{\infty} \exp(-u^2)\operatorname{erfc}[\frac{\sigma_0}{\sigma_1}u + \frac{\tau}{\sqrt{2}\sigma_1}]du \tag{4.22}$$

where $\tau = m_0 - (m_1 + R)$, and in summary:

$$P^1_{out} = \frac{1}{2}\operatorname{erfc}[\frac{\alpha}{\sqrt{2}\sigma_0}] + \frac{1}{2\sqrt{\pi}} \int_{\frac{-\alpha}{\sqrt{2}\sigma_0}}^{\infty} \exp(-u^2)\operatorname{erfc}[\frac{\sigma_0}{\sigma_1}u + \frac{\tau}{\sqrt{2}\sigma_1}]du \tag{4.23}$$

A similar derivation for P^2_{add} yields:

$$P^2_{add} = \frac{1}{2\pi} \int_{\frac{S_m - m_0}{\sqrt{2}\sigma_0}}^{\infty} \exp(-v^2) \int_{-\infty}^{\frac{\sigma_0}{\sigma_1}v + \frac{\tau}{\sqrt{2}\sigma_1}} \exp(-u_3^2)\operatorname{erfc}[\frac{z_1}{\sqrt{2}\sigma_2}]du_3 dv \tag{4.24}$$

where:

$$z_1 = 10\log_{10}(10^{\frac{\sqrt{2}\sigma_0 v + \tau}{10}} - 10^{\frac{\sqrt{2}\sigma_1 u_3}{10}}) - m_2 + m_1 \tag{4.25}$$

Defining:

$$\tau_1 = m_0 - (m_2 + R) \tag{4.26}$$

finally yields:

$$z_1 = 10\log_{10}(10^{\frac{\sqrt{2}\sigma_0 v + \tau}{10}} - 10^{\frac{\sqrt{2}\sigma_1 u_3}{10}}) - \tau + \tau_1 \tag{4.27}$$

In summary, equation (4.12) becomes:

$$P_{out}^2 = \frac{1}{2}\text{erfc}[\frac{\alpha}{\sqrt{2}\sigma_0}] + \frac{1}{2\sqrt{\pi}}\int_{\frac{-\alpha}{\sqrt{2}\sigma_0}}^{\infty} \exp(-u^2)\,\text{erfc}[\frac{\sigma_0}{\sigma_1}u + \frac{\tau}{\sqrt{2}\sigma_1}]du$$
$$+ \frac{1}{2\pi}\int_{\frac{-\alpha}{\sqrt{2}\sigma_0}}^{\infty} \exp(-v^2)\int_{-\infty}^{\frac{\sigma_0}{\sigma_1}v + \frac{\tau}{\sqrt{2}\sigma_1}} \exp(-u_3^2)\,\text{erfc}[\frac{z_1}{\sqrt{2}\sigma_2}]du_3 dv \quad (4.28)$$

Using equation (4.28), the outage probability in the presence of two dominant interferers, can be readily calculated. If the outage probability is higher than a certain value, the wireless connection between the train and the APs will be assumed as not dependable. The accepted maximum outage probability depends on the specific DCS system requirements, therefore, when planning the deployment of AP, we must carefully specify its value and ensure that during the whole journey along the track the P_{out}^2 remains below the operating safety threshold for the CBTC system for the selected AP deployment.

4.3 Formulation of the ADP Optimisation Problem

In this section, two mathematical models for the ADP problem are proposed, and the corresponding optimisation constraints and objective functions of ADP are illustrated.

4.3.1 System Modelling

Along a railway line, there is a continuum of positions where APs can be placed, which make the ADP optimisation process very expensive to compute. In this research, to make the optimisation formable and tractable, the track is discretized into a finite number of sections; each of the joints between sections can potentially be allocated an AP. As a result, the optimal AP deployment will be a subset of these joints. For this thesis, the AP deployment is formulated using binary code. For each section joint, if an AP is placed, the corresponding bit will be set as 1; otherwise, the corresponding bit is set as 0. Taking a 6 joint line as an example, the AP deployment can be expressed as:

$$\begin{cases} P_\mu = 1, & \text{AP is located} \\ P_\mu = 0, & \text{AP is not located} \\ \mu \in A, \ldots, F \end{cases} \tag{4.29}$$

where μ is the joint label. Consequently, the AP deployments are expressed $(P_A, P_B, P_C, P_D, P_E, P_F)$. As there are 6 joints on the track, by combining all the AP deployment scenarios, the total number of AP deployments will be $2^6 - 1$ (the all null AP deployment, (0,0,0,0,0,0), is not counted).

To have a better understanding of the AP deployment model, an indicative example is generated in Table 4.1, in which the joint label is shown in the first row, and the deployment of APs is displayed in the second row. As shown in Table 4.1, three APs are placed at joints A, D and F respectively. In this thesis, for convenience, the used AP number will be represented by the Hamming distance (Chea, 2015; Hamming, 1950) of the deployment, because the Hamming distance of an AP deployment from the null solution is equal to the number of APs deployed, which in the example shown in Table 4.1 is 3.

Table 4.1: AP Deployment Example (Author)

Join Label	A	B	C	D	E	F
AP Deployment	1	0	0	1	0	1

When discretizing the line, a key issue is to find a appropriate section length, which is a compromise between viability (long sections) and realism (short sections). To determine a meaningful subsection length which yields a compromise between accuracy and tractability, the knowledge of the correlation length of the shadowing fading in the tunnel is required. Within separations smaller than this length, the received signal will experience a typical (average) fade duration. It has been found in (Guan et al., 2012) and (Bertoni, 1999) that the correlation length range of shadowing varies significantly from 5 m to 300 m, which depends on the relevant dimensions of the signal propagation environment. In this thesis, for the case of arched tunnels a typical value for the subsection length is taken to be 60 m, which is consistent with reported shadow correlation lengths of a small number of 10s of meters in (Guan et al., 2015) and (Ai et al., 2016) .

4.3.2 Optimisation Constraints

As the outage probability can efficiently predict disconnection risk in DCS, the constraints of the ADP are based on outage probability. The maximum outage probability of the wireless connection in an AP deployment along the line must be lower than the pre-specified threshold.

The maximum accepted outage probability is related to the maximum accepted retransmission times during the handoff procedure. The detailed retransmission scheme has been proposed in section 4.2.1. For most existing CBTC systems, the maximum handoff latency must be shorter than 50 ms (Weatherburn and Arjinian, 2016*b*). To simplify the problem, it is assumed that no failure happens in handoff and r retransmissions are triggered to achieve a successful handoff in the presence of data packet losses arising from bit errors. So the handoff latency caculation is given as:

$$T_{latency} = 4 \times T_{MAC}(n) + T_{processing} + T_{probing} \leq 50\,\mathrm{ms} \tag{4.30}$$

where n is the retransmission times. As the $T_{MAC}(n)$, $T_{probing}$ and $T_{processing}$ are known in a specific DCS, the maximum accepted r can be derived. The relevant safety standard (Weatherburn and Arjinian, 2016*b*) requires that the packet loss rate in the train control system must be no greater than 10^{-3}, giving,

$$R^{r}_{outage} \times (1 - R_{outage}) \leq 10^{-3} \tag{4.31}$$

where R_{outage} is the signal outage probability threshold for a DCS. Therefore, by calculating this inequality in equation (4.31), the R_{outage} can be derived.

To assess the feasibility of AP deployments in a computable way, N sampling points are set at a certain spacing interval and the outage probability of the wireless connection between the train and the associated AP is evaluated at each sampling point. To make the problem viable, N sampling points are selected along the line. For a feasible AP deployment, there is

$$P^2_{out\_i} \leq R_{outage} \tag{4.32}$$

where $P^2_{out\_i}$ is the outage probability in presence of two dominant interferers at sampling point $i = 1, 2 \dots N$.

4.3.3 Optimisation Objectives

The aim of ADP optimisation is to provide an optimised AP deployment that can simultaneously improve the system performance and minimise the system life-cycle cost. To meet this ADP optimisation aim, three objective functions, namely minimise the maximum outage probability, minimise the mean outage probability and minimise the Hamming distance, are proposed. These three objectives can indicate the system performance stability, data exchange quality and life-cycle cost respectively.

4.3.3.1 Maximum Outage Probability

It is obvious that a small maximum outage probability means lower risk of disconnection in DCS. As a result, the maximum outage probability can indicate the DCS performance stability. The objective of minimising the maximum outage probability can be mathematically expressed as:

$$\begin{cases} \min & P_{out\_max}(x) = \max \ \{P_{out\_i}\} \\ \text{s.t.} & x = (x_1, \ldots, x_{2^J-1}) \\ & i = 1, 2 \ldots N \end{cases} \tag{4.33}$$

where J is the number of joints, i is sampling point, N is the sampling point amount, x is the AP deployment.

4.3.3.2 Mean Outage Probability

In addition to the performance stability, the optimised AP deployment is also supposed to support a high quality of wireless data exchange in DCS. It can be learnt from section 4.2.2.3 that the outage probability has a negative correlation with the SNIR, which is a fundamental indicator for assessing the wireless communication quality. Therefore, minimising the mean outage probability P_{out_mean} could be used as an objective for optimising the data exchange quality of DCS. P_{out_mean} is mathematically expressed as:

$$\begin{cases} \min & P_{out\_mean}(x) = \dfrac{1}{N} \displaystyle\sum_{i=1}^{N} P_{out\_i} \\ \text{s.t.} & x = (x_1, \ldots, x_{2^J-1}) \\ & i = 1, 2 \ldots N \end{cases} \tag{4.34}$$

where J is the number of joints, N is the number of sampling points, x is the AP deployment.

4.3.3.3 Hamming Distance

An optimised AP deployment not only has good system performance, in terms of stability and quality but also has a lower life-cycle cost. Clearly, a minimised number of used APs in the DCS leads to a lower life-cycle cost. By refereing to the concept of Hamming distance, the used AP number of a deployment is given as:

$$\begin{cases} \min \quad H(x) = \|x\|_0 \\ \text{s.t.} \quad x = (x_1, \ldots, x_{2^J-1}) \end{cases} \tag{4.35}$$

where x is the AP deployment, which is represented by a binary string, $\|x\|_0$ is the 0-norm of the AP deployment, which is equal to the number of all the non-zero items in the binary string, J is the number of joints, .

4.3.4 Problem Formulation with Mathematical Programming

The class methods for solving multi-objective optimisation programming (MOP) are dependent on adding prior preference. For example, when the weight factor for each objective is known, the ADP optimisation problem can be formulated with mathematical programming as:

$$\begin{cases} \min \quad F(x) = \sum_{i=1}^{3} w_i \times f_i(x) \\ \text{s.t.} \qquad \mathrm{x} \in \mathrm{S} \subset \Theta, \;\; w_i \geq 0 \\ \qquad\qquad f_1(x) = P_{out\_max}(x) \\ \qquad\qquad f_2(x) = P_{out\_mean}(x) \\ \qquad\qquad f_3(x) = H(x) \end{cases} \tag{4.36}$$

where $F(x)$ is the cost function, x is an AP deployment, Θ is the AP deployment set formed by all possible joint combinations, S is the feasible decision variable space, with all the deployments in Θ which satisfy equation (4.32) forming S, w_i is the weight vector, which is adjustable in different systems, but must be positive. The aim is to minimise the cost function.

4.3.5 Problem Formulation with Multi-objective Optimisation Programming (MOP)

A problem formulation of the ADP optimisation with mathematical programming is proposed in the last section. In that formulation, a self-defined weight vector is applied to set the priorities for different objective functions. However, when optimising real world systems, since more complexity is involved, it will be very difficult to define a reasonable weight vector. If an arbitrary weight vector is applied, the optimisation result will be inaccurate. Instead of adding a prior preference, some users tend to use MOEAs to search out the Pareto set and choose the best solution from the Pareto set based on their own preference. To apply MOEAs, the ADP optimisation problem is formulated as:

$$\begin{cases} \min \;\; F(P_{out\_max}(x), P_{out\_mean}(x), H(x)) \\ \mathrm{s.t.} \;\; \mathrm{x} \in \mathrm{S} \subset \Theta \end{cases} \tag{4.37}$$

where $F(x)$ is the cost function, x is an AP deployment, Θ is the AP deployment set formed by all possible joint combinations, S is the feasible decision variable space, all the deployments in Θ which satisfy equation (4.32) form S. The aim is to minimise all the objectives simultaneously.

However, in most cases, there are conflicts between objectives such that all the objectives can not be simultaneously minimised, and only a Pareto set can be addressed. The optimal result is defined as the best trade-off among this Pareto set.

4.4 Optimisation Algorithm Selection Guidance

In section 4.3.4 and 4.3.5, the ADP optimisation problem has been formulated with mathematical programming and MOP respectively. Obviously, this problem is a multi-objective optimisation problem. A number of multi-objective optimisation algorithm have been investigated in chapter 3, which can be classified into four categories, namely enumerative search based classical method, random search based classical method, overall-based multi-objective evolutionary algorithm (MOEA) and decomposition-based MOEA.

To properly chose an optimisation algorithm for different AP deployment problems, four criteria are proposed:

1. **Efficiency:** For planning the AP deployment, especially in planning a large-scale system, the computational efficiency is extremely important. The enumerative search based classical method has a very low computational efficiency. For example, based the author's calculation, to locate APs for a 2182 m long track that has 35 joints using the enumeration based optimisation strategy on a desktop (Intel i5-3570 3.4GHz, 8GB), it will take 2088 days to compute all the 3.4×10^{10} AP deployments, which can be said to be not feasible. Therefore, a large-scale system requires more efficient optimisation strategies. For a random search based classical method, if guided random search is applied, the search efficiency is improved. However, as the guidance used in the random search based classical method only comes from the elite preservation, the degree of improved efficiency is limited. For overall-based MOEA, by providing extra useful guidance through introducing domination relationship and a specific fitness assignment scheme, the search efficiency is improved from a random search based classical method. For decomposition-based MOEA, as the solution update of each subproblem is done only by taking the information from its neighbours, the efficiency is further improved.

2. **Accuracy:** For the enumeration classical method, as every solution is evaluated, the accuracy of the optimal result is guaranteed. For the random search based classical method, overall-based Multi-objective Evolutionary Algorithm (MOEA) and decomposition-based MOEA, as guided random search is used, the optimal result is not guaranteed. However, in MOEAs, as the domination relation is used to order the solutions to produce the Pareto optimal, the optimisation result could be very close to the optimum.

