MARKET-ORIENTED MICRO VIRTUAL POWER PROSUMERS OPERATIONS IN DISTRIBUTION SYSTEM OPERATOR FRAMEWORK

by

HAO FU

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

Department of Electronic, Electrical
and Systems Engineering
School of Engineering
University of Birmingham
June 2017

To my parents and supervisor

ABSTRACT

As the European Union is on track to meet its 2020 energy targets on raising the share of renewable energy and increasing the efficiency in the energy consumption, considerable attention has been given to the integration of distributed energy resources (DERs) into the restructured distribution system. This thesis proposes market-oriented operations of micro virtual power prosumers (μVPPs) in the distribution system operator framework, in which the μVPPs evolve from home-oriented energy management systems to price-taking prosumers and to price-making prosumers. Considering the diversity of the DERs installed in the residential sector, a configurable μVPP is proposed first to deliver multiple energy services using a fuzzy logic-based generic algorithm. By responding to the retail price dynamics and applying load control, the μVPP achieves considerable electricity bill savings, active utilisation of energy storage system and fast return on investment. As the μVPPs enter the distribution system market, they are modelled as price-takers in a two-settlement market first and a chance-constrained formulation is proposed to derive the bidding strategies. The obtained strategy demonstrates its ability to bring the μVPP maximum profit based on different composition of DERs and to maintain adequate supply capacity to meet the demand considering the volatile renewable generation and load forecast. Given the non-cooperative nature of the actual market, the μVPPs are transformed into price-makers and their market behaviours are studied in the context of electricity market equilibrium models. The resulted equilibrium problems with equilibrium constraints (EPEC) are

presented and solved using a novel application of coevolutionary approach. Compared with the roles of home-oriented energy management systems and price-taking prosumers, the μVPPs as price-making prosumers have an improved utilisation rate of the installed DER capacity and a guaranteed profit from participating in the distribution system market.

ACKNOWLEDGEMENT

First and foremost, I am most grateful for the continuous guidance, support and encouragement of my supervisor, Prof. Xiao-Ping Zhang. As an old Chinese saying goes: "Give a man a fish and you feed him for a day, teach a man to fish and you feed him for a lifetime". Indeed, Prof. Zhang's passion, patience and immense knowledge not only guide me through my PhD study but also shape me into someone I have always determined to become. My shepherd guides me, teaches me, through my pilgrimage to today's research milestone, with many yet to come.

I am grateful to my parents, Mr. Hanyi Fu and Mrs. Huiqin Jing. Their love and support fuel me through six years of study in the University of Birmingham.

I would like to thank Dr. Pietro Tricoli, Mr. Phil Atkins, Prof. Martin Russel, Dr. Edward Tarte, Dr. Steven Quigley and the late Prof. Mietek Brdys, for their professional guidance during my time in Birmingham. Also, I express my gratitude to the staff of the department of EESE.

A special gratitude goes out to Dr. Joachim Brandt of E. ON UK.

And finally, to everyone in my research group, especially for the guidance of Dr. Suyang Zhou, Dr. Zhi Wu, Dr. Ying Xue and Dr. Jianing Li. It was great working with all of you during my PhD study.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

RES	Renewable Energy Source
DER	Distributed Energy Resource
μVPP	Micro Virtual Power Prosumer
MG	Microgrid
VPP	Virtual Power Plant
LSE	Load Serving Entity
DG	Dispatchable Generator
ESS	Energy Storage System
DR	Demand Response
EMS	Energy Management System
HEMS	Home Energy Management System
ICT	Information and Communications Technology
IOT	Internet of Things
CL	Controllable Load
CPU	Central Processing Unit
EPC	Embedded Personal Computer
WHAN	Wireless-based Home Area Network
SOC	State-of-Charge
NETA	New Electricity Trading Arrangements

FIT	Feed-In Tariff
MO	Market Operator
TSO	Transmission System Operator
ISO	Independent System Operator
DNO	Distribution Network Operator
DSO	Distribution System Operator
DA	Day-ahead
RT	Real-time
ADS	Active Distribution System
DSM	Distribution System Market
PDSM	Passive Distribution System Market
ADSM	Active Distribution System Market
OPF	Optimal Power Flow
MCP	Market Clearing Price
PAR	Peak-to-Average Ratio
ROI	Return on Investment
LOLP	Loss of Load Probability
MILP	Mixed-Integer Linear Programming
SFE	Supply Function Equilibrium
MPEC	Mathematical Program with Equilibrium Constraints
EPEC	Equilibrium Problem with Equilibrium Constraints

FLC	Fuzzy Logic Control
MF	Membership Function
CR	Continuous Relaxation
CVaR	Conditional Value at Risk
NE	Nash Equilibrium
KKT	Karush-Kuhn-Tucker
GA	Genetic Algorithm
UL	Upper-Level
LL	Lower-Level

CHAPTER 1 INTRODUCTION

1.1 Background and Motivation

1.1.1 Clean and Affordable Electricity Delivered in Distributed Pathways

The 2020 climate and energy package, enacted in legislation in 2009 by European Commission, aims at achieving three key targets: a 20% reduction in greenhouse gas emissions, a 20% share of renewable energy sources (RES) in energy consumption and a 20% reduction in energy consumption [1]. As one of the leaders in promoting decarbonisation in the energy industry, the UK shoulders a heavier responsibility to deliver 30% renewable electricity, 12% renewable heat and 10% renewable transportation by 2020 [2]. Since then the EU has been on track to meet each of its key targets and especially it has made substantial progress in cutting emissions. The share of RES in gross energy consumption and the reduction of energy consumption, on the other hand, stood at 16% and only 11%, respectively, in 2014 [3]. As we approach 2020, the data and estimations reported by the EU Member States indicate that the trajectories to meet the RES target and consumption reduction target become steeper. In the UK, the progress summarised in 2015 showed the country is three-quarters of the way towards its 30% electricity sub-target. However, the biggest challenge remained in decarbonising the heat and transportation sector, with the share of renewables stood at only 5.64% and 4.23%, respectively [4]. While the EU should hasten its pace to be on schedule, it is crucial that the affordability is not overlooked.

Massive deployment of costly renewable projects is not the solution to boost its share in the energy mix [3]. Also, it is not preferable to sacrifice the comfort of consumers just to lower the level of energy consumption. The successful completion of the 2020 package is not marked by achieving a fixed improvement percentage but by establishing a cost-effective pathway towards a clean, affordable and sustainable energy future.

More pronounced decrease in energy consumption was found in conserving the fossil fuels rather than electricity. From 1990 to 2014, the largest reduction in energy consumption was recorded for transport via inland waterways, rails and aviation, which resulted from the advances of fuel-efficiency technologies [5]. Electricity consumption, on the other hand, rose in most of the EU Member States during the 10-year period from 2004 to 2014 [6]. Among the three dominant sectors of electricity consumption, residential consumers stand at the third place with a large share of 24.8% and it follows the consumption of industry (25.9%) closely [5]. Although the growing electrification of heating and cars in the residential sector has gradually substituted fuel-powered appliances, its savings of fossil resources could be largely offset by the consequent rising demand in electricity. As for the target of raising RES penetration level, the investment in residential sector is also less intensive. The data reported in 2015 has again showed that renewable electricity generation continues to be dominated by megawatt-scale generators that are owned by utilities and large investors [7]. In the UK, Scotland accounted for 34% of the country's wind power output in 2015 and 96% of the capacity came from large onshore wind sites such as the Whitelee 539MW wind plant [8]. The market of installing distributed, small-scale RES has just taken off, or is starting to exploit the territory of residential sector. Faced with rapid electrification of residential appliances and a schedule too tight for large-scale RES installation, it is a priority for EU to improve the efficiency of electricity consumption and to direct more investment into residential RES deployment.

Residential RES is part of a wider resource category called distributed energy resources (DERs) shown in Fig. 1. DERs refer to small- to medium-scale (10 megawatts or less) energy resources that are connected to the low voltage distribution grids and located near the end-consumers. Four key categories of resources constitute DERs:

- Dispatchable generators (DGs): power generators connected to distribution grids that can be dispatched at the request of grid operators or the owner of the generators. Typical DGs include cogeneration units, biomass plants and fuel cells.

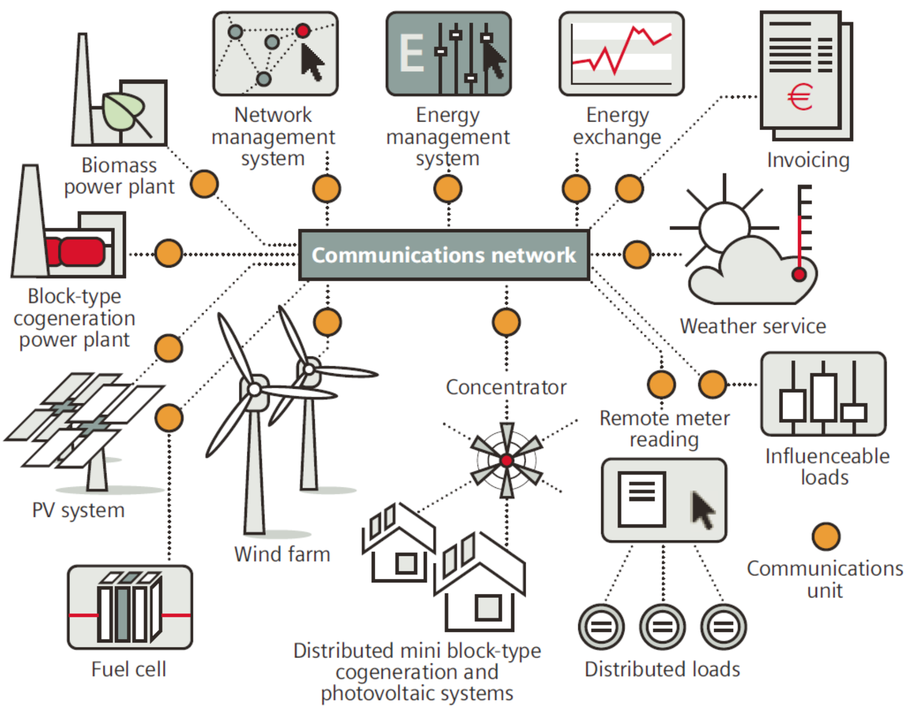


Fig. 1 A distributed energy resources paradigm [9]

- Distributed RES: In contrast to dispatchable generation, distributed RES is a group of non-dispatchable generation technologies collected from fluctuating resources such as sunlight, wind, waves and geothermal heat. Typical distributed RES systems include small-scale photovoltaic systems and small-scale wind farms.
- Energy storage systems (ESS): ESS are a collection of technologies used to store electrical energy and release at a later point of time. Typical ESS include batteries and flywheels.
- Demand response (DR): DR programs are the changes in the electric consumption of end-users to provide upward regulation or downward regulation at the grid connection point, which can be viewed as a source of distributed energy. Compared with DGs and distributed RES, DR seeks to adjust the demand to create energy headroom instead of adjusting the supply. Typical DR programs involve active switching of controllable loads (or influenceable loads) and load shedding during peak demand period.

To better exploit the potentials of DERs, the following updates should go hand in hand with the deployment of DER assets: an updated communication network capable of linking DERs with their decentralised control systems, which provides bi-directional pathways for weather-related generation/demand forecast, smart meter reading and real-time control signal; an updated paradigm of energy management systems (EMS) that is compatible to customisable portfolio of DER infrastructure, which improves energy efficiency and brings economic benefits through monitoring, control and optimisation; an updated market framework at distribution level that facilitates energy exchange among DER aggregators, mitigates network challenges and offers better billing and invoicing services to end-consumers.

The complete solution described above aims at integrating DERs rather than simply connecting them to the system. Faced with an increasing demand level, distribution network operators (DNOs) now have the alternative option of DER deployment instead of costly grid reinforcement. In addition to the increased headroom at the grid connection points, DERs also provide flexibility at both system level and local level. At system level, the DER flexibility can be utilised for balancing services, congestion management and meeting the system adequacy requirements. For instance, Germany has started a monthly auction from June 2013 to procure up to 3000MW of balancing reserves from flexible DR programs [10]. At local level, DER flexibility can be used by end-consumers to optimise their generation and consumption profiles thus improving the ability to meet their peak demand for electricity while reducing electricity bills. For instance, ESS are usually installed together with distributed RES to smooth out the intermittent output of the RES. Excess renewable generation during valley demand period could be stored and used later at peak demand times. Then the net load required by end-consumers becomes predictable and flat, reducing the electricity procurement during peak demand period which is often a period of high electricity prices. Based on the ESS market data collected from 2011 to 2017 in Germany, the number of battery-based ESS in 2020 is anticipated to triple its scale in 2016 as Fig. 2 shows. The share of ESS on solar photovoltaic systems will rise dramatically from 33% to 90% through including ESS in new PV installations or in the retrofit of exiting PV systems.

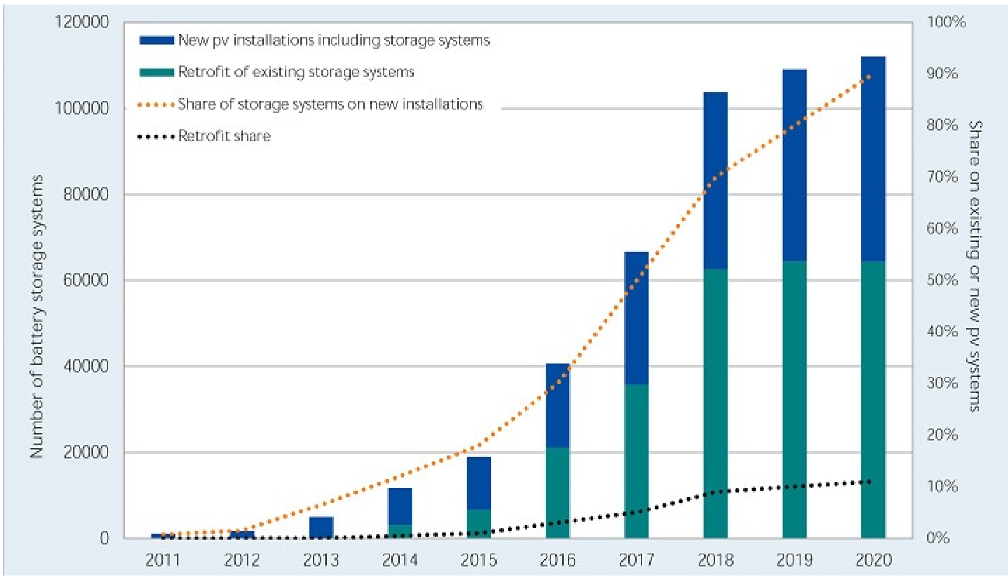


Fig. 2 Market growth of energy storage systems in Germany [11]

1.1.2 Opportunities and Challenges in DER Solutions

The DER solutions, despite their inherent advantages of being near to the consumption, have also encountered challenges towards massive deployment. First and foremost, the lack of estimation tools makes it difficult for investors to decide the installed capacity of DERs. The impact of irrational decisions on capacity is less severe for RES such as solar PV systems and micro wind turbines, their weather-dependent properties help provide information for installation and they can always export the overproduction back to the utility grid at feed-in tariff (FIT). However, the charging and discharging behaviours of ESS depend entirely on the control paradigms and consequently ESS would suffer the most from irrational decisions on installed capacity. Oversized ESS lead to low utilisation of the rated capacity and inflict tremendous waste of the investment; undersized ESS are charged and discharged too often and therefore they would reach their specified cycle lifetime prematurely. The second barrier is the negative impact on electricity networks brought by high penetration level of distributed RES. The intermittent nature of residential renewable generation can potentially compromise system reliability by inflicting balancing challenges in distribution network [12]. Also, the consequent cost of voltage and frequency control in the presence of volatile RES may overshadow the savings from capacity release [13]. Faced with high upfront costs, there is an urgent need to develop cost-competitive, low-risk and stable-return business models for the deployment of DERs. For instance, the promotion of DR programs has encountered obstacles due to expensive initial costs and customers' reluctance to reduce convenience. Surveys conducted in the UK have shown insufficient incentives for consumers to accept automation in home energy management, the unwillingness grows even stronger among low income and vulnerable consumers [14]. Additional challenges exist in reforming the current public interventions and effectively designing new ones for renewable energy subsidy schemes. Low level of FIT does not generate enough revenue for RES investors to reach break-even point. On the other hand, overcompensation in some subsidy schemes does not necessarily result in strong market growth because eventually the compensation costs are passed on to the end-consumers. As the RES technologies mature, the driving forces of the investment should shift gradually from guaranteed compensation levels determined by public authorities to the market prices [15]. The European Commission underlined the need to adjust public intervention to include DERs in the electricity market operation, stimulate self-sustainable business patterns, diminish the cost of support and ultimately end support.

Despite the challenges stated above, DERs are still regarded as promising candidates to be of significant aid in the restructured electricity systems. Their negative impacts can be mitigated and their potentials can be better exploited in aggregated approaches such as microgrids (MGs) and virtual power plants (VPPs). The concept of MG is first proposed by the consortium for electric reliability technology solutions (CERTS) in 1999. MG is defined as an electricity distribution system containing loads and DERs that can be operated in a controlled, coordinated way either while connected to the main power network or while islanded [16]. The most distinguishing feature of MG is its ability to transfer smoothly from grid-connected mode to stand-alone mode (islanded mode). Intuitively the DERs inside MG have enough capacity to support the local loads without importing any electricity from main grid. Unintentional islanding can occur when the main grid encounters faults or other unscheduled events. On the other hand, the islanding can also be intentionally executed due to network maintenance, power quality degradation in main grid or economic concerns. By reducing the dependence on the main grid, improved resiliency has been achieved which is recognised as the major perceived benefit of MGs. VPP is defined as a flexible representation of a portfolio of DERs. There are three unique characteristics that distinguish VPP from MG: firstly, the diversity of DERs aggregated by VPP lies not only in their different parameters but also in their different geographic locations. VPP creates a single operating profile from a composite of diverse DERs while incorporating the impact of the network constraints [17]. Secondly, VPP facilitates the trading of DER production in various energy markets and it offers a wider range of services to system operators. The ability to aggregate DERs in various locations makes it possible for VPP to enter either electricity wholesale market or retail market. Higher revenue can be generated from contracting DERs' output and offering services such as balancing services and ancillary services. Finally, VPP solution relies heavily on the information and communications technology (ICT) to deal with huge volumes of DER information and market data. It is safe to conclude that VPP's software infrastructure gives birth to its ability to allow any types of DERs from anywhere to trade energy in the open markets. VPP concept represents an internet of energy, tapping the existing grid networks to tailor electricity services to producers, consumers and system operators.

Many MG and VPP projects have been launched and successfully implemented in the European countries. In Portugal, a black start mechanism was designed specifically for microgrids to cope with blackouts. The project delivered a novel MG control and communication system that can achieve fast restart of low voltage networks with regulated voltage and frequency [18]. In Greece, the "More Microgrids" project proposed the standardisation of technical and commercial protocols for MG and investigated the integration of multi-microgrids [19]. The FENIX project – Flexible Electricity Networks to Integrate the expected energy evolution, has launched two large field deployments across UK and Spain to investigate the real-life implementation of VPP concept [20]. The project addressed the importance of a layered communication and control solution, as it should be able to deal with a comprehensive set of network use cases including normal and abnormal operations. Detailed analysis of the current UK and Spain markets was also conducted to demonstrate how the economics of wide-scale application of the VPP concepts into these markets would work out. At this point of DER integration, the authorities have come to realise the previous "fit and forget" approach has started to burden the electric power system with large enhancement costs and in turn impact the deployment rates of DERs adversely. The MG and VPP solutions counteract this problem by aggregating numerous and unmanaged DERs into a single and manageable profile that has similar characteristics to transmission connected generation. Then the aggregated DERs will gradually shoulder the same level of responsibilities of large conventional power plants and as a result, their flexibility could be exploited in a more secured way [21]. However, there still exist some urgent questions that need to be answered.