3. **Complexity:** For the classical method, the multiple objectives are scalarised into one overall objective by adding a prior preference, the enumerative search (e.g., brute force search (BFS)) or guided random search (e.g., genetic algorithm (GA)) can be inherently applied, which makes the implementation very straightforward. The implementation of MOEAs is more complex. Because the optimisation problems are treated as a whole, the overall-based MOEA is more straightforward than decomposition-based MOEA.

4. **Potential Risk:** For the classical method, the main potential risk comes from the potentially arbitrary prior preference setting. When the system scale is large and complex, the prior preference could easily be arbitrary, which could lead to an inaccurate optimisation result. Instead of adding a prior preference, in MOEAs users are able to add a posterior preference in a Pareto set, based on their needs, which can minimise the potential risk of the optimisation result. In addition to the risk caused by arbitrary prior preference setting, in MOEAs some risks come from poorly spread solutions. In overall-based MOEAs, the solution diversity must be carefully maintained, otherwise, some extreme solutions will not be well preserved. However, in decomposition-based MOEA, due to the decomposition, the diversity of solutions can be inherently maintained. In general, the first type of risk is more likely to happen and can result in a worse hazard than the second.

Table 4.2: Optimisation Algorithm Selection Guidance(Author)

	Efficiency	Accuracy	Complexity	Risk	
Classical Method (Enumerative Search)	Low	Very High	Low	Very High	Small & Simple
Classical Method (Random Search)	Average	Low	Average	High	Large & Simple
MOEA (Overall Based)	High	Average	High	Average	Small & Complex
MOEA (Decomposition)	Very High	High	Very High	Low	Large & Complex

The emphasis of different optimisation problems on these four criteria is different. To have a better understanding of the optimisation algorithm selection of AP deployment planning optimisation, a selection reference table is set out in Table 4.2. When planing the AP deployment in a small and simple system, the computation demand is low and the user can easily define a proper prior preference. As a result, an enumerative search based classical method will be a good option for this kind of optimisation problem. When planning the AP deployment for a large and simple system, the computation demand will be high, therefore, the random search based classical method will be preferred. When planning the AP deployment in a small and complex system, it will be difficult for the designer to set an accurate prior preference, so MOEA will be a wise choice. When the AP deployment planning work is taken in a large and complex system, the computation efficiency will be the most critical criterion, and a better spread solution will be necessary. Consequently, decomposition-based MOEA is more suitable.

4.5 Summary

To have a better understanding of the ADP optimisation problem in CBTC systems, it is necessary to investigate the underlying challenges for the wireless communication in DCS, and formulate the optimisation problem in a mathematical way. In this chapter, the main challenges that could affect the wireless connections have been investigated. Then the formulations of ADP optimisation have been presented in the form of mathematical programming and MOP, and the choice of a suitable optimisation algorithm has been discussed.

Chapter 5

Development of an Integrated Data Communication System Performance Simulation Platform

5.1 Simulation Platform Integration

To evaluate the data communication system (DCS) performance under different scenarios (e.g., different AP deployments) in a CBTC system, a simulation platform that can test the data exchange quality under railway traffics is necessary.

Even though propagation simulators, packet level simulators and train simulators exist, integrating them together and using them as a combined tool to undertake an overall wireless control network optimisation is a new area of study. A number of studies have been done to develop a railway control simulation environments in order to simulate CBTC system performance (Alcala et al., 2011; Oh et al., 2014; Xu and Tang, 2007) and, as a result, some software packages, such as OpenTrack (Montrone et al., 2016), SIMULINK and OPNET (Hasan et al., 2009), *etc.* are commercially available off-the-shelf. However, there are some drawbacks to these software packages:

1. Most commercial simulators are not open source, which means it is almost impossible for users to extend or customise their functionality.
2. DCS utilises wireless technology to exchange data between trainborne equipment and the wayside infrastructure, however, due to the features of wireless communication, the quality of service (QoS) cannot be as good as track-circuit or other wire based technology. Unfortunately, most existing railway control simulators treat the QoS of DCS as perfect.
3. Even though some railway control simulators can set parameters to model QoS imperfection, e.g., increase the packet drop out rate in the wireless communication, this kind of method is unrealistic. In the dynamic working environment of the real world, the wireless communication quality can be randomly affected by a number of factors, so simply setting constant parameters to adjust the QoS level is far from representative.

As a very important subsystem of CBTC systems, developing a DCS test environment and making it work as part of a railway simulator is very desirable. For most existing CBTC systems, if a reliable test could be carried out to examine the performance of the DCS in different harsh conditions, some potential risks in CBTC systems may happen could be eliminated. Furthermore, for CBTC systems at the design stage, a proper DCS test platform could help engineers to optimise the DCS deployment.

To test the performance of the DCS in a CBTC system, a novel simulation platform has been developed, which integrates two separate simulators, namely a railway simulator and a network simulator (Wen et al., 2015).

5.1.1 Railway Network Simulator

The railway network simulator is a microscopic simulator, developed by the Birmingham Centre for Railway Research and Education at the University of Birmingham. This railway simulator is structured into different components, which are illustrated in Figure 5.1.

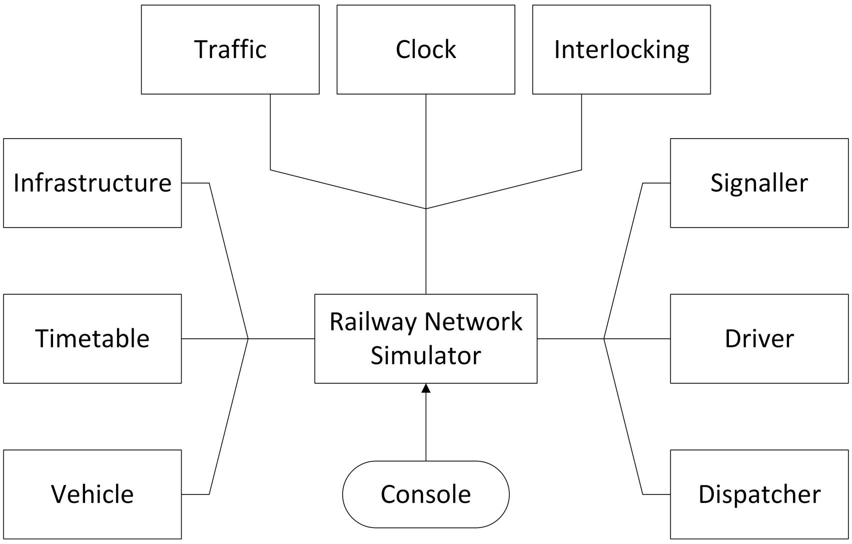


Figure 5.1: The structure of the railway network simulator (Author)

For each component, there is a panel of functions, for instance, in the vehicle component, the coach type, locomotive type, acceleration ability, braking ability and the traction curve can be configured by the user. In Figure 5.1, the vehicle panel is illustrated. By configuring these panels, the railway traffic can be realistically generated and the different types of railway control system, including track circuit-based train control systems and radio-based train control systems (e.g., European train control systems (ETCS) and CBTC systems), can be realistically simulated. However, in this railway simulator, as the wireless propagation is assumed to be perfect, no data transmission failure is accounted for and, therefore, the simulation of radio-based train control systems will not be realistic. As a result, to fill this gap, there is a motivation to connect a communication nework simulation to this railway network simulator as a functional extension.

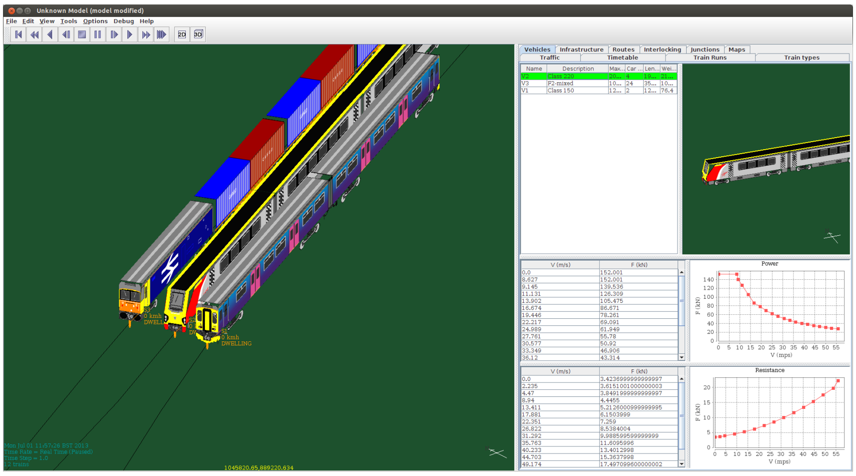


Figure 5.2: The vehicle panel (Author)

5.1.2 Communication Network Simulator

OMNeT++ is an open source object-oriented modular discrete communication network simulation framework and has different levels of modules. By assembling different modules into a larger block, users can simulate the data exchange with different protocols between different network layers under different types of physical environmental impacts. As the architecture of this simulation framework is generic, it can be adopted in simulating a large range of problems, in particular modelling wired and wireless communication networks (Varga, 2016).

There are a number of significant uncertainly factors in railway traffic, including the very dynamic terrain and station environment (e.g., the presence of other trains can alter the propagation environment significantly), relative movement between transceivers, time-variable potential co-channel interference sources, *etc.* These uncertainties can degrade the system capacity (achievable bit rates) and signal coverage (percentage of space and time where the minimum acceptable bit rate is achieved). However, in this proposed railway simulator, the impacts on wireless communication caused by these uncertain factors have not been taken into account. To achieve a realistic simulation for the radio-based train control system equipped railways, it would be necessary to add the imperfect wireless data channel into the railway traffic simulator.

By integrating these two simulators, a novel simulation environment is built. The data

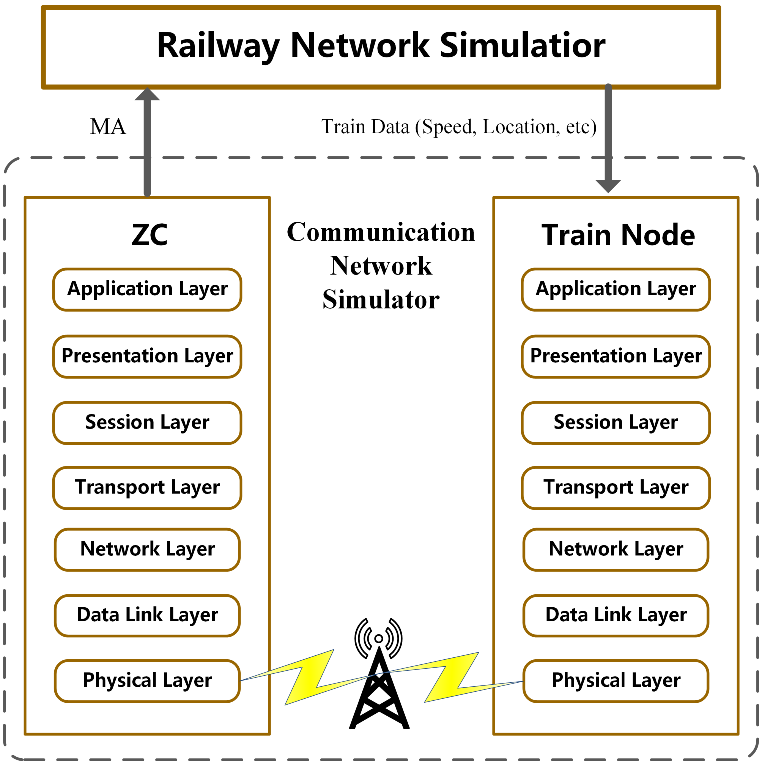


Figure 5.3: The data flow in the simulator integration (Author)

flow between the communication network simulator and the railway network simulator is illustrated in Figure 5.3. In this integrated simulation environment, the train data generated by the railway network simulator go through different network layers created in OMNeT++ to evaluate the communication performance of the railway network simulator, if the train date is received with an acceptable quality by the ZC, moving authority (MA) will be produced for the train node, otherwise, the corresponding train node will be not able to run further; in the physical layer of OMNeT++, a realistic wireless channel can be configured, which is used to simulate the realistic channel environment and determines the data transmission quality in the railway simulator. To the best knowledge of the author, this is the first time a railway network simulator has been integrated with a communication network simulator and, as a result, a much more realistic DCS performance simulation can be carried out in this combined simulation environment.

5.2 Functionality Overview of the Integrated Simulation Platform

In this part, some key functionalities of the integrated simulation platform, including path-loss type, radio medium type, interference and noise type, packet reception and railway traffic, are briefly introduced. To have a clear overview of these functionalities, some of the default settings in this integrated simulation platform are indicated in Table 5.1

Table 5.1: The Default Setting of the Integrated Simulation Platform (Author)

Parameter	Default Setting	Parameter	Default Setting	Parameter	Default Setting
Modulation Type	BPSK	MAC Protocol	IEEE 802.11	Tx Power	30 mW
Background Noise	-90 dBm	Carrier Frequency	2.4 GHz	Bandwidth	22 MHz
Medium Control	CSMA/CA	Train Top Speed	50 km/h	Sensitivity	-85 dBm
Energy Detection	-110 dBm	SNIR Threshold	0 dB	Date rate	1 MB/s
Path-loss Exp.	2	Update Interval	0.1 s	Shadowing factor	2

5.2.1 Path-loss Type

In OMNeT++, the default setting of the pathLossType parameter is FreeSpacePathLoss, but other path-loss types, like TwoRayGroundReflection, RayleighFading, RicianFading, LogNormalShadowing and some others, are optional. In this thesis, the pathLossType parameter is set as LogNormalShadowing, where consists of an empirical path loss model and a stochastic shadowing fading model. The formulation of this path loss type was investigated in chapter 4.

5.2.2 Radio Medium Type

In this thesis, the radio medium type APSKScalarRadio is used to model the radio frequency. In this radio medium type, a number of radio related parameters, including backgroundNoise, carrierFrequency, bandwidth, power, headerBitLength, sensitivity, energyDetection, snirThreshold and etc., can be adjusted for configuring the APSKScalarRadioMedium. The users can set these parameters based on their own demands.