Firstly, stronger incentives should be given to investors to procure DERs in the first place. On the one hand, innovations in the manufacture of DERs lead to the continuous decrease of upfront cost. The cost of residential PV systems is expected to decline 55% in 2020 compared with historical price in 2010 and in 2030 the upfront cost will be only 30% of the cost in 2010 [22]. Also, the current high initial investment for ESS is predicted to drop 20-30% annually and reaches a commercial/utility level at 2020 [23]. On the other hand, there is a lack of strong business cases to guarantee reasonable return on investment (ROI) and it is still unclear to investors what is the impact of different DER/RES on penetration levels. Secondly, the economic rationale should be explained when determining the role of aggregated DERs – intuitively MG solution is suitable for remote areas without reliable access to the main grid, but in urban areas it might bring more benefit to stretch the flexibility of DERs to act like VPPs. Compared with utility-scale DER owners, small residential investors are more vulnerable to the risks brought by ill-advised investment decisions. Hence, the research of DER solutions at this stage should dedicate its effort to develop technically sound control paradigms, restructure the current electricity systems, facilitate market evolution and build sustainable business models.

1.1.3 Motivation

Back in 2001 when UK reformed its electricity market by introducing New Electricity Trading Arrangements (NETA), domestic consumers were encouraged to claim their savings by switching electricity supplier [24]. In 2016 there were already 4 million electricity consumers who switched their suppliers and received up to £200 savings on their electricity bills [25]. The valuable lesson from market reform also applies to the deployment of DER solutions, it is all about delivering what has been promised to consumers, stakeholders and system operators – reliable power supply, fast tracts to recoup the investment and restructured market frameworks to generate more value streams.

The small-scale capacity of DERs and intermittency of RES make MGs/VPPs more vulnerable to shortage risks due to volatility in market prices, demand and generation compared with macrogrid. Therefore, it is critical to guarantee the reliability of power supply for MGs/VPPs, not from purchasing the balancing power from expensive spot market, but by dispatching their DER assets optimally and tapping into the flexibility of nearby MGs/VPPs. Risk hedging techniques should be incorporated into the energy management strategies to counter the risks brought by uncertainties. Secondly, the variety of DERs provides the opportunity to mix different categories of resources and measure how far these assets can be stretched to create value for both investors and customers. Beside significant reduction on electricity bills, extra revenue is expected from participating in the restructured electricity markets which welcome MGs and VPPs as new entries.

1.2 Research Focuses, Objectives and Contributions

1.2.1 Research Focuses

Considering the small-scale DER generation capacity and the residential level demand, this thesis proposes the concept of micro virtual power prosumer (μVPP) to include MGs and VPPs that are connected to the restructured distribution system. μVPP is defined as an extension to the MG concept and the DERs located within the μVPP have a capacity that can either cover part of the load or generate excess electricity to be consumed by other μVPPs. μVPP is considered as the fundamental building blocks of the MGs and VPPs and it has the following flexibilities: firstly, the DER capacity is not strictly required to satisfy the peak demand. μVPP can operate full-time in grid-connected mode and the ability to operate in islanded mode remains optional. The flexibility in μVPPs' DER configuration provides the opportunity to investigate the impact brought by different levels of DER penetration and RES penetration. Secondly, μVPP has all the necessary ICT interfaces ready for entering the local energy-reserve markets, the flexibility to switch from a passive consumer to an active market participant helps establish the optimal business model for μVPP owners. By investigating the transformation of μVPPs' role in the distribution system, the benefits to system operators and end-consumers are also identified.

This thesis takes a structured approach to present different layers of the μVPP integration, depicting the evolution towards market-oriented μVPPs in the distribution system. The design of a distribution system operator framework also goes hand in hand with the evolution of μVPPs, providing a hospitable market environment for the μVPPs to take root and blossom. The main research focal points are summarised as follows:

Firstly, the control and optimisation paradigm of a configurable μVPP is studied in the context of providing managed energy services. The research is based on an exemplar μVPP designed, manufactured and deployed in Sweden by the joint endeavours of the University of Birmingham, E. ON UK and E. ON Sweden. The μVPP is equipped with solar PV systems, controllable loads (CLs), a scalable ESS and other critical household appliances, representing a typical residential community with a mix of DERs. The research focuses on designing a home energy management system (HEMS) to coordinate the interworking of various DER assets, establishing multiple energy services based on the different combinations of DERs and creating persuasive business cases that explain the economic rationale behind the selection of energy services. To facilitate the complex decision-making and satisfy the requirement for real-time control, this thesis firstly concentrates on developing a generic μVPP algorithm that accommodates all energy services and can be easily configured to achieve different optimisation goals. The metaheuristic control method – fuzzy logic control (FLC) is of interest to the first section because of its fast response, computational efficiency and compatibility for μVPP of any scale.

Secondly, the thesis considers the possibility of the μVPP to enter the distribution level energy-reserve market and studies its behaviours as a market participant. With the high penetration level of intermittent RES and the small-scale generation capacity, the μVPP could be easily exposed to shortage risks brought by volatile market prices, demand and

RES outputs. Therefore, the second focal point of the thesis is to derive the strategic proposition for a μVPP in terms of optimally dispatching its resources, mitigating the risks and maximising profits. A two-stage settlement market model and a stochastic, mixed-integer linear programming (MILP) formulation are used to capture the stochastic nature of the μVPP energy profile. The thesis then progresses to solve the following problems: how to achieve a good-quality approximation of uncertain generation, demand and prices without inflicting heavy computational burden; what is the method of choice to hedge against the risks under the two-stage stochastic modelling framework; what are the impacts brought by different penetration levels of DERs and RES and how will the rivals' strategies affect the market behaviours.

Thirdly, the role of μVPP is further evolved to an active price-making prosumer compared with the price-taker model used in the second part of the research. A novel active distribution system market is proposed where μVPPs compete with the traditional retailers in an oligopolistic environment. This section concentrates on building the market equilibrium model and incorporating the optimality of market clearing process into the optimisation of μVPPs' individual profits. The third focal point is to accurately model the multi-leader-follower games in the proposed market structure, develop efficient algorithm to obtain good-quality equilibrium solution and address the impact of different market frameworks. When designing the algorithm to solve the equilibrium model, a coevolutionary method is of interest to this section.

1.2.2 Objectives

Following the research focuses mentioned above, this thesis aims at achieving the following objectives:

1. The first objective of the thesis is to present a pre-commercial µVPP with configurable and managed energy services. The proposed HEMS should be able to monitor and control various DERs on site and switch smoothly between different operation modes. These operation modes correspond to various optimisation goals such as maximising self-consumption, responding to price dynamics and applying load control, which are summarised and categorised as different energy services. The managed energy services are designed to bring reductions to the end-consumers' electricity bills and generate revenue streams to µVPP owners. Considering the difference in µVPPs' DER mix (i.e. µVPP can be characterised by the different types of DERs it owns) and the potential upscaling of DERs, the multiple energy services should be hosted in a generalised architecture and the switch between them should be achieved easily without any re-engineering in the code.

2. The second objective of the thesis is to derive the bidding strategy of a price-taking µVPP when participating in a distribution level energy-reserve market. A chance-constrained two-stage stochastic formulation is proposed to maximise µVPP's profit and guarantee the security of supply by controlling the loss of load probability (LOLP). In addition, this section aims at investigating the impact on the

μVPP's bidding behaviours and profits brought by different penetration levels of DERs and RES, different uncertainty levels, the competition between rivals and the implementation of carbon tax policy.

3. The third objective of the thesis is to present the equilibrium model of an active distribution system market where price-making μVPPs compete in a non-cooperative game, then a coevolutionary approach is proposed to derive the pure strategy Nash Equilibrium (NE) of the market operation. The maximisation of μVPPs' individual profits is modelled as upper-level problems and the maximisation of the social welfare in the market clearing process is formulated as the lower-level problem. The proposed bilevel problem and the coevolutionary solution aim at considering the upper-level optimality and lower-level optimality simultaneously. The pure strategy NE obtained should demonstrate Pareto optimality, that is, no single μVPP can obtain a higher margin by deviating unilaterally from its pure strategy NE profile without decreasing the social welfare of the market. In addition, μVPPs' performances under different market structures should be compared and the economic rationale behind the selection of an active distribution system market should be explained.

To sum up, the first objective of the thesis is to design and implement a home-oriented μVPP that facilitates multiple energy services in a generic algorithmic architecture. End-consumers can receive significant savings on their electricity bills while the investors can benefit from fast return on investment. The second objective is to derive bidding strategy for the μVPP to make profit when it enters the distribution system market as price-takers. The ability to meet the peak demand considering uncertainties in the operations can be guaranteed by controlling the loss of load. The third objective is to model an active distribution system market where multiple μVPPs compete as price-makers, and to solve the market equilibrium model using coevolutionary approach. The proposed market setup and the obtained bidding strategy should provide the μVPPs with guaranteed profit.

1.2.3 Contributions

The contributions of the thesis are threefold based on the research focuses and they are summarised as follows:

Firstly, the thesis presents a configurable μVPP with managed energy services and the contributions are identified as:

- The μVPP has gone through design, hardware/software construction, installation and finally it has been commissioned in an actual residential community, which would be a good reference for future industry developments on the subject.
- The multiple energy services provided by the μVPP demonstrate various levels of energy and money savings from maximising the self-consumption, responding to price dynamics and applying load control, addressing the need to choose the right service to achieve higher asset utilisation and higher return on investment.
- The detailed business model seizes the opportunity of declining ESS capital cost in recent years and proves the feasibility of massive market promotion of the proposed μVPP.

Secondly, the thesis derives the bidding strategy of a μVPP from a chance-constrained two-stage stochastic formulation. The contributions are identified as:

- μVPP is established as an active contributor of a distribution level energy-reserve pool. The value stream is described elaborately to justify the motivation of the μVPP.
- To reduce the computational burden, a three-dimensional forward selection algorithm is

applied to reduce the number of RES generation and load scenarios. The obtained scenario subset is an accurate approximation of the initial data sample while reducing the computation time considerably.

- Compared with the classical Monte Carlo recourse method, the proposed chance-constrained formulation produces a less conservative bidding strategy which leads to higher profit and controls the load loss under expected level.
- The system formulation could be used to assess the impact brought by reducing forecast errors, relaxing loss of load tolerance and implementing carbon tax. The thesis argues that the additional profit brought by relaxing the LOLP is only significant for the μVPPs with large share of dispatchable generators, while more accurate load forecast is beneficial to all μVPPs with different DER capacity allocations.

Thirdly, the thesis presents a novel active distribution system market framework that facilitates the trading among μVPPs in the energy and reserve markets. The market equilibrium problem is formulated as bilevel equilibrium problems with equilibrium constraints (EPEC) where the upper-level problem aims at maximising each μVPP's profit and the lower-level problem aims at maximising the social welfare in the market clearing stage. A novel coevolutionary approach is proposed in the thesis to find the pure strategy NE of the market. The main contributions are identified as follows:

- An active distribution system market framework is established to better utilise the emerging μVPPs. The potential of their DERs are optimally exploited to contribute to the energy-reserve equilibrium at retail level.

- The joint operation of the energy and reserve markets is formulated as bilevel EPEC combining the optimality conditions of all upper-level problems. Also, the dual role of μVPP as either "producer" or "consumer" and their heterogeneous DER assets are addressed.
- To the best of the author's knowledge, it is the first attempt to utilise coevolutionary approach to derive pure strategy NE in an active distribution system market. Compared with conventional methods, the proposed coevolutionary approach demonstrates its effectiveness when handling nonlinear market model and renders pure strategy NE under strict convergence criteria.
- The thesis argues that an active distribution system market structure is more beneficial to the μVPPs as the price-maker position leads to better utilisation of DERs and higher profit compared with that of pure MG. In addition, the price-maker role can guarantee the projected profit to be delivered as expected.

1.3 Thesis Outlines

The rest of the thesis is organised based on the research focuses and the content of each chapter is summarised as follows:

Chapter 2: a literature review is carried out to identify and evaluate the available literature in the subject area of the research focuses. This chapter summarises prior research efforts and establishes the links between them and the proposed study. Also, the gaps in current knowledge are identified to address the contributions of the thesis.

Chapter 3: A configurable µVPP with managed energy services is presented in this chapter. The system infrastructure of the µVPP is presented, followed by the illustration of multiple energy services and the business model of the µVPP. Then a generic µVPP algorithm embedded on the HEMS is presented with case studies demonstrating different levels of optimisation effects by switching between energy services.

Chapter 4: A two-stage chance-constrained stochastic optimisation is presented in this chapter to derive the bidding strategy of the µVPP in the local energy-reserve pool. The market structure and the business model are illustrated first, then the two-stage chance-constrained formulation is presented. In the case studies, the interrelation between µVPP design and its projected profit is addressed. Chance-constrained method and the Monte Carlo recourse method are compared in terms of their risk-hedging abilities. Finally, results show the impacts from the rivals' strategy and from the implementation of carbon tax policy.

Chapter 5: This chapter presents the bilevel EPEC formulation of an active distribution system market and proposes a coevolutionary approach to find the pure strategy NE of the equilibrium model effectively. Firstly, three market frameworks including the current distribution system market, a passive distribution system market and an active distribution system market and their differences are illustrated. Then the proposed active distribution market is modelled as a bilevel EPEC optimisation, followed by the presentation and application of a coevolutionary computation approach to find the pure strategy NE solution. In case studies, the effectiveness of the proposed coevolutionary approach in finding the equilibrium is demonstrated. Also, μVPP's performance under three types of market frameworks is evaluated.

Chapter 6: The research is concluded and the key findings are addressed in this chapter. The future research topics which could add to the body of knowledge are also included.

The main research work is presented in Chapter 3, Chapter 4 and Chapter 5 which corresponds to the three research focuses respectively. Chapter 3 depicts the infrastructure of a μVPP elaborately, addressing its role and beneficiaries in the optimisation of local power flow. Chapter 4 incorporates the μVPP in a distribution level energy and reserve market, analyses their bidding behaviours as price-takers. Chapter 5 further evolves the μVPP as a price-maker and considers the competition of an active distribution system market consists of many μVPPs.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive review that covers the three research focuses of this thesis. Firstly, the current development of home energy management systems (HEMS) is reviewed. Secondly, the existing studies about the bidding strategies of the MGs and VPPs are critically evaluated in terms of market participation, modelling of the market behaviour and the hedging methods against risks. Thirdly, an overview is provided for the construction of active distribution systems, the application of market equilibrium models and the solution techniques for the equilibrium problems.

2.2 Overview of the Development of HEMS

The main driving force of introducing the HEMS is that households, being the second largest sector in dominant energy use, is faced with a continuous energy price rise. HEMS monitor the energy consumption, manage the appliances automatically and help keep the domestic electricity cost in check. When using the human body metaphor to describe a μVPP, various DERs constitute the limbs, ICT infrastructures function as the nervous system and the HEMS is the brain to perform monitoring and control.

2.2.1 Definitions, Architectures and Functions of HEMS

HEMS is viewed as an umbrella acronym for a variety of solutions range from pieces of hardware that monitor and control single energy end-use systems; to monitoring devices that track multiple DERs allocated in a building or a residential community; to platforms that only rely on software tools which tap into the consumer data, building characteristics and geographic location information to conduct sophisticated data analysis and yield schedules to guide the operation of appliances [26]. HEMS belong to a broader category of energy feedback programs, in which the energy information from the supply and/or the demand side is pooled together and cost-saving opportunities are identified after analysing the data.

HEMS originate from the computer-aided tools used by operators of electric utility grids to monitor, control and optimise the performance of the generation, transmission and distribution systems. In 1988, J. L. Ryan was among the first to become aware of home automation, which uses interactive communications to monitor and control household appliances [27]. Interestingly, he accurately predicted the trends of the development process for HEMS: "it could begin as a set of lighting controllers, then proceeds to the heating sector and finally these islanded devices merge to form a larger system." With the decentralisation of the once vertically integrated electricity systems and the emergency of DERs, energy suppliers, private investors and end-consumers are gradually gaining access to energy management systems and HEMS are developed to suit domestic sectors. The hardware and software HEMS units shipped in 2017 are expected to triple the level in 2010 across Europe as shown in Fig. 3. Despite the dropping retail prices of HEMS, the market revenue is estimated to reach $ 2.01 billion in 2018 compared with the $ 1.14 billion in 2013. In recent years, the vast development in big data and the internet of things (IoT) has provided a wider platform for HEMS. Under the IoT framework, HEMS will have the potential to expand its definitions beyond energy management and tap into other functions such as access, surveillance, fire detection, and so on [28].

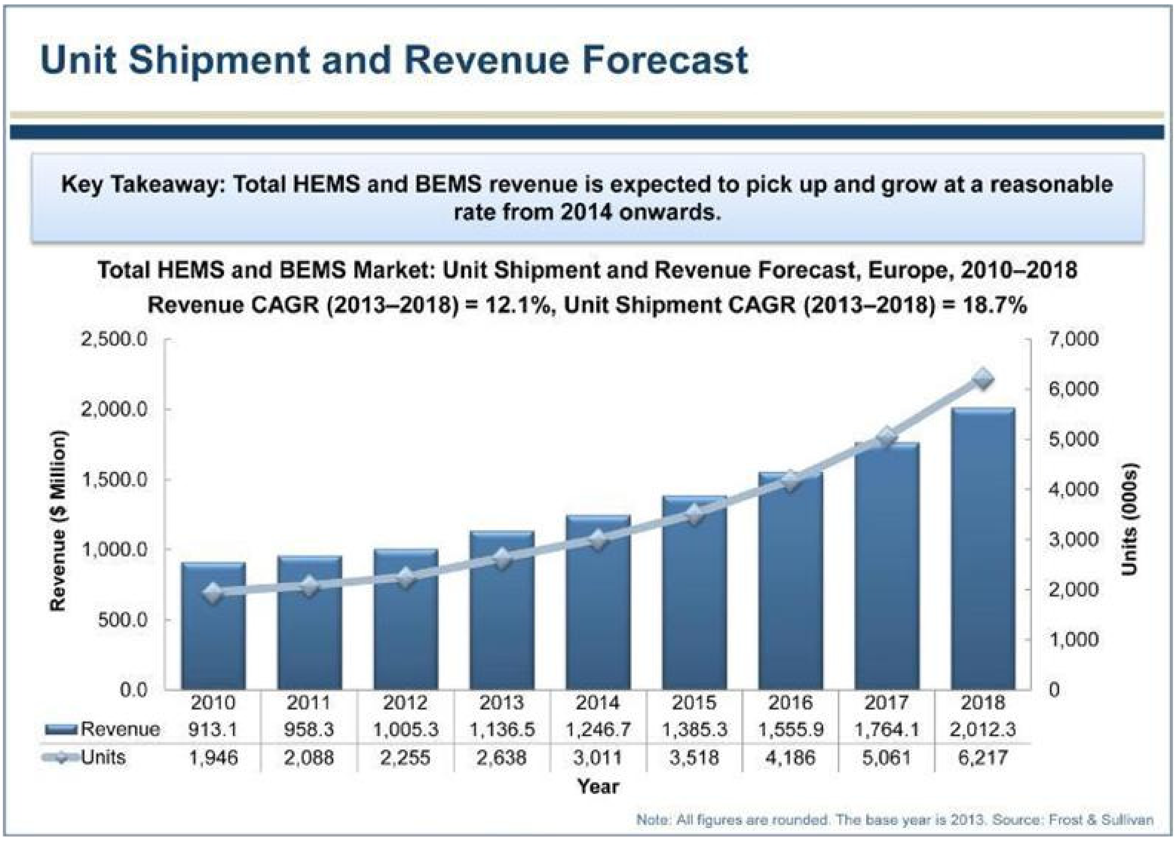


Fig. 3 Total HEMS and BEMS market in Europe [29]

Two crucial components constitute HEMS: a central processing unit (CPU) to host control algorithms and a wireless-based home area network (WHAN) to facilitate the two-way communication between various appliances and the CPU. By utilising a wireless-based network, the rewiring need could be reduced to minimum which makes HEMS cost-effective and nonintrusive to residential consumers. Also, a wireless-based network provides the flexibility to upscale the HEMS by adding new appliance nodes or to downscale the HEMS by removing existing appliance nodes [30]. Popular wireless protocols such as Wi-Fi, Bluetooth and ZigBee have already been applied in developing the WHAN for HEMS. In [31], a Bluetooth-based HEMS solution was proposed to reduce consumers' peak demand and bring energy savings. In [32], ZigBee-based WHAM was used to aggregate the energy data from numerous household appliances, compare them, and create useful statistical analysis to minimise the energy cost. Compared with Bluetooth, ZigBee shows a much bigger potential in becoming the industry standard of HEMS. ZigBee supports a wider operation range from 10 to 100 metres, and can be upgraded to up to 400 metres if multiple households are managed together; ZigBee can accommodate as many as 65000 devices in a single network, making it extremely scalable in building solutions and community solutions; ZigBee has been developed specifically to permit low power consumption instead of being constantly alert like Bluetooth devices, addressing the energy management issue in the ICT infrastructure itself; last but not least, the protocol uses a 128 bit encryption and a user-definable application layer, which increases the security and flexibility of the network for HEMS [33].