5.2.3 Interference and Noise

The interference modelling can be either turned on or turned off. When the interference modelling is turned on, the effect of interference, including adjacent channel interference and co-channel interference will be taken into account. At the receiver part, the received unwanted signal that share the same channel frequency with the wanted signal will be considered as interference. For the noise, the backgroundNoise parameter decides the level of background noise. Interference and noise affect the signal-to-noise-plus-interference ratio (SNIR), which is a key system performance metric of DCS.

5.2.4 Packet Reception

The packet reception in OMNeT++ is dependent on a number of metrics, such as sensitivity, energyDetection and snirThreshold. If the received signal can not fully fulfil all of the system requirements on these metrics, the packet will be assumed as received, otherwise the packet will be dropped out.

5.2.5 Railway Traffic

The railway traffic can be configured in the traffic component (see Figure 5.1) of the railway network simulator. The train departure time, arrival time, departure location, arrival location, calling at stations, operation speed can be configured as required. In the communication network simulator, the train node movement is dependent on the generated train traffic in the railway network simulator, in an certain time interval (the default setting 0.1 second), the railway network simualtor will update the train location with the communication network simulator, as a result, the movement can be generated in OMNeT++.

5.3 Simulation Model

In this section, a functioning demonstration is described that was be carried out to test the functionality of the simulation platform. This functioning demonstration is based on the track layout of Heifei Metro Line I in China, which is 29 km long and where a CBTC system is employed as the train control system. For the wireless part, 2.4 GHz-WLAN is in charge of wireless communication.

The functioning demonstration is shown in Figure (5.4), where 105 APs (antenna[0] to antenna[104]) are distributed alongside the track in order to ensure a seamless radio coverage. One zone controller (ZC) is modelled, which is located at the top left of the map and connected with all the APs. It is worth mentioning that, in reality, the metro is divided into different zones and controlled by multiple ZCs, however, in this simulation model, to simplify the problem, it is assumed that the whole track is governed by one ZC. When a train moves into an AP's coverage, a connection between the train and the associated AP will be built. In the uplink, the train reports its location, velocity and direction to the AP, then the AP will put forward the data to the railway simulator via the ZC; in the downlink, the MA, which is generated by the railway simulator, is delivered to the train. If the connection between the train and AP is lost in OMNeT++, the railway simulator cannot know the exact location and speed of the train and an MA will not be generated. The train must then apply the emergency brake.

To test the functionality of the integrated simulation platform, 16 APs was assumed disabled in OMNeT++. In the railway simulator, two trains, train A and train B respectively, were arranged to operate on the track successively. During the whole

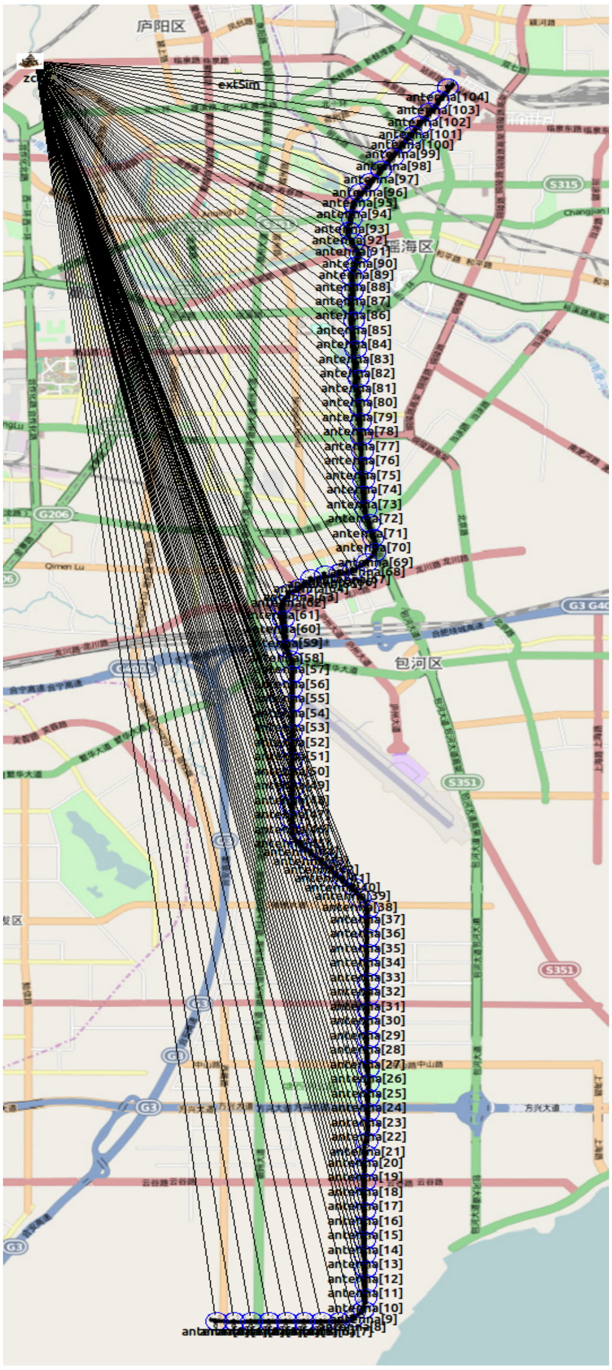


Figure 5.4: The distribution map of APs in OMNeT++ (Wen et al., 2015)

journey, the signal strength of every input packet to the APs and the received MAs to the trains are tracked. The receiver sensitivity threshold of each AP was -84 dBm, which means when the power of the received packet is lower than -84 dBm the packet will be assumed as dropped. The test result is shown in Figure 5.5. Due to the failure of 16 APs, from time 1100 to 1680 Train A lost connection to the AP, and as a result, the ZC

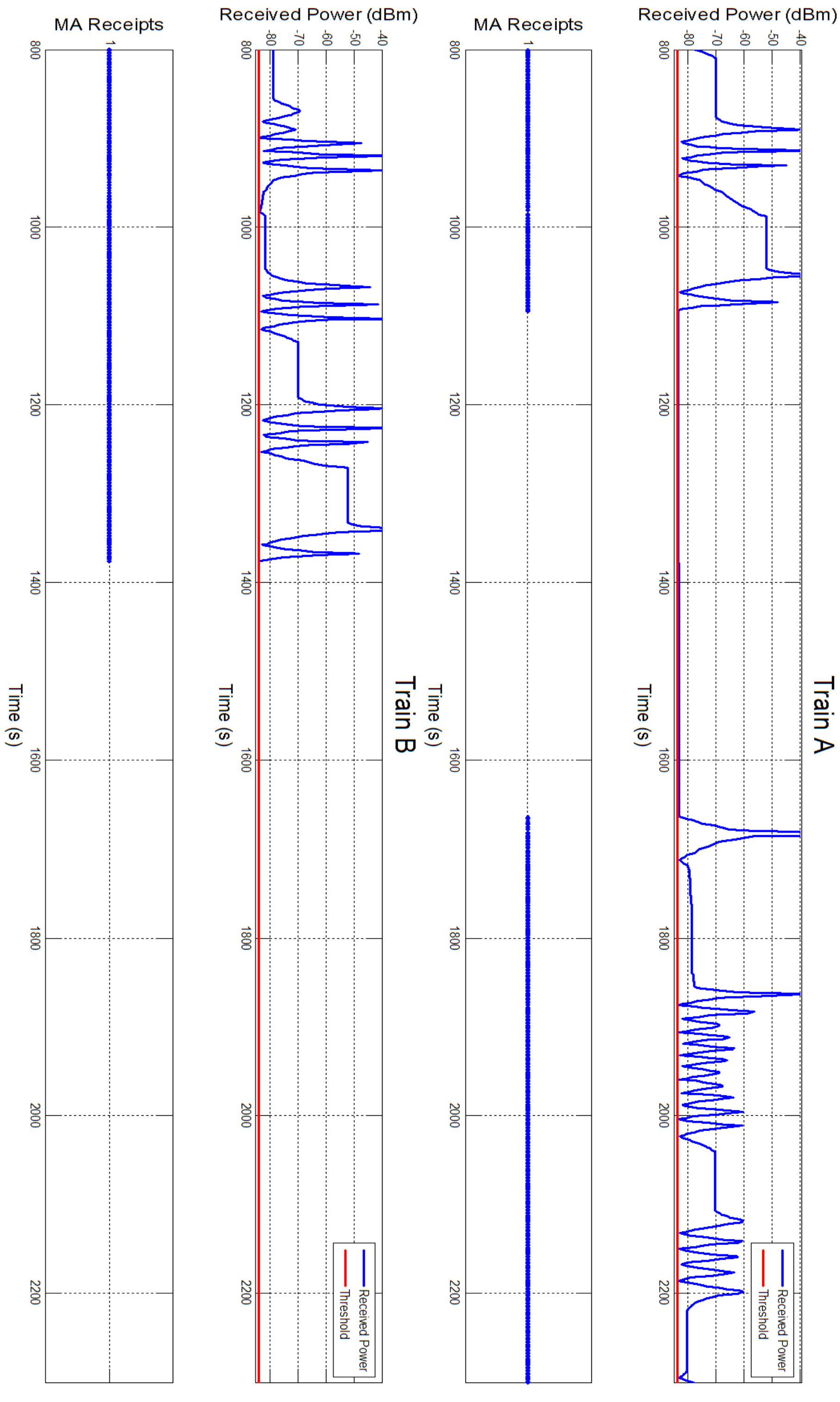


Figure 5.5: The received packet power and receipt result (Wen et al., 2015)

stopped generating MA for Train A. Because there is no train in front of Train A, no braking is applied to Train A. When the connection between train A and AP was built again from time 1680, ZC resumed generating MAs for Train A. Train B lost connection to the AP from time 1380, and Train had no MA receipt immediately. Because train B operated behind train A, to avoid a collision happening, train B could not move forward without MA.

5.4 Summary

Finding a way to evaluate the performance of DCS in CBTC systems under railway traffic is significant for achieving a well-planned AP deployment. In this chapter, a simulation platform which is integrated by a communication network simulator and a railway network simulator has been proposed. To test the functions of the integrated simulation environment, a simulation model of the integrated simulation platform has been developed to implement a functioning demonstration, where a CBTC-enabled railway track was modelled, two trains were scheduled to operate on this track successively. To test the functions of CBTC, 16 AP were assumed to be disabled, therefor, there was no train-to-wayside AP wireless connection when trains enter the area covered by these APs. The result shows that when the wireless connection is lost, the ZC will stop generating MAs and, therefore, the corresponding trains brake to stop, and the potential collision is avoided. This result demonstrates a good data integration between the communication network simulator and the railway network simulator.

Chapter 6

Methodology Application for Solving Small-scale ADP Optimisation Problems

6.1 Introduction

A methodology for access point (AP) deployment planning (ADP) problems through using mathematical programming has been proposed in chapter 4. In this chapter, a methodology application for solving small-scale ADP problems is conducted. In this application, different weight factors are given to each objective, which are derived based on the engineering experience of each objective, therefore, a convex cost function is formed and used to find the global optimum by utilizing exhaustive search. An indicative case study is carried out in a tunnel section area and the optimisation result is evaluated in the integrated simulation planform, which has been proposed in chapter 5.

6.2 ADP Problem in Tunnel Sections

Generally, in tunnel-based metro systems, there are two types of environment; one is the tunnel section area, the other is the station area. As the structure is simpler, the radio propagation will be easier to predict in tunnel section areas. In this chapter, the ADP problem will be considered in a tunnel section.

6.2.1 System Modelling

In tunnel-based metro systems, a tunnel section is defined as the part of the line between two adjacent stations. Typically, in most newly built metro systems, there are two types of tunnel section; one is a single track tunnel, the other is a double track tunnel. In a single track tunnel, there is only one track operate a single direction, which means that no passing trains can obstruct the train-to-wayside wireless connection. With cut and cover, the intersecting surface of the tunnel is square. However, as the shield tunneling machine is widely used in building metros, most tunnel sections are arched. In this chapter, the tunnel section will be assumed to be an arched one-way tunnel environment.

As discussed in chapter 4, to make the optimisation computationally tractable, the track is discretised into a number of subsections. For a track with 5 subsections, there will be 6 joints, namely A, B, C, D, E and F. Therefore, the APD problem is modelled as:

$$\begin{cases} P_\mu = 1, & \text{AP is located} \\ P_\mu = 0, & \text{AP is not located} \\ \text{s.t.} \quad \mu \in A, \ldots, F & \end{cases} \tag{6.1}$$

where μ is the joint label. Consequently, a specific AP deployment is expressed by a particular value of the 6 bits long binary string $(P_A, \ldots, P_F)$. It follows that there exist 63 possibilities of AP deployment (the all null AP deployment is not counted), one of which is the optimum.

6.2.2 Problem Formulation with Mathematical Programming

In chapter 4, the ADP optimisation problem is formulated with mathematical programming, see equation (4.36), a cost function has been proposed. By adopting this equation, the optimisation problem of the ADP in a tunnel section can be formulated. However, as the order of magnitude of each objective are sharply diverse, to prevent any objective becoming dominant in equation (4.36), and to maintain the solution diversity, the objectives are rewritten as:

$$\begin{cases} f_1(x) = [P_{out\_mean}(x) \times 10^3]^2 \\ f_2(x) = [P_{out\_max}(x) \times 10^2]^2 \\ f_3(x) = H^2(x) \end{cases} \tag{6.2}$$

The aim of the optimisation will be finding the AP deployment $\tilde{\mathrm{x}}$, which can minimise the cost function. The optimisation aim is mathematically expressed as:

$$\tilde{\mathrm{x}} = \arg\min_{\mathrm{x} \in \mathrm{S}} F(x) \tag{6.3}$$

To find out the optimal AP deployment $\tilde{\mathrm{x}}$, a proper search algorithm must be applied. Since in the cost function an overall objective has been addressed and the optimisation problem is carried out just in a single tunnel section, the brute force search (BFS) will be a good choice. BFS is straightforward and can be inherently adopted to solve weighted multiple objective optimisation problems, moreover, BFS can guarantee an optimal solution.

6.3 Case Study in a Tunnel Section

To investigate the methodology application for solving small-scale ADP problems, a case study in a tunnel section is conducted. Firstly, the network environment is configured.

Then, by formulating the problem through mathematical programming and implementing BFS, the optimal AP deployment in the tunnel section is addressed. Finally, to evaluate the optimal AP deployment, all the feasible AP deployments are tested on the integrated simulation platform and the simulation results are compared.