The WHAN in the HEMS topology is made up of three layers and they are summarised as follows [34]:

- Physical layer: the transceivers known as smart meters and smart controllers installed in the electrical outlets or directly integrated into the controllable appliances.
- Middleware layer: the WHAN servers that collect, concentrate and forward data from DERs/appliances to the CPU.
- Application software: the user interface which provides administrators and consumers

access to the consumption information and the authority to change system configurations.

The overall objective of HEMS is to reduce consumers' energy bills by optimising their consumption. The function of HEMS, however, evolves from monitoring the energy use of a single connection point, to coordinating multiple DERs in the same residential area, and finally to a more systematic decision-making concerning the electricity tariff schemes, weather forecasts and the impact on distribution networks. Many HEMS designs have been proposed in [32, 35-38]. An intelligent HEMS architecture proposed in [32] established the information pathways between household micro-generation and consumption. Estimated renewable generation data was collected and used to schedule appliances. In [35], ESS in the form of stationary batteries was incorporated into the DER mix and its charging/discharging activities were designed to serve those appliances with high priority and the simulation results showed further reduction in the energy consumption. The deployment of utility scale ESS in the residential households also raises concerns for high initial investment and wasted system resources such as oversized battery capacity. While serving the purpose of reducing the electricity bills for end-consumers, only a few of the proposed HEMS took the stability of the distribution system into consideration. In DNO's point of view, power peak-to-average ratio (PAR) is regarded as an important metric to describe the load patterns. In [36], HEMS were designed to tap into the real-time pricing mechanism and alleviate the PAR. The proposed algorithm was designed not only to allocate appliances to low-price period, but also to mitigate the risk of creating harmful peak load in those valley price periods. In recent years, the landscape in which ESS is dedicated to a single household has changed and a shared ESS paradigm becomes the trend. In [37, 38], an ESS was shared by multiple households as the means to compensate peak demands and provide backup power during outages. However, both designs lacked the evidence of an optimised local power flow where the surplus power from micro-generation can be immediately redistributed to supply those with demand.

Only a few of the HEMS designs were demonstrated on hardware testbeds and the testbeds were developed only for the demonstration of basic concepts. In [39], a Wi-Fi based HEMS was designed to respond to dynamic pricing and the main focus was to establish comprehensive communication interfaces. In [40], a ZigBee-based HEMS was presented for DR applications with majority of the work being done in developing load controllers. Similarly, a showcase was presented in [41] to demonstrate the control of air conditioning by a Wi-Fi enabled thermostat. The ICT electronics were fully constructed in the works above but consumer loads were often simulated simply using high-wattage light bulbs or hair dryers, not to mention the absence of RES and DER in the testbed setup. With the merging incentive policies for smart household energy renovations and funding filtering down to support the establishment of pilot projects, there is a pressing need to move on from laboratory display towards industrial implementation, to include the full asset portfolio of a smart energy community and to explore the viability of business models that creates profitable value streams for stakeholders.

2.2.2 Application of MILP and FLC in HEMS

As smart controllers are gradually replacing the outdated timer switches for domestic appliances such as electric heat pumps (eHeat Pumps) and boilers, the operation status of these appliances in the context of HEMS is treated as binary variable, representing ON or OFF status with their designated consumption power in each working interval. When designing control algorithm for HEMS, the optimisation problem with both binary and continuous variables was often addressed as a MILP by many previous works. In [42], a MILP-based demand response strategy was proposed to utilise electric vehicles (EVs) as bi-directional storage systems in smart homes. However, the investigation was conducted under the assumption that the EV user preferences and driving behaviours were known perfectly before each optimisation horizon. And the results showed that the robustness of the decision sets was highly influenced by the accuracy of user behaviours. To produce reliable real-time control signals, various risk-hedging methods were adopted by the MILP approach to mitigate the negative impact brought by uncertainties. In [43], the Monte Carlo simulations and scenario reduction techniques were applied under MILP framework in order to minimise the risks associated with uncertain real-time electricity prices. Considering the time-consuming characteristic of the Monte Carlo simulations and the rigid requirement of real-time signals, [43] made the compromise to reduce stochastic scenarios down to single digits so decisions can be delivered for every 5 minutes. In [44], a MILP-based EMS was introduced and a rolling horizon strategy was applied to mitigate negative impacts originated from forecasted inputs. As [45] pointed out, the forecast capability could be embedded in the EMS or it may take the form of external forecasting services. Either way the forecast cost is not negligible to the total investment, especially if the forecast horizon is required to be distant and the resolution should be high. Apart from the struggle in delivering good-quality real-time decisions and to obtain accurate but cheap forecast data, MILP becomes complex when the HEMS are scaled up and more appliances are involved. Due to the non-deterministic polynomial-time hardness (NP-hardness) of the MILP approach, the computational burden grows significant with an increasing number of binary variables [46]. In addition, the application of the MILP approach in HEMS means that the objective function must be executed every 3-5 minutes with all the relevant constraints considered. Any changes in the μVPP configurations, including the installation and removal of DERs, will lead to the re-engineering of the software and disadvantages in the view of a diversified customer group.

Compared with the classical MILP optimisation approach, metaheuristic methods have a good reputation in dealing with automated systems with model uncertainty and complex decisions. The context-independent property of metaheuristic methods allows them to work and solve several course timetabling problems without using any explicit constraints. If there exists a change in the system inputs or parameters, the researcher does not need to invest time and effort to construct a new solution algorithm [47]. Among them, fuzzy logic control (FLC) method is of interest in this thesis for the development of HEMS. HEMS as a multi-agent system has various DERs and a constant need to expand and involve more decision-making nodes. FLC has the required context-independent property and fast response for HEMS to derive the control signals for each agent in parallel. FLC is defined as a set of linguistic control rules which capture the approximate, inexact nature of the real word decision-making process and convert the linguistic inference based on expert knowledge into an automatic control strategy [48]. Unlike classical control strategy, FLC resembles the inference process of human being in which fuzzy or ambiguous answers are often involved. FLC was firstly proposed by Professor L. A. Zadeh back in 1965 and in his work a fuzzy set was defined as a “class” with a continuum grades of membership [49]. In the notion of a classical set, the object lies within a given range with a sharp boundary which means the object can either belong to the set or not belong to the set (point-to-point inference). In a fuzzy set, however, an object corresponds to a broader degree of memberships and the boundary becomes smooth. The mapping of the members of the set is no longer black-and-white but becomes tolerant to ambiguity that a member can belong to a set to some partial degree (range-to-point or range-to-range inference). In [50], the difference between a classical set and a fuzzy set was clarified using a temperature example as follows:

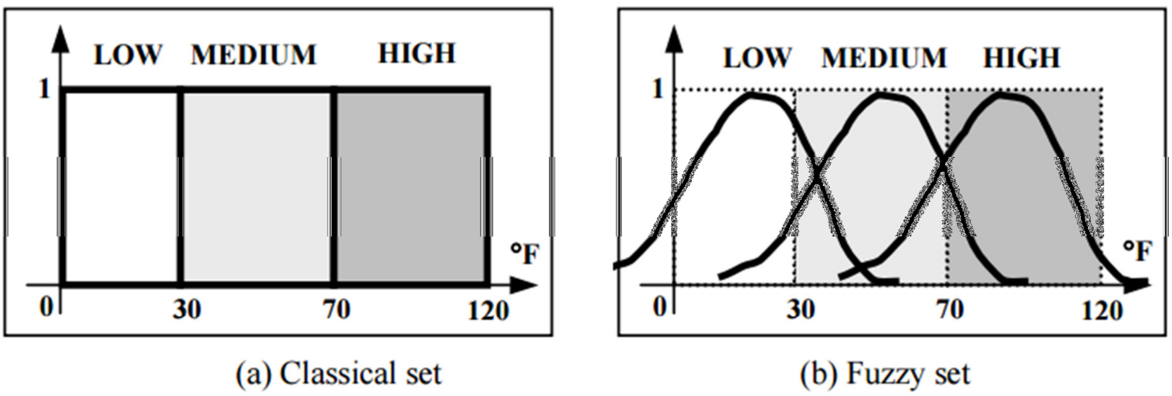


Fig. 4 The temperature example: (a) Classical set; (b) Fuzzy set [50]

In a classical set, temperatures ranging from 0 °F to 120 °F are strictly categorised as “Low”, “Medium” and “High” in Fig. 4(a). In the fuzzy set shown in Fig. 4(b), one temperature reading can belong to multiple subsets at the same time. For example, temperature 50 °F can belong to “Low” and “High” simultaneously, but at a very low degree of 0.2. When considering it as a member of the “Medium” subset, the degree is almost 1. The advantage of a vague set is to avoid premature and arbitrary decisions, combine all sources of input and make well-informed judgement. Professor Zadeh pointed out that FLC has the potential to be applied to a wider scope, particularly in the fields of pattern recognition and information processing [49].

The implementation of FLC consists of the following steps:

Step 1) Fuzzification: the crisp data is converted into fuzzy data or membership functions (MFs).

Step 2) Fuzzy inference: the membership functions of all inputs are combined to derive the fuzzy output based on the inference rules.

Step 3) Defuzzification: the fuzzy output is converted back to its crisp format using a lookup table.

The FLC has drawn the attention of HEMS development. In [51], a multi-agent, FLC-based EMS was proposed to address the suitability of FLC as the control scheme. The hybrid system was not controlled as a global system but rather as a cluster of independent entities that collaborate with each other. A multi-agent system architecture matched FLC’s quick response to the real-time changes from all participating agents and the results demonstrated

FLC's ability to let the system work without perturbation. In [52], a battery auxiliary power unit was designed based on FLC and the proposed system could be easily retrofitted for a wide range of DERs by identifying device-specific input variables and determining the corresponding human expertise rules. The adoption of FLC in MG development was further addressed in [53], where conclusions were drawn that FLC can not only encompass subjective decision-making process but also fit the plug-and-play concept to achieve low cost expansion for residential solutions. Three control approaches namely MILP, continuous relaxation (CR) and FLC were compared in terms of cost optimisation, computational efficiency and implementation [54]. The comparative study pointed out the MILP and CR approaches consume much more computational resources with insignificant contribution to the accuracy of optimisation results. To sum up, the FLC approach surpasses classical optimisation counterparts from a practical point of view: it does not need forecast information nor extra efforts in mitigating the risks brought by uncertainty; secondly, it does not consume large computational resource and hence can be accommodated on low cost CPUs. Furthermore, it provides compatibility for appliance clusters of any category and scale without dramatically increasing the processing time. Finally, the credit should be given to the quality of the decisions obtained by FLC. The FLC decision sets are, if not the most optimal for all times, at a very satisfactory level towards the optimisation goal and obtained via the most economic pathway.

2.3 Overview of the Bidding Strategies for MGs and VPPs

The introduction of power brokerage and electricity auction markets was considered as a key step in the deregulation of electric utility industry when the reform started around 1986 [55]. Different from the central dispatching scheme, generation companies in the auction markets need to compete against each other by marketing their product. The conventional rate-of-return regulation pricing would be replaced by market pricing in the competitive regime. With the emergence of MGs and VPPs, the concept of auction markets has been extended to distribution system level and it is crucial for MGs and VPPs to position themselves correctly in the markets considering their own strengths and weaknesses.

2.3.1 Electricity Auction Markets

The electricity auction markets consist of many producers and consumers and they are managed by a market operator (MO). Electricity producers submit a set of energy blocks and their corresponding prices to the market for profit maximisation. The constraints that generation companies comply to include the fuel costs, generation capacities, ramping limits and minimum up/down time, etc. The incorporation of the consumers in the auction process defines the market regime as “double-sided auction”, which has been demonstrated to be more efficient and competitive than producer-only auctions [56]. The consumers often appear in the wholesale electricity market as large load serving entities (LSEs), submitting a pair of demand blocks and their purchasing prices for cost minimisation [57]. The main concerns for demand bidding are different from supply offering and they are summarised as follows:

- The bidding strategy should secure the energy supply required by the end-consumers, which is the first and foremost task of LSEs.
- The bidding strategy should allocate the energy purchase in the day-ahead market as much as possible, given the lower average price than the real-time market.
- The bidding strategy should include hedging methods against the risks brought by any volatility in the real-time operation.

After receiving the energy bids/offers from both producers and consumers, the MO clears the market by releasing the market clearing price (MCP), the power production of every offering generation block and the consumption level of every demand bidding block [58]. The decisions are broadcasted for every hour of the market horizon and the target is to maximise the social welfare. There are two types of price settlement, namely the first-price rule and the second-price rule, which determine at what rate the winners should pay or receive for their bids [59]. The first-price rule is also known as “pay-as-bid” auction, where bidders pay and suppliers receive at the price equal to their individual bids. The second-price rule is known as “uniform-price” auction as oppose to the discriminatory nature of the “pay-as-bid” auction. Under the second-price rule, winners are paid or charged at the price of the first losing bid or equivalently the price of the last accepted bid. The mechanism of the second-price rule is depicted in Fig. 5. The supply offers are aggregated and sorted by price in ascending order to create the aggregated supply curve. If the demand bidding is not included, the point where the fixed demand crosses the supply curve is the

MCP that prices the transactions. On the other hand, if the demand bidding is included in a double-sided auction, the demand bids are also aggregated but sorted by price in descending order to create the aggregated demand curve. The intersection of both curves is identified as the MCP.

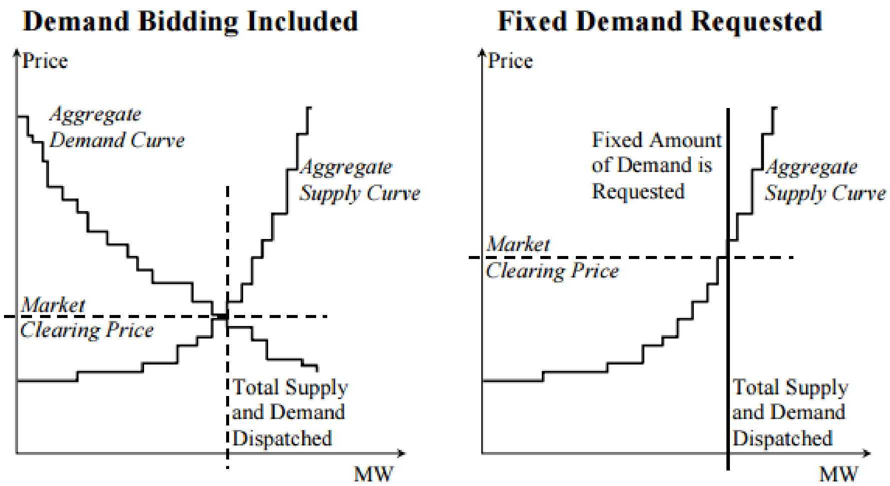


Fig. 5 Second-price rule mechanism [60]

Analysis of the efficiency of the first-price rule and the second-price rule was performed in the England and Wales electricity pool market [61]. The results showed that small agents are at a clear disadvantage to the large agents in the first-price auctions, when it comes to the knowledge of the market trends. The results also showed that the imbalance could be mitigated under the second-price settlement because all agents, regardless of their sizes, receive the benefit of a collective decision. However, the disadvantages grow far more severe if MGs and VPPs are introduced to the electricity wholesale market. Lacking the same market power of those large agents, MGs/VPPs would have small influences on the market clearing results and sometimes be forced to submit zero energy supply offers to avoid losses. Considering their limited generation capacities and a role as new entries, it is imperative for MGs and VPPs to compete with entities of their own sizes. The current electricity retail market is a promising candidate to welcome MGs and VPPs to compete with traditional suppliers.

2.3.2 Modelling of the Bidding Behaviours

Previous works have designed a two-stage market consisting of a day-ahead (DA) market and a real-time balancing (RT) market for MGs and VPPs. In the DA market, MGs/VPPs coordinate their energy production and consumption based on the forecasted information. Then the RT market follows to clear up the unbalanced power left in the DA settlement or caused by unforeseen events, such as over and underproduction by RES [62]. In [63] and [64], the basic function of MGs and VPPs as energy market participants was described in the buying or selling of electricity. However, MGs and VPPs are more vulnerable to shortage risks due to the volatility in market prices, demand and generation output compared with Macrogrid. If they practice as sole electricity market players, the only hedging method against shortage risk is to purchase from grid at spot prices, which can be quite high at times of peak load [62, 65]. Thus, references [66-68] suggested that MGs and VPPs should contribute to the equilibrium of a joint energy and reserve market. The generation capacity of MGs/VPPs is required to not only relieve possible network congestions within themselves, but also transfer energy to the nearby feeders of the distribution network when necessary. Also, the small-scale MGs/VPPs participating in the electricity auction markets were modelled as price-takers in [62-64, 69], which corresponds to the arguments in section 2.3.1 that small agents lack the market power to influence the MCP. Their bids and offers consist of only quantity to be traded which respond to volatile price signals broadcasted by the DSO.

The bidding behaviour of MGs/VPPs could be modelled as a deterministic linear programming problem with linear fuel cost for dispatchable generator in [53, 70, 71]. An approach to account for the uncertainties by using the deterministic model was described in [72], where the DA plans were made based on a more accurate quasi real-time status of generation and load profiles. To better address the considerable impact of the uncertainties on the economic rationale and technical viability of MGs/VPPs, stochastic models were applied in [73-78]. In [74], a stochastic energy scheduling solution was proposed and an iterative method was adopted to minimise the expected loss from the intermittent RES. However, the iterative search method could lead to a premature convergence to local optimums. In [75], the fluctuations in the generation and demand were often assumed to follow a normal distribution and adequate number of scenarios were generated to form the uncertain profile. In [76], the optimal offering strategy of a large-scale VPP was proposed and the uncertainty of its rivals' strategies was considered besides the intermittent generation and consumption. Faced with a multi-period scheduling scheme and potentially thousands of scenarios, reference [77] addressed the necessity to apply scenario reduction techniques and improve the computational efficiency. While references [74-77] identified the amount of the electricity to be purchased from and sold to utility grid and commitment of DERs that serve their optimisation purposes, they lacked concerns for the reserve flexibilities. The reserve requirement was settled as a fixed percentage of the load in [73], of which the percentage itself was difficult to determine. A modified approach was proposed in [78] to assess the reserve capacity for each time interval separately. However, the reserve resource in the works above was not contributing to the other participants of the reserve pool, thus its opportunity to generate a value stream was denied.

2.3.3 Risk-hedging Methods to Cope with Uncertainties

The integration of RES into the European electricity market has not been the smoothest ride by far. In Spain, for instance, RES and cogeneration facilities were not obligated to sell their production in the market but receive a remuneration based on administrative premiums. The difficult-to-predict nature of the RES made the system operator obligated for a greater spinning and supplemental energy reserves, to balance the errors between the estimated RES output and the actual production [79]. The impact of volatile electricity prices in the RT market was addressed in [80], combining with the variation in the quantity, the volatility could lead to considerable financial burdens on the bidders. The risks associated with the production scheduling are the unexpected deviations from DA schedules caused by RT uncertainties. The risks include but are not limited to renewable generation curtailment, involuntary disconnection of load, failure to deliver the offering capacity and loss of revenue (known as value at risk). These risks are often assessed based on the probability of their occurrence. Under the circumstances, futures contract was introduced as a financial tool to mitigate the risks for μVPPs. The futures contract is defined as a legally binding agreement made between two parties to buy or sell a commodity or financial instrument, at an agreed price, on a specified date in the future delivery date [81]. However, the difficulties in determining the terms and conditions of the financial contracts were also recognised and risk management should be incorporated in the production scheduling.