6.3.1 System Environment

An indicative track line geometry is shown in Figure 6.1. The whole track is divided into 5 subsections, which form 6 junctions, namely A, B, C, D, E and F. The first two

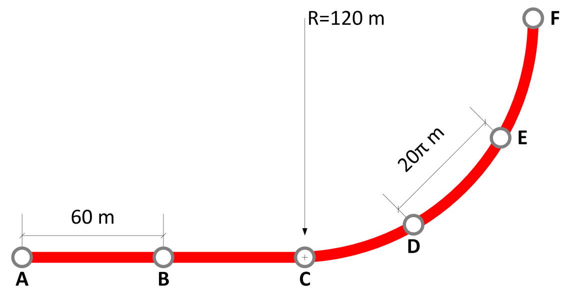


Figure 6.1: The track line geometry layout (Author)

subsections are straight and have equal length of 60 m; the remaining three subsections are 20π m long. The whole track is assumed to be in a tunnel environment and the specification of the tunnel adopts the tunnel dimensions proposed in (Guan et al., 2012), which is a wide arched tunnel with dimensions from 9.6 m to 9.8 m in width and 6.1 m to 6.2 m in height.

6.3.2 Network Environment Configuration

The key network parameters are defined in Table 6.1 and the key channel parameters are defined in Table 6.2. To make these defined parameters more realistic, some of them are informed by measurements in (Guan et al., 2012).

In WLANs, one important system performance metric is referred to as signal-to-interference-plus-noise ratio (SNIR), which must be lower than the protection

Table 6.1: The Network Parameters (Author)

Space Name	Duration	Parameter Name	Value
Medium Access Control	CSMA/CA	MAC Protocol	IEEE-802.11
Carrier Frequency	2.4 GHz	Modu. Scheme	DSSS
Transmission Power	30 mW	Modulation Type	BPSK
Antenna Gain	13 dB	Rx Sensitive	-85 dBm
Max BER	10^{-6}	Data Rate	1 MB/s
Max Latency	50 ms	Channel Bandwidth	22 MHz

Table 6.2: The Wireless Channel Parameters (Author)

Shadowing Var. σ_0	Shadowing Var. σ_1	Shadowing Var. σ_2	Path-loss Exp.	Ref. Distance
2.75 dB	2.75 dB	2.75 dB	3	1 m

ratio in a reliable wireless connection. There are two typical scenarios in WLANs, which are having a noise-limited system and an interference-limited system, respectively. For a noise-limited WLAN system, P_n is a dominant limiting factor in SNIR, such that signal-to-noise-ratio (SNR) is used instead of SNIR. However, in a more general scenario, due to the working channel frequency fully or partially overlapping with other nearby transmissions, the system is referred to as an interference-limited system. This describes co-&adjacent-channel interference when the SNR is always stronger than the minimum receiver sensitivity. The relevant performance metric in interference-limited WLAN systems is the signal-to-interference-ratio (SIR), which must be higher than the SIR threshold in a reliable wireless connection, otherwise an outage occurs.

For the SIR threshold R, this figure highly depends on the BER value. In DCS, the accepted maximum BER is between 10^{-3} to 10^{-6} (Briso, 2007; Weatherburn and Arjinian, 2016*a*), therefore, in this case study, the DCS requirement on the maximum BER is assumed as 10^{-4}, which yields (John Proakis, 2007):

$$\text{BER} = \frac{1}{2}\text{erfc}(\sqrt{\frac{E_b}{I_0}}) \leq 10^{-4} \tag{6.4}$$

By using equation (6.5) (Goldsmith, 2005),

$$\text{SIR[dB]} = 10\log_{10}(E_b/I_0) + 10\log_{10}(f_b/B) \tag{6.5}$$

where the channel bandwidth B and data rate f_b have been defined in Table 6.1, it can be derived that the SIR threshold R_{sir} is -5 dB.

The maximum accepted outage probability is related to the maximum accepted retransmission times during the handoff procedure. For most existing CBTC systems the maximum handoff latency must be shorter than 50 ms (Weatherburn and Arjinian, 2016*b*), there is,

$$T_{latency} = 4 \times T_{MAC}(n) + T_{processing} + T_{probing} \leq 50\,\text{ms} \tag{6.6}$$

In WLANs, to avoid potential collisions, carrier-sense multiple access with collision avoidance (CSMA/CA) is adopted (Goldsmith, 2005), the frame spacing durations in CSMA/CA are shown in Table 6.3.

Table 6.3: Frame Spacing Durations (Author)

Frame	CW Backoff(1)	CW Backoff(2)	CW Backoff(3)	CW Backoff(4)
Duration (ms)	31	63	127	255
Frame	SIFS	DIFS	ACK Timeout	
Duration (ms)	10	50	20	

To simplify the problem, it is assumed that no failure happens in handoff and n retransmissions are triggered to achieve a successful handoff in the presence of data packet losses arising from bit errors. To achieve a conservative handoff latency, it is assumed that DCS chooses the longest backoff time slot necessary; as the signal propagation time is very small, this delay is considered negligible and ignored, therefore, by adopting the frame spacing durations data provided in Table 6.3, the MAC layer delays caused during the handoff procedure is given in Table 6.4.

Table 6.4: MAC Layer Delay Durations (Author)

Delay	$T_{MAC}(0)$	$T_{MAC}(1)$	$T_{MAC}(2)$	$T_{MAC}(3)$	$T_{MAC}(4)$	$T_{processing}$	$T_{probing}$
Duration (ms)	0.080	0.780	2.120	4.740	9.920	10	30

Combining equations (6.6) and referring to Table 6.4, there is,

$$T_{MAC}(n) \leq 2.5\,\text{ms}, \tag{6.7}$$

i.e., the maximum latency caused by sending the reassociation request frame is not longer 2.5 ms. As a result, the maximum retransmission time n should be no greater than 2. The relevant safety standard (Weatherburn and Arjinian, 2016*b*) requires that the packet loss rate in the train control system must be no bigger than 10^{-3}, giving,

$$R_{outage}^2 \times (1 - R_{outage}) \leq 10^{-3} \tag{6.8}$$

where R_{outage} is the signal outage probability. Therefore, calculating this inequality implies that R_{outage} must be less than 3.2%. However, this is just a theoretic deduction, and for a more conservative consideration the maximum acceptable outage probability is set as 2% in this case study.

6.3.3 Brute Force Search Result

In this case study, the sampling interval is set as 5 m. Using the stochastic function proposed in chapter 4 to calculate the outage probability at each sampling point along the track for each AP deployment, the BFS algorithm enables the determination of the optimal AP deployment.

To account sufficiently for the impact caused by co-channel interference, it is assumed that the AP deployments are with a minimum of 3 APs and only two adjacent interferers can dominantly affect the communication quality. An indicative layout of the dominant interferers is shown in Figure 6.2, where AP1, AP2 and AP3 are three neighbouring APs, the interference made by AP1 and AP3 are the dominant interference to AP2.

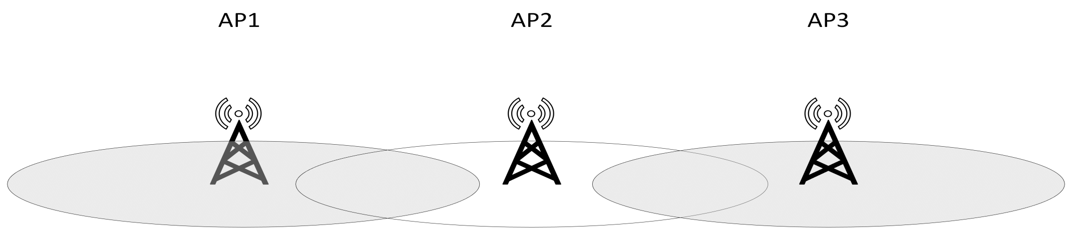


Figure 6.2: The sketch map of the dominant interferers (Author)

Since this case study is sufficiently small to compute exhaustively, this facilitates the empirical determination of suitable objective weights w_1, w_2 and w_3 in equation (4.36). After carrying out extensive trials, based on the author's experience, the objective weights are found to be 17.5, 2 and 1 respectively. Therefore, by referring to equation (4.36), the cost function in this case study is defined as:

$$\begin{cases} \min & F(x) = 17.5 \times f_1(x) + 2 \times f_2(x) + 1 \times f_3(x) \\ \text{where} & f_1(x) = [P_{out\_mean}(x) \times 10^3]^2 \\ & f_2(x) = [P_{out\_max}(x) \times 10^2]^2 \\ & f_3(x) = H^2(x) \\ \text{s.t.} & P_{out\_max}(x) \leq 2\% \\ & H(x) \geq 3 \end{cases} \tag{6.9}$$

By using equation (6.9) and the BFS exhaustive search algorithm, every AP deployment is evaluated. The exhaustive search results are shown in Table 6.5. From these search result, the result can be arrived at that the optimal AP deployment is (011010).

Figure 6.3(a) shows that as the mean of the outage probability is increasing, the CF is exhibiting a monotonically increasing trend, which demonstrates that the calculated CF can discriminate the different performance of each AP deployment in terms of the mean outage probability. From Figure 6.3(b), it can be seen that, as the mean of the outage probability is increasing, the CF rank tends to increase as well, which illustrates that there is a positive correlation between the mean outage probability and the overall

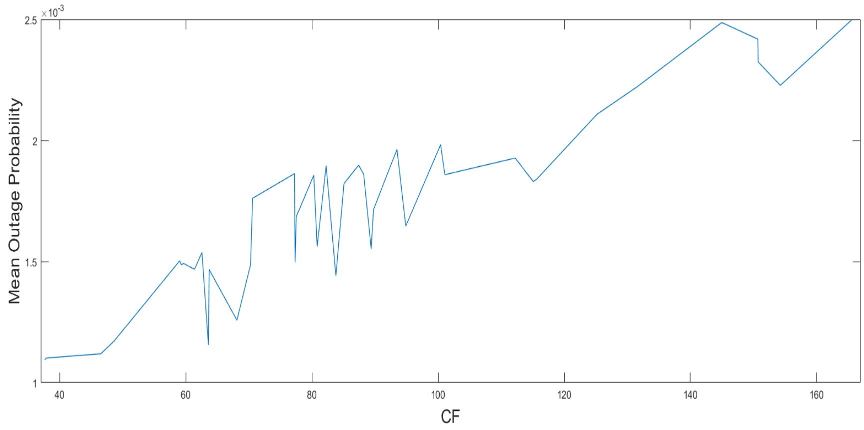
Table 6.5: The Optimisation Search Result (Wen et al., 2017)

Rank	Dep.	HD	Max ($\times 10^2$)	Mean ($\times 10^3$)	CF	Rank	Dep.	HD	Max ($\times 10^2$)	Mean ($\times 10^3$)	CF
1	011010	3	1.956	1.095	37.621	25	011110	4	3.963	1.442	83.788
2	001011	3	1.956	1.101	37.890	23	101011	4	2.341	1.822	85.078
3	010110	3	2.793	1.119	46.514	24	100011	3	2.781	1.898	87.399
4	110100	3	2.793	1.171	48.608	25	110011	4	2.412	1.860	88.197
5	011001	3	2.290	1.503	59.029	26	001111	4	3.951	1.552	89.387
6	110010	3	2.241	1.486	59.294	27	010111	4	3.339	1.715	89.753
7	010011	3	2.412	1.493	59.621	28	111011	5	1.956	1.835	91.545
8	011011	4	1.956	1.468	61.371	29	100101	3	2.919	1.963	93.480
9	101010	3	2.467	1.538	62.556	30	111100	4	3.963	1.647	94.873
10	001110	3	3.951	1.155	63.577	31	110101	4	2.793	1.983	100.380
11	100110	3	2.920	1.467	63.701	32	110111	5	2.793	1.859	101.067
12	011100	3	3.963	1.258	68.098	33	101110	4	3.951	1.927	112.217
13	110110	4	2.793	1.486	70.256	34	111110	5	3.963	1.831	115.070
14	000111	3	1.910	1.761	70.588	35	011111	5	3.963	1.839	115.576
15	111000	3	1.934	1.863	77.234	36	011101	4	3.963	2.108	125.189
16	101100	3	3.919	1.496	77.320	37	101101	4	3.818	2.226	131.603
17	111010	4	2.421	1.687	77.512	38	111001	4	3.219	2.487	144.977
18	010101	3	2.950	1.718	78.038	39	100111	4	4.021	2.419	150.694
19	101001	3	2.341	1.857	80.287	40	101111	5	3.951	2.324	150.752
20	001101	3	3.818	1.561	80.822	41	111111	6	3.963	2.228	154.263
21	110001	3	2.274	1.896	82.234	42	111101	5	3.963	2.497	165.546

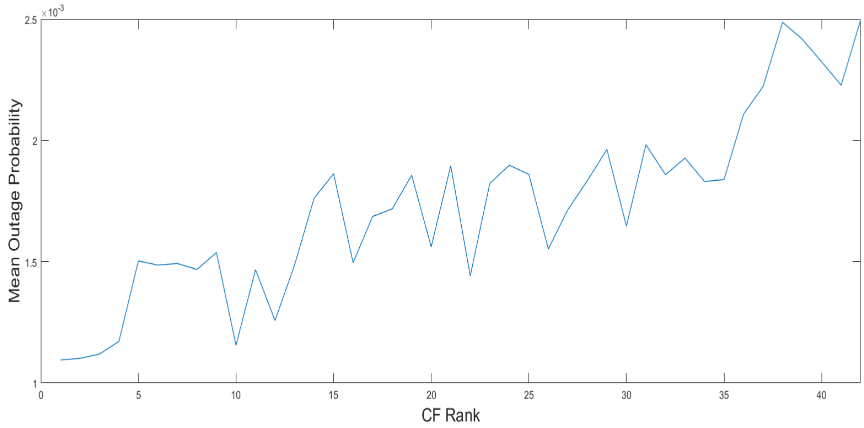
performance of the AP deployment. Lower mean outage probability results in better overall performance. From Figure 6.3(c), it shows that as the CF are increasing, the overall AP deployment performance are degrading under a smooth way, which expounds that the CF are well-spread.