Various optimisation techniques were applied to hedge against the risk in the production scheduling problems. A Monte Carlo recourse method was introduced in [82] to work with the deterministic optimisation to increase the reliability of the solution. Monte Carlo sampling is one of a broad class of computational methods that rely on repeated random sampling to define a domain of uncertain inputs that have a probabilistic interpretation. In the proposed paradigm above, the decision variables involved in the deterministic optimisation stage were determined firstly before the realisation of randomness in the problem. Then sampling techniques such as the Monte Carlo sampling were applied to "recourse" the deterministic decisions and make them less vulnerable to uncertainty risks.

References [63, 83, 84] utilised robust optimisation to construct a solution that is deterministically immune to any realisation of the uncertainty in the given set. Conditional value at risk (CVaR) was introduced as a risk management scheme in [76, 77, 85] to control the trade-off between the expected economic profit and the variability caused by uncertain components. Like the robust optimisation and the CVaR, chance-constrained optimisation was introduced as a reliable solution to stochastic optimisation problems. In the chance-constrained optimisation, some constraints can be relaxed with a predefined small level of probability, or must be satisfied with a high level of probability. The concept of chance-constrained programming was proposed firstly by Charnes and Cooper in 1959 [86]. Under the stochastic programming framework, it was pointed out that the decisions obtained may not satisfy the constraints rigorously, but the probability of them satisfying the constraints can be controlled at a confident level. By applying the chance-constrained method, the stochastic linear programming model has the following form:

$$\begin{aligned} \min \quad & C^T X \\ \text{s.t.} \quad & \Pr\left(AX \le b\right) \ge \alpha \\ & X \ge 0 \end{aligned}$$

where X is an n dimensional vector to be determined, A and b are random coefficients and α is the confidence level that the first constraint should satisfy. The confidence level here means that the probability of the value of AX being lower than or equal to b should be at least α .

The early application of the chance-constrained method was found in the unit commitment problems which consider uncertain demand and random outages of power system components [87, 88]. In recent years, there has been an increasing interest in utilising chance-constrained optimisation due to the rising penetration level of RES. A chance-constrained optimal power flow (OPF) algorithm was proposed in [89] to distribute both RES generation and regulation in a manner that saves operational costs and yields better technical performance. In [90], the possibility of changing transmission network topology was explored to keep raising wind penetration without jeopardising grid security and reliability. In the transmission switching program, chance constraints were applied to ensure that the wind energy utilisation exceeds a satisfactory level for most of the times. In [91], a chance-constrained solution was proposed for unit commitment problems with wind integration. Three potential negative impacts brought by intermittent wind generation were modelled as chance constraints, namely the loss of load probability, the loss of wind probability and transmission line overloading probability, aiming at improving the reliability of the system while guaranteeing a good utilisation rate of the RES. However, to the best of the author's knowledge, applications of the chance-constrained optimisation in deriving the μVPPs' bidding strategy has not been discussed yet. The uniqueness of the application is twofold: firstly, μVPPs are connected to the distribution system and have limited generation capacities. Conservative strategies based on worst-case-scenario could lead to insufficient offering capacity and therefore low income from participating in the market. Secondly, μVPPs are responsible for satisfying the peak demand of their end-consumers and the probability of involuntary loss of load should be guaranteed to be very low. In some cases, a producer μVPP could be reconfigured and becomes consumer μVPP to meet the internal demand.

Compared with the proposed chance-constrained method, robust optimisation can be too conservative with its worst-case-oriented decisions [92]. Although the CVaR method is a similar probabilistic risk measure, it only controls the variability indirectly in financial terms. On the other hand, the proposed chance-constrained method interacts directly with the uncertainties in the actual physical system such as loss of load probability (LOLP). LOLP is the likelihood of involuntary load disconnection occurring due to the disruption in power supply. Based on the risk-preparedness regulation issued by the European Parliament, 95% to 99% of the time no one should be involuntarily disconnected.

2.4 Overview of Distribution System Market with Equilibrium Model

It has been more than ten years since the electricity retail markets were liberalised, evident barriers to entry remain for small suppliers still. It is hard for small suppliers to secure contracts of small quantity to match their load profile, for the long duration they are seeking and at a price that is competitive with the large vertically integrated suppliers [93]. Another prominent barrier is the expectation of low or even negative margins for small-scale retail-only business. In contrast, such as in the UK retail market, the six large suppliers continue to dominate the electricity retail segments with a combined market shares of 85% [25]. However, their consumers have not experienced significant price reductions while the consumption level continues to rise from 2012 to 2016, resulting in high electricity bills.

In recent years, there is a growing trend to introduce MGs and VPPs as new entries into the electricity retail market and overcome the barriers mentioned above. MGs and VPPs' access to supply is guaranteed by local distributed generation, they do not share the same level of reliance on wholesale market as their vertically integrated supplier counterparts. This should reduce losses in the transmission of wholesale electricity and potentially justify a reduction in the network charges that end-consumers pay [94]. Accordingly, the participation of MGs and VPPs will require an updated market framework in the retail segments and a more decentralised management.

2.4.1 Active Distribution System and its Market Framework

In the traditional and centralised electric power system, there are three almost independent subsystems including the generation system, the transmission system and the distribution system. The distribution system is defined as the system to distribute the electricity from generation facilities to individual end-consumers within a specific geographical area [95]. The manager of the distribution network, DNOs, own and operate the distribution network consisting of towers and cables that bring the electricity from the transmission network to homes, businesses and industries [96]. The emerging DERs could not isolate themselves from the traditional distribution system, and if they are integrated properly the following benefits could be brought to the distribution system [97]:

- Electricity quality improvement: dynamic voltage support.
- System reliability improvement: urgent power supply functions, local service restoration such as intentional islanding.
- System efficiency improvement: self-consumption in local areas, loss reduction from the transmission and distribution.

However, the traditional distribution system is faced with many limitations which may lead to significant deviations from what have been expected of DERs. “Fit-and-forget” is concerned as the most typical approach to install DERs, in which the dispatching and the monitoring of DERs are excluded from the daily operation of the distribution system. In recent years, DNOs are gradually evolving their approach to better connect the DERs to the distribution system. UK power networks is a DNO company that manages the distribution networks covering London, the South East and the East of England. In its "Flexible DG connection" scheme, the connection of the DERs is based on a "last-in-first-out" principle where each DER is assigned a position within the local priority stack [98]. When DERs apply for a connection in the area, they are given a position at the bottom of the priority stack and they will be curtailed first during a constraint event. The discriminatory agreement was determined considering the bigger picture of network stability, but it could demotivate the DER investors even with a seemingly profitable compensation scheme.

Considering the small-scale generation capacity and the residential level demand, the concept of μVPP is proposed here to include MGs and VPPs that are connected to the restructured distribution system. μVPP is defined as an extension to the MG concept since the DERs located within the μVPP has a capacity that can either cover part of the load or generate excess electricity to be consumed by other μVPPs. To optimally exploit μVPPs' potentials, the concept of active distribution system (ADS) has been brought forward. The International Council on Large Electric Systems (CIGRE) defined ADS as an unified system with some active control approaches for a combination of DERs including DGs, ESS and DR programs [99]. In the restructured ADS, the traditional DNOs are transformed to DSOs with added responsibilities [100].

A few works studied the trends and challenges in the implementation of ADS [101-103]. In [101], the technical and economic rationale of the ADS framework was further addressed as the following points:

- Better TSO/DSO coordination: ADS has a better grasp of the generation and consumption information in the area, which in turn helps transmission system operators (TSOs) to make better judgements in terms of system balancing and security services.

- Localised energy solution: DERs can provide local balancing and voltage control without affecting the upstream transmission system negatively and even help its operation.

- Network investment reduction: ADS has a much wider range of network access options, which effectively reduces the reinforcement investment.

Case studies were applied on a real UK distribution network and the results showed that the proposed ADS could accommodate high levels of RES penetration, reduce the deviations of dispatching schedules and become self-sufficient in terms of reserves. Reference [102] pointed out that the DERs in ADS could provide a wide range of ancillary services including reactive power consumption, asymmetry reduction and harmonic mitigation. Competent as the DERs are in the provision of energy services, the DER owners or the μVPPs may not utilise them if the incentives are shadowed by the operation costs. In addition, reference [103] addressed the urgent need to design a new market mechanism for the emerging ADS, which can involve the μVPPs in the electricity trading and generate value streams for them.

The design of the new market framework for ADS should comply with two basic rules that were used to guide the decentralisation of European electricity market. The first rule is the unbundling of energy supply and generation from the operation of networks [104]. If a single DSO operates the distribution network and owns the DERs at the same time, it may have an incentive to obstruct other DERs' access to infrastructure. The second rule is to ensure non-discriminatory access to the network for all third parties of producers and consumers [105]. An active distribution system market (ADSM) should be constructed that mimics the wholesale auction market under the clearing pricing rule. µVPPs and traditional retailers as market participants tender supply and demand bid curves in the format of quantity and price bids. The DSOs then construct aggregated hourly supply and demand curves to determine market clearing prices as well as the corresponding supply and demand schedules [59]. The benefits of implementing such an auction market in ADS are shared by all market participants: for µVPP owners, the electricity generated from their DER assets now has the same market value as the electricity purchased from wholesale market [106]. µVPP owners are expected to receive a higher return on investment than the current low feed-in tariff [107]. For DSOs, the growing entries of µVPPs reduce the system operators' exposure to the risk associated with the unpredictability of spot market prices and volatility in consumption patterns [108]. Ultimately for end-consumers, they pay at cheaper electricity retail rates due to the increased competition in the restructured retail market.