6.4 Result Simulation and Evaluation

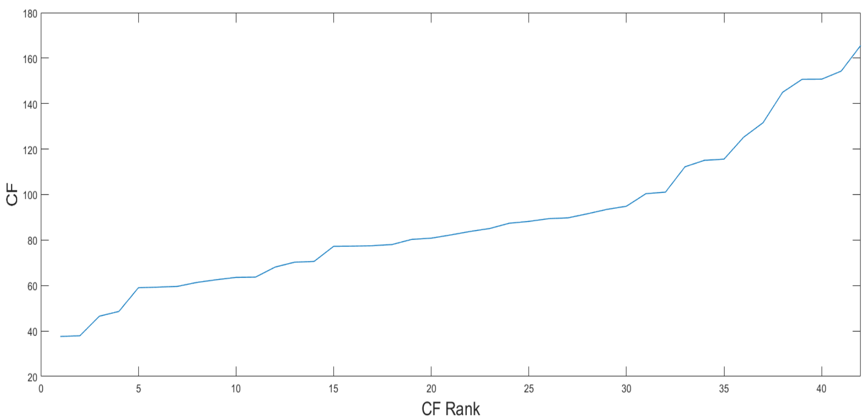
To evaluate the exhaustive brute force search result and prove the accuracy of the optimal AP deployment, simulations of all the feasible AP deployments are carried out on the integrated simulation platform in order to test the performance of each feasible AP deployment in a realistic railway environment.



(a) Mean outage probability vs CF



(b) Mean outage probability vs CF rank



(c) CF vs CF rank

Figure 6.3: The optimisation search result analysis (Wen et al., 2017)

From Table 6.6 we can see there are only 6 AP deployments which are compliant with the criterion that the maximum outage probability must be lower than 2%. As a result, it is only necessary to evaluate these 6 feasible AP deployments. Evaluations are conducted to check the overall DCS performance by using the integrated simulation environment, which integrates two separate simulators, namely a railway simulator and a communication network simulator, which is known as OMNeT++ (Wen et al., 2015).

A screenshot of the simulation is shown in Figure 6.4. The interface of the OMNeT++ is shown in the left part of the figure, where the propagation environment is configured by the radioMedium model, APs are deployed along the track line based on the optimisation result and connected to the ZC via a switch, the ZC is a gateway exchange the data with the railway network simulator; the interface of the railway network simulator is shown in the upper right part of the figure, where the train movement is scheduled along the track line; a graphic indicator is shown in the lower right part of the figure, where shows whether the packet is received or dropped out. During the simulation, the railway network simulator updates the train location with the communication network simulator every 0.1 second, as a result, the train movement is generated in the OMNeT++. Every 0.1 second, a packet will be transmitted from the train to the ZC via APs, the packet will go through the environment created by the radioMedium model and, suffers path-loss and fading.

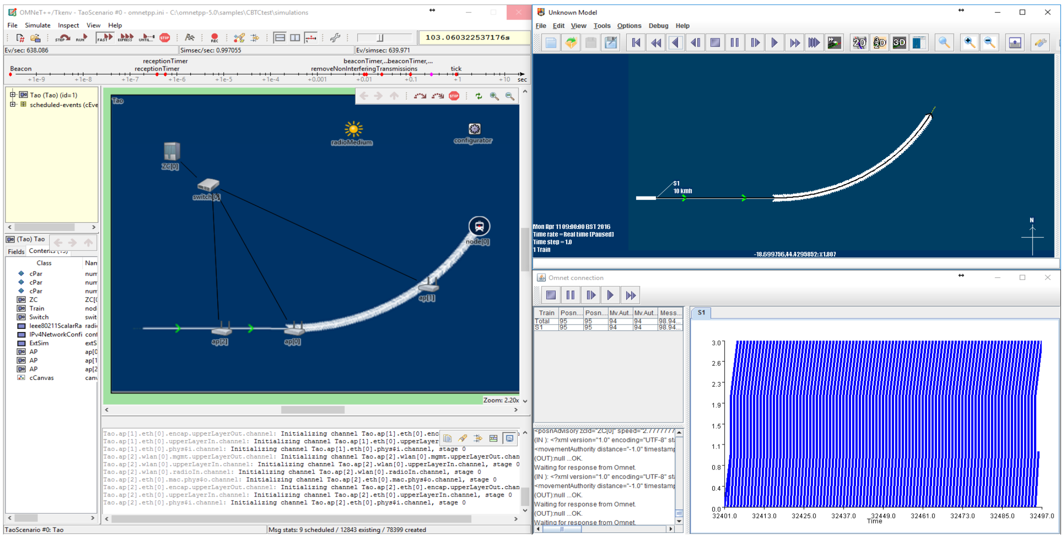


Figure 6.4: A screenshot of the simulation environment (Wen et al., 2017)

In the evaluation, the packet error rate (PER) is utilized to measure the overall DCS performance, this is because: 1) PER is a fundamental indicator for measuring the performance of a network; 2) For a certain network configuration, the PER has a positive correlation with the outage probability, which is the key element in the proposed cost function; 3) PER can be easily obtained from OMNeT++, the network simulation. The result of the evaluation is shown in Table 6.6, from the evaluation result we can see that the AP deployment of 011010 has a better and more stable performance on the PER, lower mean outage probability and the minimised number of deployed APs. As a result, a conclusion is drawn that 011010 is the optimal AP deployment.

Table 6.6: The Evaluation Result (Wen et al., 2017)

Dep.	Outage:mean ($\times 10^3$)	Counts	RcvdPk (%)	PER:sqrsum	PER:stddev	PER: mean(%)
000111	1.761	2791	100	152.39	0.23	6.28
001011	1.101	2872	100	166.58	0.22	5.80
011010	1.095	3039	100	151.46	0.20	4.98
111000	1.863	2929	100	167.24	0.29	6.72
011011	1.468	3838	100	213.83	0.23	6.36
111011	1.835	4642	100	310.12	0.25	7.58

The PER cumulative density of these 6 AP deployments is shown in Figure 6.5, which are illustrated by different colours. In this figure, the X-axis presents the PER, Y-axis presents the cumulative density, when the PER is 0, the selected optimal AP deployment, 011010, has the highest cumulative density with 0.92; as the PER is increasing, the selected optimal AP deployment always has the highest cumulative density. Therefore, it can be concluded that the selected optimal AP deployment, 011010, always has a better performance than any others, in terms of the key system performance metric, PER.

The evaluation demonstrates that the proposed AP deployment optimisation method achieved a good result. However, for large-scale planning problems the efficiency of the BFS algorithm could be computationally unfeasible. For instance, if the track is extended to 1.2 km long, under the same optimisation configurations and procedures, it will require more than 3 years of computation on the existing hardware platform to complete the exhaustive search! Thus, it is concluded that using the BFS algorithm to carry out exhaustive search for an entire metro system planning work is likely to be computationally impossible even off-line. As a result, a more efficient replacement is

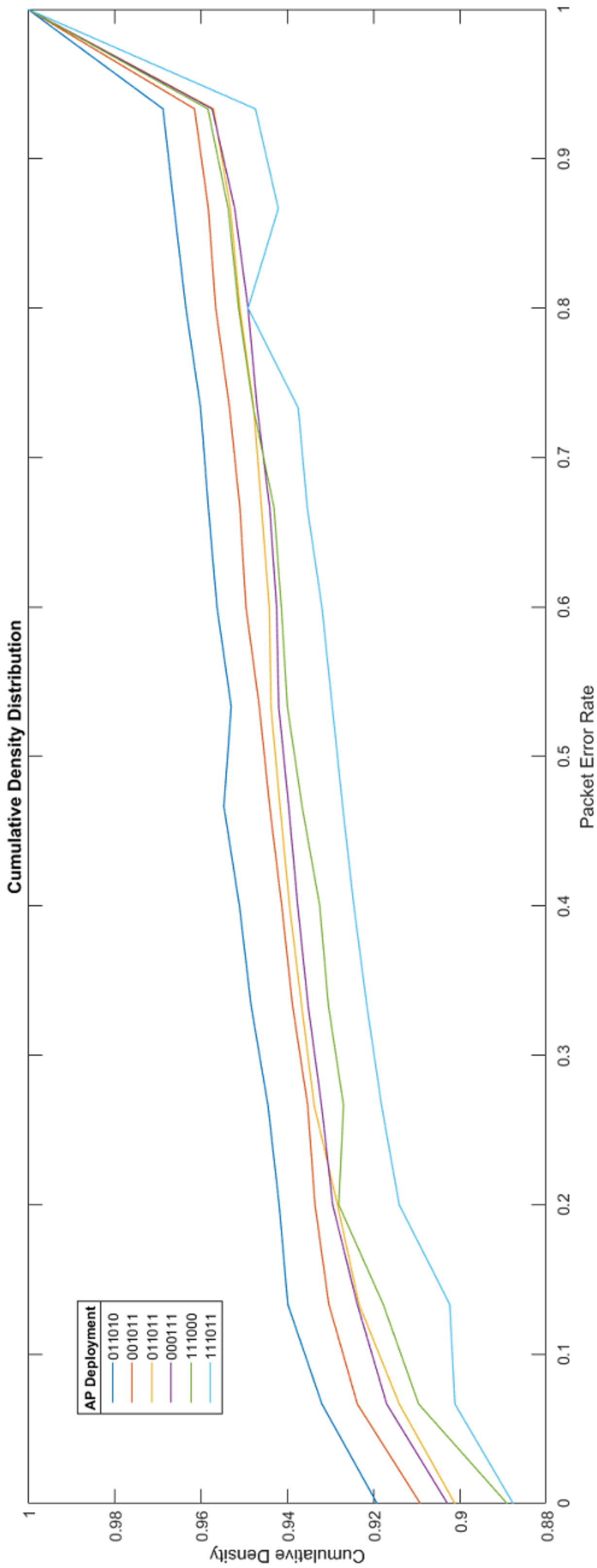


Figure 6.5: The cumulative density of the packet error rate (Wen et al., 2017)

required. Apart from the optimisation algorithm, determine suitable simplifications leading to approximate optimisation of the CBTC system, compliant with functional constraints will be another way to further improve the optimisation efficiency. Moreover, in reality, the railway environment is dynamic, therefore, develop a parametric tunnel propagation model which can be customised for specific scenarios is necessary. All of these aforementioned issues will be considered in the next chapter.

6.5 Summary

In this chapter, a methodology application for solving the small-scale ADP optimisation problems is proposed and an indicative case study is presented in a tunnel section. In this application, by integrating Hamming distance, max and mean value of outage probability plus the predefined weigh factor, a cost function is defined. This cost function can be minimized by the optimal AP deployment. To solve this optimisation problem, BFS algorithm is used to search each of the AP deployments and get their cost function value. To evaluate the optimisation result, each of the feasible AP deployments is simulated in an integrated simulation environment, and the evaluation result proves that the optimal AP deployment is accurate.

Chapter 7

Methodology Application for Solving Large-scale ADP Optimisation Problems in Real-world Metros

7.1 Introduction

A methodology application for optimising the small-scale access point (AP) deployment planning (ADP) problems was proposed in the previous chapter. However, only the exhaustive brute force search is implemented to find the result, which is computationally infeasible in planning large-scale DCS systems. Therefore, there is a strong motivation to further extend the work presented in chapter 6. In this chapter, a methodology application for solving the large-scale ADP optimisation problems is proposed and a case study is implemented in a real-world metro system.

7.2 Outage Probability and Its Approximations

To meet the requirements of DCS for reliable wireless connection, the received power strength of the desired signal must be higher than the minimum receiver sensitivity. However, owing to shadowing fading, the power density of any radio signal undergoes a random spatial attenuation and, unless making use of a complex ray-tracing method or a full-wave propagation prediction method that incur a prohibitively expensive computational overhead, it is almost impossible to predict the exact signal strength at a certain distance. As the shadowing follows a log-normal distribution (Büyükçorak et al., 2015; Salo et al., 2005), a probability can be used to quantify the likelihood of radio link outage at each spatial location. This probability is referred to as the outage probability.

In noise-limited communication systems, if the received signal power is too close to the noise level, the wireless connection will be terminated; this situation is referred to as an outage. The outage probability in noise-limited systems is expressed as (Jakes, 1974):

$$P_{out} = \frac{1}{2}\,\mathrm{erfc}[\frac{\bar{P}_r - S_m}{\sqrt{2}\sigma}] \tag{7.1}$$

where σ is the signal strength standard deviation in dB; m is the average received signal power in dB; S_m is the receiver sensitivity in dB.

However, in interference-limited communication systems, which most DSC of CBTC belong to, the impact of co-&adjacent-channel interference must be carefully accounted for. The signal-to-interference ratio (SIR) will be the system performance metric, if the SIR is lower than the threshold, outage occurs. There is no practical means of predicting the exact received signal power or SIR, a stochastic function can be used to measure the outage probability in the presence of interference exactly, which is proposed in (Yeh and Schwartz, 1984) and summarised by Sowerby in his Ph.D. thesis (K. W. Sowbery, 1989). However, it could still be prohibitively computationally expensive to determine the outage probability in the presence of multiple interferers. To tackle this problem some approximate methods have been proposed in (Chan, 1984; Fenton, 1960; Schwartz and Yeh, 1982), which can dramatically decrease the computational cost in computing the outage probability.

In order to more efficiently calculate the outage probability in the presence of multiple interferers, three approximation methods has been proposed by Chan (Chan, 1984), Wilkinson (Fenton, 1960) and Schwartz & Yeh (Schwartz and Yeh, 1982) respectively. To investigate the performance of these proposed approximation methods, a performance comparison between the exact method (Yeh and Schwartz, 1984) and these approximation methods was drawn by Sowerby (K. W. Sowbery, 1989), which is shown in Table 7.1. The table shows that every aforementioned approximation method can provide a very good result when σ is between 3 dB and 6 dB, which is a common range in the metro environment (Guan et al., 2012).

Table 7.1: A Comparison of the Outage Probability Approximation Methods ((K. W. Sowbery, 1989))

Actual Parameters			*Wilkinson*	*Schwartz&Yeh*	*Chan*	*Exact*
σ dB	τ_1 dB	τ_2 dB	P^2_{out}%	P^2_{out}%	P^2_{out}%	P^2_{out}%
3	5	5	34.1	34.2	32	34.1
3	5	10	18.6	18.4	18.5	18.4
3	10	20	1.1	1.0	1.2	1.1
6	10	10	23	23.7	20.5	23.6
6	10	20	13.3	13.4	12.9	13.4
6	20	20	2.2	2.1	2.3	2.2

In the interest of computational efficiency in calculating the approximated outage probability in the presence of multiple interferers, Chan's method (Chan, 1984) will be employed to compute the outage probability in this paper. For the presence of n interferers, with the received power excess $(\tau_1, \tau_2, \ldots, \tau_n)$ Chan proposes an equivalent interfering signal τ_{eq} given by,

$$\tau_{eq} = -10 \times \log_{10}(\sum_{i=1}^{n} 10^{\frac{-\tau_i}{10}}) \tag{7.2}$$

$$\tau_i = \bar{P}_r - (\bar{I}_i + R) \tag{7.3}$$

where $\bar{I}_i$ is the average power of the i^{th} interferer of the n interferers at the receiver in dBm; R is the system minimally accepted SIR ratio in dB, which is also known as the protection ratio, the derivation of the protection ratio has been proposed in chapter 4. So the outage probability in the presence of n interferers is,

$$P_{out} = \frac{1}{2}\mathrm{erfc}[\frac{\tau_{eq}}{2\sigma_{eq}}] \tag{7.4}$$

where σ_{eq} equals the σ_{dB} of the desired signal.

7.3 ADP Problem in Real-world Metro Systems

In this part, the optimisation problem in real-world CBTC systems will be formulated and an advanced optimisation algorithm will be introduced and customised to carry out the optimisation result search.

7.3.1 System Modelling

In tunnel-based metro systems, there are two main types of architecture, namely tunnel sections and stations. A tunnel section is defined as the part between two adjacent stations. The tunnel section is an isolated single track in double track tunnel. The station is typically an underground building that has entrances and exits for trains going through, a double line tunnel track is laid. A typical station design drawing is shown in Figure 7.1.

This figure shows that the track is divided into a station part and a tunnel section part, the partition boundaries denoted by $\mathrm{K}25+737.8$ and $\mathrm{K}25+926.8$ in Figure 7.1. The propagation behaviour of raidowave in tunnel section and station is totally different. In the tunnel section, wireless propagation is mainly determined by the tunnel intersecting surface shape and dimensions, and the tunnel curvature; on the other hand, in the station wireless propagation is much more complex and varied.

In this chapter, as it is difficult to characterize wireless transmission in stations

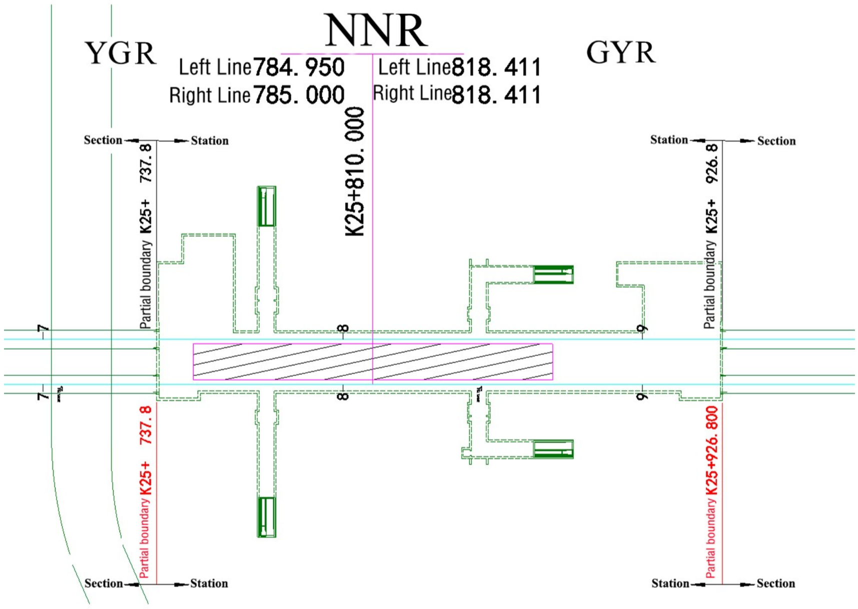


Figure 7.1: The design drawing of a metro station (Hefei Metro, 2012)

(deterministically or stochastically), the existing AP deployments will be adopted in stations and only perform the AP deployment optimisation in the sections between stations. It can be realized from Figure 7.1 that the station entrance and exit are connected to separate tunnels; when a train is running through the station entrance or exit, the line of sight (LOS) signal propagation between station and tunnel section will be to a great extent obstructed by the train, which can cause significant power reduction (Guan et al., 2012). As a result, for a worst case scenario consideration, it is assumed that the tunnel section and its neighboring station area are fully isolated, and that no radiowaves pass through. Therefore, in this paper, it is proposed that the existing AP deployments are adopted for stations and AP deployment optimisation is only performed for the tunnel sections between stations.

In tunnel sections, it is assumed that the railway track is a continuous line, which means there are countless places where APs can potentially be located. To render the problem tractable, the railway track is discretized into a number of subsections. At the joint between adjacent subsections there is a potential placement of an AP, and binary integers are used to show whether there is an AP placed in the joint or not. For a track discretized into N subsections, the problem is formulated as:

$$\begin{cases} P_\mu = 1, & \text{AP is located} \\ P_\mu = 0, & \text{AP is not located} \\ \text{s.t.} \;\; \mu \in 1, \ldots, N+1 \end{cases} \tag{7.5}$$

where μ is the joint label. Consequently, a specific AP deployment is expressed by a particular value of the $N+1$ long binary string $(P_1, \ldots, P_{N+1})$. It follows that there exist $2^{N+1}-1$ AP deployments (the all null AP deployment is not counted). The set of all the AP deployments is denoted as Θ.

7.3.2 Problem Formulation with a MOP

In the previous chapter, experience-based system optimisation factors and exhaustive search are employed to formulate the problem and search out the result respectively, which achieved a good performance in a small-scale case study. However, a number of concerns arise if the brute force exhaustive search method were to be applied to larger-scale AP deployments.

1. **Prohibitively high computational cost:** If the subsection length is set as 60 m, for a 2182 m track, there are 35 subsections. By implementing the same methodology proposed in our prior work on a desktop (Intel i5-3570 3.4GHz, 8GB), it needs 2088 days (based on the author's own calculation) to compute all the 3.4×10^{10} AP deployment combinations, which is almost impossible, as already mentioned in chapter 6.

2. **Improper preference setting:** In order to implement the exhaustive search, multiple objectives are converted into an overall objective through adding the experience-based preference (e.g., the weight factors). However, when the system scale is large and the system is complex, due to there being insufficient knowledge and analysis, this predefined preference is highly likely to be unreasonable, which

can lead to a bias or even inaccurate optimisation result.

To relieve these concerns, in this chapter the ADP optimisation problem is formulated with the multi-objective programming (MOP), which was proposed in chapter 4, the involved objectives were presented in equation (6.3). By adopting this MOP formulation, without adding any prior preferences, the ADP optimisation problem is presented as:

$$\begin{cases} \min \quad F(f_1(x), f_2(x), f_3(x)) \\ \text{where} \qquad f_1(x) = [P_{out\_mean}(x) \times 10^3]^2 \\ \qquad\qquad f_2(x) = [P_{out\_max}(x) \times 10^2]^2 \\ \qquad\qquad f_3(x) = H^2(x) \\ \quad \mathrm{s.t.}\ \mathrm{x} \in \mathrm{S} \subset \Theta \end{cases} \tag{7.6}$$

where P_{out_mean} is the mean value of the outage probability, $P_{out\_max}(x)$ is the max value of the outage probability, $H(x)$ is the Hamming distance of the AP deployment x to a null AP deployment, Θ is the search space that consists of all the AP deployment combinations, S is a subset of Θ that is formed by all the feasible AP deployments. To assure the system reliability in case of an AP failure, the AP deployment in S should satisfy that

$$\begin{cases} P_{out\_i}(x) \le R_{outage} \\ \quad \mathrm{s.t.}\ \ i \in 1, \ldots, I \end{cases} \tag{7.7}$$

where x is an AP deployment in Θ. P_{out_i} is the outage probability at sampling point i, I is the number of the sampling points; R_{outage} is the system outage probability threshold. However, in order to ensure the train-to-wayside wireless connection still work when an AP breaks down, the AP deployment also need to satisfy that

$$\begin{cases} P_{out\_i}(\dot{x}) \le R_{outage} \\ \quad \mathrm{s.t.}\ \ i \in 1, \ldots, I \end{cases} \tag{7.8}$$

where $\dot{x}$ is the AP deployment x with a broken AP. The aim of the optimisation is expressed as:

$$\tilde{\mathrm{x}} = \underset{\mathrm{x} \in \mathrm{S}}{\arg\min} F(x) \tag{7.9}$$

where $\tilde{x}$ is the optimal AP deployment.

7.3.3 Optimisation Algorithm for Solving the Real-world ADP Problems

After formulating the optimisation problem, an efficient algorithm is required to search the optimisation result. As the objective functions in a MOP problem are very likely to be contradictory, without adding any preference, it will be difficult to have a solution that optimises all the objectives simultaneously and the optimal result will be the solution that has the best trade-off among these objectives.

To determine the best trade-off efficiently, an advanced search algorithm MOEA/D (Zhang and Li, 2007) is customized, as it has been proven to be a good tool for solving MOP problems. In MOEA/D, the MOP problem $F(x)$ proposed in equation (7.6) is decomposed into M scalar optimisation subproblems by using the Tchebycheff approach (Miettinen, 1999), so the cost function of the k^{th} subproblem is expressed as:

$$g^{te}(x|\lambda^k, z^*) = \max_{1 \leq i \leq 3} (\lambda^k | f_i(x) - z_i^*) \tag{7.10}$$

where g^{te} is the decomposition cost, λ^k is the weight vector; $z_i^* = (z_1^*, z_2^*, z_3^*)^{\mathrm{T}}$ is the reference vector, which is expressed as:

$$\begin{cases} z_1^* = \min(f_1(x)|x \in S) \\ z_2^* = \min(f_2(x)|x \in S) \\ z_3^* = \min(f_3(x)|x \in S) \end{cases} \tag{7.11}$$

By changing the weight vector λ^k in equation (7.10), different optima of the subproblem will be found. To provide sufficient and well spread optimum candidates, in MOEA/D the weight vector is uniformly spread. As the g^{te} is supposed to be continuous with regard to λ, MOEA/D considers that if λ^k is close to λ^t, the optimum of the k^{th} sub-problem should be close to the optimum of the t^{th} subproblem. Therefore, MOEA/D defines that the neighbourhood of λ^k is formed by T closest (in terms of Euclidean distance) weight vectors in $(\lambda^1, \ldots, \lambda^M)^{\mathrm{T}}$, and the neighbourhood of k^{th} subproblem is formed by the sub-problems whose weight vectors are the neighbors of λ^k.

In each iteration, only the neighbouring subproblems are exploited through using genetic algorithm (GA) (Mitchell, 1996), and the optimum of each subproblem will be updated if a better one is found. When the maximum iteration number is reached, an external population (EP) will be generated, in which all the found non-dominated optima are stored. These stored optima and EP are better known as the Pareto optimal (PO) and the Pareto front (PF) (Miettinen, 1999) respectively.

7.3.4 Decision Making

The optima stored in the EP are the optimal result candidates. As each member of the EP is non-dominated, this means there is no perfect solution among the EP, such that the system designers need to define a dedicated trade-off by themselves. To define such a trade-off, the posterior preference must be specified on each objective.

In some cases, if the system designers demand a more stable throughput in the train-to-wayside communication, the maximum outage probability should have more priority; in some protocols, i.e., User Datagram Protocol (UDP), the mean outage probability is a privileged metric, because UDP is a best effort transmission, and a lower mean outage probability leads to a higher cumulative throughput. Unlike the prior preferences (i.e., the predefined weight factors), adding posterior preferences can provide a much broader solution space, which can bring an extra gain in planning AP deployment in DCS.

7.4 Case Study in the Hefei Metro Line-I (HML-I)

To investigate the methodology application for solving the large-scale ADP problems, a case study was conducted in a real-world metro system. First, the system environment was introduced and the network environment configured. Then, by formulating the optimisation problem through multi-objective programming (MOP) and implementing customized MOEA/D, the optimized AP deployments were addressed. Finally, to evaluate the result, the performance of the optimized AP deployment and the original AP deployment were simulated and compared, which showed that the optimised AP deployment is better.

7.4.1 System Environment

The case study was conducted in Hefei Metro Line-I (HML-I) in China, which is the first urban rail transit system in Hefei, the capital city of Anhui province in China. The construction of this metro line began in June 2012 and it was opened to the public at the end of 2016. HML-I has a length of 29.06 km and 23 stations, all the metro system is operated in a tunnel environment and is fully managed by a WLAN-based CBTC system. A track layout is shown in Figure 7.2.

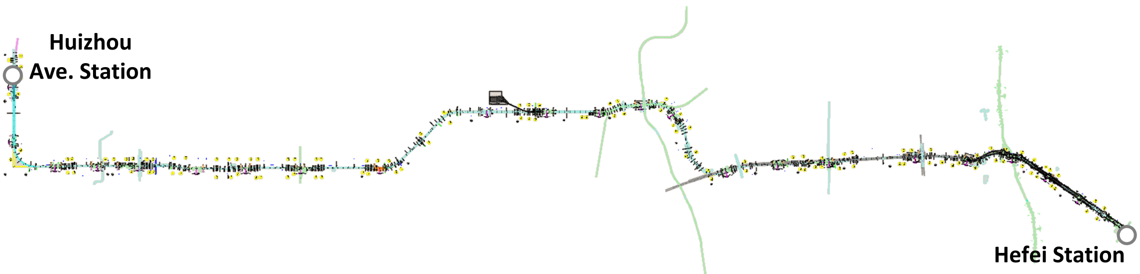


Figure 7.2: The track layout of the Hefei Metro Line-I (Hefei Metro, 2012)

By refereing to the HML-I design drawing (Hefei Metro, 2012), the detailed start and end points and lengths of stations and sections are listed in Table 7.2, which shows that there are 22 sections between the stations, where the longest station is Hefei Station, which is

577 m long, the shortest station is Dadongmen Station at 147 m long, the longest tunnel section is between Huayuan Avenue Station and Jinxiu Avenue Station, which is 2182 m long, the shortest tunnel section is between Yungu Road Station and Naning Road Station, which is 315 m long. As discussed in chapter 7.3.1, only the optimisation in tunnel sections will be implemented.

Table 7.2: The Station List of the HML-I ((Hefei Metro, 2012))

Station				*Section*
Station Name	*Start*	*End*	*Length* (m)	*Length* (m)
Hefei Sta. (HFS)	4K+306	4K+883	577	558
Fengyang Rd. Sta. (FYR)	5K+441	5K+628	187	551
Mingguang Rd. Sta. (MGR)	6K+179	6K+448	269	524
Dadongmeng Sta. (DDM)	6K+972	7K+119	147	739
Wuhu Rd. Sta. (WHR)	7K+858	8K+016	158	877
Nanyihuan Sta. (NYH)	8K+893	9K+099	206	1449
Taihu Rd. Sta. (THR)	10K+548	11K+010	462	476
Shuiyangjiang Rd. Sta. (SYJ)	11K+486	11K+685	199	799
Gedadian Sta. (GDD)	12K+484	12K+684	200	1428
Wanghucheng Rd. Sta. (WHR)	14K+112	14K+388	276	466
Gaotie Sta. (GTS)	14K+854	15K+120	266	633
Fanhua Ave. Sta. (FHA)	15K+753	15K+917	164	795
Dalian Rd. Sta. (DLR)	16K+712	17K+063	351	856
Huayuan Ave. Sta. (HYA)	17K+919	18K+114	195	2182
Jinxiu Ave. Sta. (JXA)	20K+296	20K+497	201	1353
Ziyun Rd. Sta. (ZYR)	21K+850	22K+018	168	849
Zhongshan Rd. Sta. (ZSR)	22K+867	23K+062	195	718
Fangxing Ave. Sta. (FXA)	23K+780	24K+047	267	906
Yungu Rd. Sta. (YGR)	24K+953	25K+422	469	315
Nanning Rd. Sta. (NNR)	25K+737	25K+926	189	582
Guiyang Rd. Sta. (GYR)	26K+508	26K+702	194	923
Hunan Rd. Sta. (HNR)	27K+625	27K+814	189	726
Huizhou Ave. Sta. (HZA)	28K+540	29K+010	470	0

7.4.2 Network Environment Configuration

The radiowave propagation behavior varies between different sections. In this subsection, the parameters used for describing the large-scale fading characteristics for different types of tunnel section are discussed.

7.4.2.1 Tunnel Section Scenarios

Straight Tunnel Section For the sake of simplifying the problem, in this chapter, the tunnel section with a curvature less than 10 degrees will be regarded as straight. In (Molina-Garcia-Pardo et al., 2009) and (Choi et al., 2006), it has been found that under the assumption of an arched tunnel with dimensions of around 8 m in width and around 6 m in height the radiowave will encounter around a path-loss exponent of 2 and a shadowing deviation around 5 dB. As the parameters were measured in a tunnel that has similar dimensions to the tunnels in HML-I, and was at a similar working frequency of 2.4 GHz, therefor, these two proposed parameters to describe the radiowave propagation channel will be adopted in this case study.

Curved Tunnel Sections In this chapter, the tunnel section with a curvature more than 10 degrees will be regarded as curved. The large-scale fading characteristics in different types of curved railway tunnel at 2.4 GHz have been addressed in (Guan et al., 2015). As the tunnel dimensions encountered are similar, these addressed parameters to describe the large-scale fading characteristics in the curved tunnel of HML-I will be adopted in this optimisation. The detailed fading parameters are shown in Table 7.3. When the train runs in different curvatures, the large-scale fading parameters will be adaptive, subject to the train's location.

7.4.2.2 Simulation Parameters

The relevant key network parameters are assumed in Table 7.3. In this case study, the acceptable BER is set as lower than 10^{-6}, therefore, there is (Giordano and Levesque, 2015),

$$\text{BER} = \frac{1}{2}\text{erfc}\left(\sqrt{\frac{E_b}{2 \times I_0}}\right) \leq 10^{-6} \tag{7.12}$$

Table 7.3: The Simulation Parameters (Author)

Network Parameters		*Fading Parameters*		
Parameters	Value	Curvature R.	Path-loss Exp.	Std. [dB]
Protocol	IEEE-802.11	300 m	5.50	4.09
Frequency	2.4 GHz	350 m	5.47	4.23
Modu. Scheme	FHSS	380 m	5.45	4.32
Modu. Type	BFSK	450 m	5.40	4.52
Data Rate	1 MB/s	Straight	2	5
Channel Bandwidth	3 MHz			
No. of Hopping	25			
Trans. Scheme	CSMA/CA			
Trans. Power	15 dBm			
TX Gain	14 dBi			
RX Gain	12 dBi			
FHSS Proc. Gain	14 dB			
Rx Sensitive	-85 dBm			
Max BER	10^{-6}			
Max Latency	50 ms			

where E_b/I_0 is the ratio of energy per bit to co-channel interference power spectral density. By using the equation (7.13) (Goldsmith, 2005),

$$\mathrm{SIR[dB]} = 10\log_{10}(E_b/I_0) + 10\log_{10}(f_b/B) \tag{7.13}$$

where f_b is referred to as the channel data rate; B is referred to as the channel bandwidth, therefore, the system protection ratio can be derived, which is around 8.5 dB.

In chapter 4, a retransmission schema has been described to minimise the accepted maximum outage probability, which is determined by the maximum accepted retransmission latency. In HML-I, the requirement on maximum latency is no more than 50 ms, and by following the derivation described in chapter 6.3.2, it can be deduced that the corresponding maximum accepted outage probability is 3.2%.

As an IEEE-802.11 FHSS-based WLAN is used in the DCS of HML-I, there will be a processing gain, in which the parameter of interest is the hopping channel number (Abu-

Rgheff, 2007; Fakatselis, 1998):

$$\mathrm{G_p[dB]} = 10 \times \log_{10}(\mathrm{HN}) \tag{7.14}$$

where the HN is the hopping channel number. By referring to the system manual of HML-I, there are 25 hopping channels in DCS, as a result, the processing gain in data transmission is 14 dB.

7.4.3 Optimisation Algorithm

In this part, the MOEAD/D is customised and configured to search out the optimal AP deployments for HML-I. This customised algorithm works in a sequence of input configuration, initialisation, update and output.

7.4.3.1 Input Configuration

The required input of this algorithm is given as: The MOP function is equation (7.6); the iteration time *it* is set as 20; 500 subproblems are accounted, as a result, there will be 500 evenly spread weight vectors, namely $\lambda^1, \ldots, \lambda^{500}$; the neighborhood size is 75; the outage probability threshold is set as 0.032 and the $O_t = (0.032 \times 100)^2$.

Algorithm 1: Input

1 MOP = equation (7.6), which contains three objectives;
2 iteration times (it) =20;
3 $M = 500$, the number of subproblems;
4 $T = 75$, the size of the neighborhood;
5 $O_t = (0.032 \times 100)^2$.

7.4.3.2 Initialisation

After setting the input, external population (EP) is initialized, which is used to store the optimisation solutions. At the first step, it is necessary to find the T neighbors of each sub-problem by measuring the Euclidean distance between the accompanied weight vector. The index of these neighbours are stored in $L = (k_1, \ldots, k_M)^{\mathrm{T}}$. Then, randomly select AP deployments x_t as the initial population, where $x_t \in S$, $t = 1, \ldots, M$, and if $f_1(x_t) \leq O_t$ store the corresponding $F(x_t)$ as the CF_t, otherwise store the $F(x_t)$ as ∞. Finally, based on experience, set the initial reference points $z^* = (z_1, z_2, z_3)$.

Algorithm 2: Initialisation

set EP = [ ];
create M Subproblems;
generate M even spread weight vectors $(\lambda^1, \ldots, \lambda^M)^{\mathrm{T}}$;
find the T closest neighbors for each weight vector;
store the T neighbors' index for each weight vector in $L(k) = (k_1, \ldots, k_M)^{\mathrm{T}}$;
randomly pick M feasible solutions $x_1, \ldots, x_M$. For the t^{th} subproblem, if $f_1(x_t) \leq O_t$, set the $CF_t = F(x_t)$, otherwise set $CF_t = \infty$, where $t(\in 1, \ldots, M)$;
set the initial reference points $z^* = (z_1, z_2, z_3)^{\mathrm{T}}$;

7.4.3.3 Update

For the t^{th} sub-problem, two indexes ξ and θ from k_t will be randomly chosen, and use x_ξ and x_θ to generate an offspring y^t by using a genetic operator. Then, to update the neighbourhood, MOEA/D uses the g^{te} as the indicator to compare the $g^{te}(y^t|\lambda^t, z^*)$ with all the $g^{te}(x_i|\lambda^t, z^*)$, where $i \in k_t$. If $g^{te}(y^t|\lambda^t, z^*)$ is smaller than $g^{te}(x_i|\lambda^t, z^*)$ and $f_1(y^t) \leq O_t$, store the $CF_t = F(y^t)$ in EP if there is no member of that EP dominates it, and remove all the vectors dominated by $F(y^t)$. If $f_1(x_t) > O_t$, set $CF_t = \infty$. During this process, to update the reference points z^*, if $f_{ii}(y^t)$ is smaller z_{ii}, where $ii \in (1, 2, 3)$, update the z_{ii} with $f_{ii}(y^t)$.

Algorithm 3: Update

for *it = 1, . . . , 20* **do**
    for $t = 1, \ldots, M$ **do**
        for t^{th} subproblem, randomly chose two indexes ξ and θ from k_t;
        use x_ξ and x_θ as parents to generate offspring y^t by using an one-point genetic operator;
        for *each index* $i \in k_t$ **do**
            if $g^{te}(y^t|\lambda^t, z^*) \leq g^{te}(x_i|\lambda^t, z^*)$ && $f_1(y^t) \leq O_t$ **then**
                $x_i = y^t$;
                $CF_t = F(y^t)$;
            else
                $CF_t = \infty$
            end
        for *each* $ii = 1, 2, 3$ **do**
            if $z_{ii} \geq f_{ii}(y^t)$ **then**
                $z_{ii} = f_{ii}(y^t)$
            end
        for *each* $CF_{iii} \in$ EP **do**
            while CF_t *is dominated by* CF_{iii} = *false* **do**
                add CF_t to EP;
                if CF_{iii} *is dominated by* CF_t = *true* **then**
                    delate CF_{iii} from EP;
                    end
                end
            end
        end
    end
Return EP
for *each* $iiii = [EP.Location]$ **do**
    if $f_1(\dot{x}_{iiii}) \geq O_t$ **then**
        $delete\ EP$
    end
Output EP;

7.4.3.4 Output

After 20 iterations, check whether every corresponding [*EP.Location*] fulfills the constraint stated in equation (7.7). Then output the eligible EP.

7.4.4 Optimisation Search Result

After defining all the relevant parameters and customizing the MOEA/D, in this part, the optimisation search is implemented. As an indicative example, the search result for the tunnel section between FYR and HFS is shown in Figure 7.3. At the upper part of Figure 7.3, there is a 3D figure, and all of the four PO are marked by red dots. The X-axis, Y-axis and Z-axis represent $\mathrm{M}^2_{\mathrm{max}}$, $\mathrm{M}^2_{\mathrm{mean}}$, and HD^2 respectively, i.e., $f_1(x)$, $f_2(x)$ and $f_3(x)$ in equation (7.6) respectively. As all the PO have the same value on the Z-axis, for the sake of clarity, this 3D figure is casted to a 2D one. In this 2D figure, by fitting the four PO, a solid line is drawn, that is the PF. This PF assumes an order of results which has only one objective better than the others.

The overall optimisation result is shown in Table 7.4. In this table, for each tunnel section, two PO from the Pareto set are selected to display, namely, minimized AP number preferred (when there are multiple options, chose the one with a lower mean value of outage probability) and minimized mean value of outage probability preferred. The result shows that the number of AP usage, for different preferred PO, are decreased by 21% and 13% respectively, which corresponds to a significant reduction in the overall system cost.

7.4.5 Result Accuracy Verification

To verify the accuracy of the search result, for the tunnel section between HZA to HNR, the PFs achieved by brute force search (BFS) and MOEA/D are compared. The comparison is shown in Figure 7.4, where the result departure between BFS and

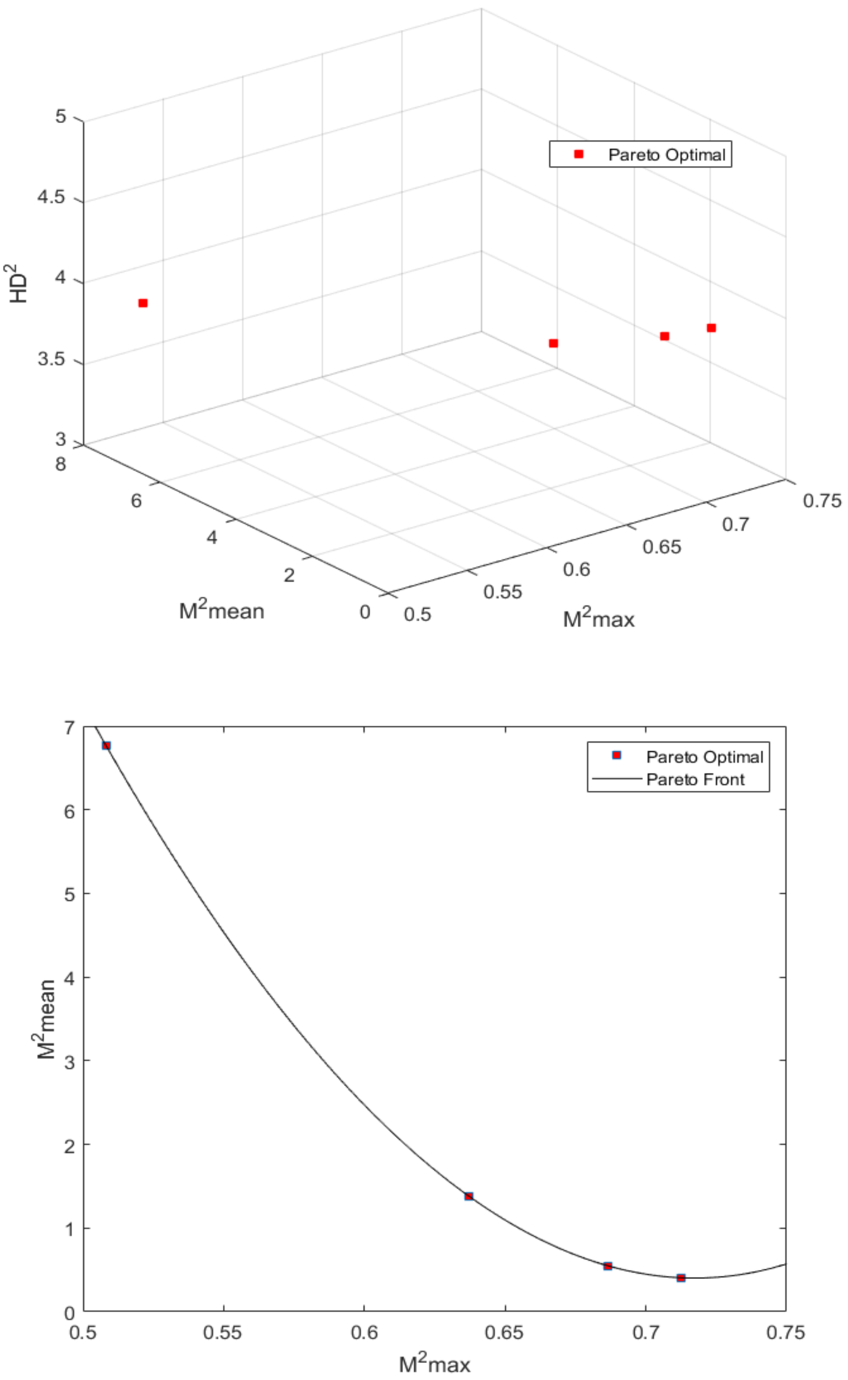


Figure 7.3: Search result for the tunnel section between Fengyang Road Station (FYR) and Hefei Station (HFS) (Author)

MOEA/D is tiny. Therefore, the accuracy of the MOEA/D is deemed to be very good indeed.

Table 7.4: The Overall Optimisation Result (Author)

Section		*Length*	*R. of cur.*	*Joints*	*Spacing*	*Pareto Optimal*		*AP No.*
From	To	(m)	(m)		(m)	Less AP used	Lower Mean Outage Prob.	Original
HZA	HNR	726	Straight	13	60	3-9	3-9	3
HNR	GYR	923	380	16	60	3-6-11	3-6-11	4
GYR	NNR	582	Straight	10	60	3-7	3-7	2
NNR	YGR	315	Straight	6	60	2-4	2-4	1
YGR	FXA	906	Straight	16	60	4-8-11	4-8-11	4
FXA	ZSR	718	Straight	13	60	5-10	5-10	4
ZSR	ZYR	849	Straight	15	60	5-8-12	5-8-12	3
ZYR	JXA	1353	Straight	24	60	3-10-12-16-24	3-10-12-16-24	5
JXA	HYA	2182	350/450	35	60	1-2-5-13-19-26-27-32-34	1-2-5-13-19-27-28-30-31-33	10
HYA	DLR	856	Straight	15	60	7-10	7-10	4
DLR	FHA	795	Straight	14	60	5-8	5-8	3
FHA	GTS	633	350	14	60	1-4-14	2-4-7-11	3
GTS	WHC	466	350	9	60	3-5	3-5	2
WHC	GDD	1428	350/450	25	60	2-12-15-20-22	2-3-5-6-8-12-16-22-25	8
GDD	SYJ	799	Straight	14	60	5-12	5-12	3
SYJ	THR	476	Straight	9	60	4-7	4-7	3
THR	NYH	1449	Straight	25	60	7-13-16-18-20	7-13-16-18-20	6
NYH	WHR	877	Straight	16	60	5-11-15	5-11-15	3
WHR	DDM	739	300	13	60	4-7-9	3-5-7-9	3
DDM	MGR	524	Straight	10	60	4-7	4-7	3
MGR	FYR	551	Straight	10	60	4-7	4-7	2
FYR	HFS	558	Straight	10	60	4-7	4-7	3
						66 (-21%)	73 (-13%)	84

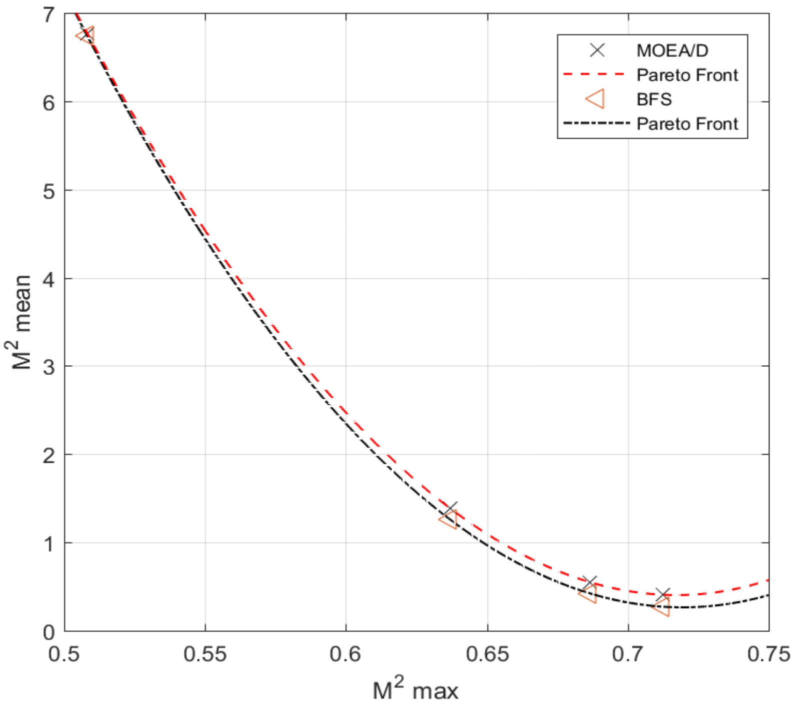


Figure 7.4: The search result comparison between the BFS and the MOEA/D (Author)

7.5 Result Simulation and Evaluation

To prove that the optimised AP deployments have a better performance than the original planned layout, the optimised and original AP deployments are simulated between DDM and FYR, and the simulation results are compared. The AP locations of the optimised AP deployment and the original AP deployment are specified in Table 7.5, and graphicly shown in Figure 7.5.

Table 7.5: The Optimised and Original AP Deployment Between DDM and FYR (Author)

	DDM-MGR			MGR-FYR	
Original	K6+822	K6+662	K6+482	K6+008	K5+758
Optimised	K6+784	K6+604		K5+999	K5+640

(a) The original AP deployment with 8 APs (b) The optimised AP deployment with 7 APs

Figure 7.5: The AP deployment layout in OMNeT++ (Author)

To evaluate these two AP layouts, simulations have been carried out on the integrated simulation platform, which has been introduced in chapter 4. In the simulations, DCS performance of the optimised and original AP deployments are tested in a realistic physical environment. A screenshot of the simulation is shown in Figure 7.6. In this figure, the interface of OMNeT++ is shown in the right part, where the propagation environment is configured based on the parameters specified in Table 7.3, APs are deployed along the track based on the AP locations specified in Table 7.5; the interface of the railway network simulator is shown in the left part, where the railway traffic is scheduled. The train departs from DDM station, via MGR station, and arrives at FYR station, with a top speed at 50 km/h and no deceleration in MGR station. The whole journey is 112 seconds.

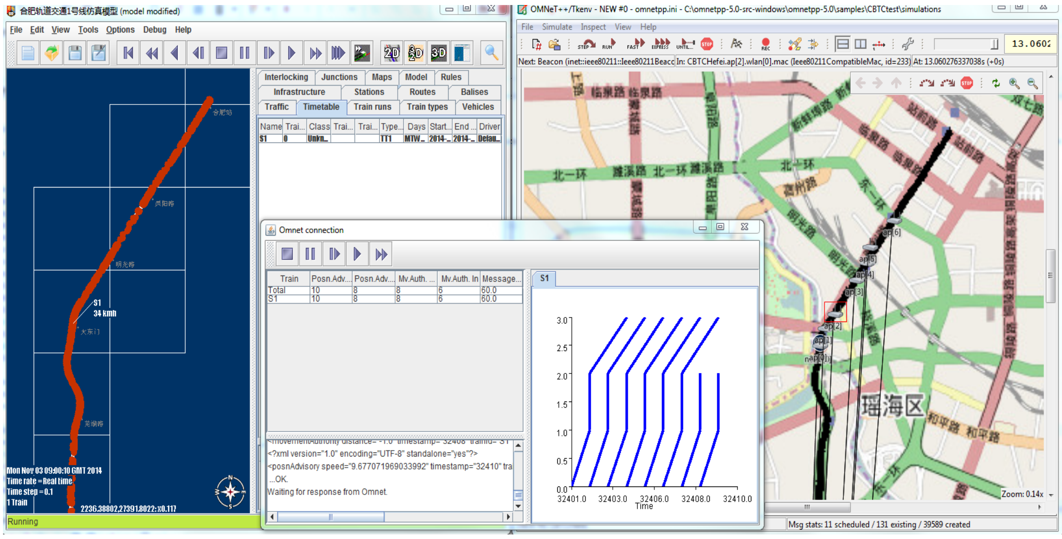


Figure 7.6: The screenshot of the simulation (Author)

During the simulation, the railway network simulator updates the train location with the communication network simulator every 0.1 second, as a result, the train movement is generated in the OMNeT++. Every 0.1 second, a packet will be transmitted from the train to the associated AP. To be realistic, during the packet propagation, path-loss, interference and shadow fading are accounted and generate negative impacts on the packet reception, therefore, when the packet quality is lower the DCS requirements, dropout happens. The simulation result is summarized in Table 7.6, where shows the optimised AP deployment achieved a greater mean and minimum signal-to-interference-plus-noise ratio (SNIR), a smaller mean and maximum bit error rate (BER), and a better packet error rate (PER), with a reduced AP number. Therefore, a conclusion is drawn that the optimised AP deployment is better than the original planned AP layout.

Table 7.6: The Simulation Result (Author)

	AP	Counts	mean:SNIR	min:SNIR	mean:BER	max:BER	PER
Optimised	7	7977	6.09×10^{10}	10.01	2.43×10^{-5}	1.9×10^{-1}	1.25×10^{-4}
Original	8	9086	2.94×10^{10}	0.46	8.49×10^{-5}	4.3×10^{-1}	2.20×10^{-4}

7.6 Summary

In this chapter, by customizing and adopting MOEA/D, an accurate and more efficient search algorithm, a real-world ADP was implemented for the HML-I, optimised AP deployments were generated for the 22 tunnel sections in HML-I. To evaluate the optimisation result, simulations were conducted for the sections between DDM station and FYR station on an integrated simulation platform, the DCS performance of both the original AP planned layout and optimised AP deployment were well tested. The simulation result shows that the optimised AP deployment has a better data transmission quality than the original planned AP layout with a reduced AP usage.

Chapter 8

Conclusions and Future Work

8.1 Conclusions

In radio-based train control systems, e.g., Communication-based Train Control (CBTC) systems, European Train Control Systems (ETCS) and Chinese Train Control Systems (CTCS), the deployment of the data communication systems (DCS) is not only vital for a reliable system performance, but significant to the system cost. To improve the DCS reliability and simultaneously reduce the system cost, a systematic strategy for planning the access point (AP) deployment in DCS has been presented in this thesis. By utilising the proposed strategy, AP deployment planning (ADP) problems were formulated and solved in a tunnel-based section and a real-world metro system respectively. The presented ADP optimisation strategy consists of adaptive problem formulations and dedicated search algorithms.

In order to have a simulation platform to carry out the performance evaluation of the AP deployments, a test platform was developed by integrating with the railway traffic simulator, which has been developed by the Birmingham Centre for Railway Research and Education (BCRRE) at the University of Birmingham, and the communication network simulator used in this thesis, which is known as OMNeT++. In this platform, all the wireless communications generated in the train control system need to go through the physical environment created by OMNeT++ to suffer negative impacts, which makes the evaluation of the AP deployments realistic.

Then, to have a better understanding of how to optimise the AP deployment in small-scale metro systems, mathematical programming and weighted factors are presented to formulate the ADP optimisation problem. With consideration of the low computational demand and low environmental complexity in this proposed problem, brute force search (BFS) was adopted to solve the optimisation problem by implementing exhaustive search. To investigate the methodology application, a case study with a tunnel-based section environment was conducted. All the feasible AP deployments in this case study are tested on the integrated simulation platform, and the test result shows that the addressed optimal AP deployment has the best performance for minimised required AP, which proves that this optimisation strategy is a competent tool for planning the AP deployment in section areas.

However, as BFS has a low efficiency in dealing with high computation demand problems, to optimise the ADP in a real-world metro systems, a methodology application for the large-scale ADP problems is presented. With the consideration of different optimisation demands, the ADP problem is formulated through using multi-objective programming (MOP). By referring and customising the multi-objective evolutionary algorithm based on decomposition (MOEA/D), an accurate and more efficient algorithm is derived without arbitrarily adding any prior optimisation preference, which makes the optimisation result provide sufficient well-spread AP deployments which can be selected. A case study was undertaken for the Hefei metro line-I (HML-I) in China, where the number of APs was significantly reduced from the original AP deployment, whilst also ensuring that a better system performance is achieved by the DCS with the optimised AP deployment.

8.2 Future Work

The work in this thesis has focussed on formulating and solving ADP optimisation problems in DCS of CBTC systems in tunnel sections and in real-world metro system environment. In the future, the author intends to extend the work as follows:

1. It is worthwhile extending the ADP optimisation methodology to solve AP planning issues under more complex environments. In this thesis, due to the difficulties in predicting signal propagation behaviors, the ADP optimisation is not applied to stations. To fill this gap, accurate propagation models dedicated to station areas will be addressed, which will be accounted to a series of on-site measurement campaigns.

2. The ADP optimisation methodology should be extended to plan the DCS deployment in radio-based mainline railway control systems (e.g., ETCS and CTCS). In mainline railways, there are a number of different environments, including urban, suburban, rural, viaduct, cutting and mountain, which are not involved in tunnel-based metro systems. To precisely optimise the AP deployment in DCS in mainline railways, these featured environments will be carefully accounted for in the strategy.

3. More objectives should be considered in problem formulations. The DCS is a complex system that consists of many different functional components, therefore, there could be different ideas about what a good DCS should be like (e.g. safety, reliability, capacity and system cost). To address these diverse ideas, more objectives must be considered in the ADP optimisation. Meanwhile, it is also worth investigating the relationships between these objectives and quantifying their impacts, which could give a clearer understanding of the ADP in DCS and help to formulate the optimisation problem in a better way.

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