2.4.2 Application of the Equilibrium Models in the Electricity Market

The equilibrium of the market is defined as a state of the economic system where there are simultaneous equations for supply and demand. K. J. Arrow and G. Debreu were among the first to investigate and prove that the equilibrium state in competitive markets does have a solution [109]. The equilibrium models for economic systems were therefore developed to study the behaviour of supply, demand and prices in the markets, seeking for the equilibrium solutions from the interaction of supply and demand. To evaluate the quality of the equilibrium solutions, the concepts of Pareto optimality and Nash Equilibrium (NE) are introduced to characterise the effectiveness of the equilibrium.

Pareto optimality has been widely applied to assess the efficiency of a market equilibrium [109]. Pareto optimality is a state of allocation of resources from which no redistribution can improve the position of one individual without marking at least one other individual worsen off. The mathematical representation of Pareto optimality was shown in [110]. The problem consists of N players that do not cooperate and each of the players i has a strategy set X_i . The payoff function $F_i\left(x_i, x_{-i}\right)$ of player i is associated not only with the strategy of the player itself but also with the strategies x_{-i} formed by the rest of the players. With each player trying to minimise its payoff functions over the strategy set X , the equilibrium $\overline{x} \in X$ can be defined as a Pareto equilibrium if

$$\begin{aligned} F_i\left(x_i, \overline{x}_{-i}\right) &\leq F_i\left(\overline{x}_i, \overline{x}_{-i}\right) \qquad \forall i \\ F_i\left(x_i, \overline{x}_{-i}\right) &< F_i\left(\overline{x}_i, \overline{x}_{-i}\right) \qquad \exists i \end{aligned}$$

where the inequality above must hold for a least one player. The concept of Nash Equilibrium (NE) is closely tied to the Pareto optimality but they are not equivalent. NE exists when the strategy is the player's best response to the strategies of the opponents. Under the circumstance, no player has an incentive to unilaterally deviate from the NE solution. The mathematical formulation of NE was presented in [111]. In the same noncooperative game that consists of N players, the strategy x_i of each player belongs to a feasible set $X_i(x_{-i})$ corresponding to the strategies of its rivals. The equilibrium is defined as NE if it satisfies the following condition:

$$F_i(x_i, \bar{x}_{-i}) \le F_i(\bar{x}_i, \bar{x}_{-i}) \qquad x_i \in X_i(x_{-i}), \forall i$$

Considering the mathematical presentation of Pareto optimality and NE, conclusion can be drawn that NE is Pareto optimal if no other outcome could help some players without harming others at the same time. It is not guaranteed that a NE solution is Pareto optimal, such as the NE in the Prisoner's Dilemma, but NE provides strategically feasible solutions that could be applied in the industrial to guide the dispatching of resources.

Finding the equilibrium of the active distribution system market described in section 2.4.1 is crucial. DSOs as the market managers use the equilibrium model to monitor and assess the market while the participants use the model to make strategic decisions on their bids and offers. The studies of electricity market are often performed using oligopolistic equilibrium models where there are limited number of participants. Popular models include the Bertrand equilibrium, Cournot equilibrium, supply function equilibrium (SFE) and Stackelberg equilibrium. Despite their different assumptions and applications, these equilibrium models all aim at solving the market equilibrium as an optimisation problem. The result of the optimisation includes a set of prices, generating power outputs, transmission line flows and load demand levels [112]. Among the equilibrium models, a noncooperative game-theoretic model such as Stackelberg equilibrium has demonstrated the following advantages [113]:

- The equilibrium formulation in a game-theoretic point of view preserves the behavioural and strategic complexity of the participants. For instance, the bids and offers involved in the electricity market could have multiple parts and they can be well incorporated in game-theoretical models.

- The game-theoretic equilibrium models are flexible in terms of institutional sophistication. In other words, different market types, market settlement rules and participant configurations can be easily accommodated, which facilitates the implementation of any new policies and the comparative study between different market topologies.

Using a bilevel optimisation formulation, each market participant in the game faces an optimisation problem that can be modelled as a mathematical program with equilibrium constraints (MPEC). When considering multiple participants in the market, the competition is therefore recast as equilibrium problems with equilibrium constraints (EPEC) [114]. EPEC arise when analysing multi-leader-follower games where multiple firms compete non-cooperatively in an oligopolistic market. EPEC formulation captures the relationship between generation companies and system operators in the transmission system as a hierarchical relationship between two autonomous, and possibly conflictual, decision makers [115]. This description is also fitting for the distribution system market: DSOs expect minimised cost for clearing the market, however, an optimal market clearing results should bring profits to μVPPs – otherwise the μVPP owners are deterred from entering the market and the μVPPs become isolated MGs. Once the DSOs have cleared the market, μVPPs react to the clearing price and quantities and refine their bidding/offering strategies such that their profits are maximised. The maximisation of the individual profit is called the upper-level problem and the minimisation of the DSOs' cost is called the lower-level problem. The hierarchical relationship results from the fact that the optimisation problem related to the individual μVPP's behaviour is part of the DSO's constraints and it is the hierarchical structure that defines the bilevel optimisation.

2.4.3 Solution Technologies for EPECs

In [76, 116, 117], the bilevel EPECs were reformulated as a single-level optimisation problem by using Karush-Kuhn-Tucker (KKT) conditions and dual theory. Reference [116] presented a decision-making model for distribution companies with DERs in a competitive wholesale market, in which the distribution companies submitted quantity bids/offers sourced from their DERs. Reference [76] applied a more practical market setting by including the price variables in the offers. In [117], the bilevel model was implemented in ADSM and the economic benefits of DER aggregators were addressed, however, those aggregators were still prohibited from participating in the price-making process hence the market power of their DER generation was not analysed.

There are two inherent disadvantages when applying the KKT conditions and dual theory in realistic electricity market:

- This method is based on the optimistic assumption of a convex lower-level problem.
- The reformation towards a single-level problem brings many Lagrange multipliers which make the procedure difficult for practical markets with detailed constraints [118].

Under the optimistic assumption, the “follower” (i.e. DER aggregators such as μVPPs) altruistically submits an optimal bid/offer that also benefits the “leader” (system operators such as DSOs) [119]. However, the leader is not able nor allowed to influence the followers’ decision in a non-cooperative market environment and the followers should determine bids/offers based on their own economic benefits.

Alternative methods were proposed to solve bilevel EPECs. In [120], a primal-dual approach was proposed to solve the bilevel market equilibrium model under the same optimistic assumption of a convex formulation. Binary expansion approach was implemented in [121, 122] to transform nonconvex problem into MILP with acceptable loss of accuracy. An iterative approximation algorithm was used in [123] as another alternative method but the results were not guaranteed to be NE.

Coevolutionary computation is a relatively new form of agent-based simulation approach developed from classical evolutionary algorithms, which adopts the notion of ecosystem where multiple species coevolve towards mutual benefit [124]. Consequently, it is very suitable for bilevel optimisation problem which has a hierarchical structure between two decision-making groups. Coevolutionary computation solves the two levels sequentially, improves solutions on each level separately, while periodically exchanging information to get a good overall solution [125]. Coevolutionary computation is an extension to the standard genetic algorithms (GAs) in the overall category of evolutionary algorithm. Standard GAs and their applications were firstly proposed by J. Holland in the 1960s as the means to import the natural adaptation mechanism into computer systems. They were also seen as innovative methods to tackle large and complex optimisation problems. Optimisation is in fact the searching among an enormous number of possibilities for "solutions" while the process of evolution, in biology terms, is also the searching for highly fit organisms based on an enormous set of genetic sequences [126]. The fittest organisms which survived the natural selection of the evolution demonstrate their ability to adapt to the given environment, just like the solution (global optimum or local optimum) of an optimisation problem delivers good objective function value while complying with the constraints. However, in a complex system where multiple players participate, the fitness of an individual can't be determined unilaterally by the individual's own actions. Instead, the fitness value should be considered as the consequence of the interactions between this individual and the others. Therefore, the idea of coevolution was incorporated into the GA framework by adding various feedback mechanism between the individuals and driving the evolution towards a mutually beneficial result [127].

The application of coevolutionary computation was first seen in a predator-prey problem described by W. D. Hills [128]. This pioneer work addressed the fundamental difference that distinguishes the coevolutionary approach from the standard GAs, that is, the introduction of a partial, continuous fitness evaluation embedded in a fine-grained, step-by-step algorithm. Coevolutionary computation was successfully applied in modelling the wholesale electricity market with Cournot and SFE formulation. Reference [129] addressed coevolutionary computation as a parallel and global search algorithm, even if the results obtained are local optima. However, references [130, 131] pointed out that the coevolutionary Cournot/SFE approach may not be effective if market players have heterogeneous cost functions, which was exactly the case in ADSM where μVPPs have a mix of different DERs. Revisiting the benefits of game-theoretic equilibrium models in section 2.4.2, the different configurations of DERs could be well accommodated in the multi-leader-follower equilibrium games. How to utilise the novel coevolutionary computation approach to solve the proposed EPEC is the research focus of this thesis and will be explored in chapter 5.

CHAPTER 3 A CONFIGURABLE μVPP WITH MANAGED ENERGY SERVICES

3.1 Introduction

This chapter describes an exemplar micro virtual power prosumer (μVPP) which is the fundamental building block of the market-oriented μVPPs. The μVPP presented in this thesis has gone through planning, design, hardware/software construction and finally it has been installed in a residential community in Sweden. Since July 2014 the system has been successfully operated and become the flagship project which received significant attention and support from the local government [132]. As an industry-oriented work, the hardware depiction includes all detailed components and the schematic reflects actual hardware which would be a good reference for future industry developments on the subject. The development of software considers real engineering conundrums where some crucial forecast data is hard or impossible to obtain and certain algorithmic process takes an empirical approach to solve. Most importantly, the year-long test data and the electricity tariff were obtained not from unreliable sources but from the same site via smart meters, which makes the data analysis authentic and trustworthy. Secondly, a detailed business model is proposed and tested for its economic rationale. Taking advantage of the simulation test bed and actual data, this chapter has presented a very comprehensive case study that demonstrates different levels of optimisation effect.

3.2 µVPP System Architecture

The µVPP has been deployed in a residential community and it controls eight residential apartments. Each apartment has its own solar PV micro-generation and four apartments share an ESS to optimise their power flow. Smart meters and micro-controllers were already embedded into the PV systems and controllable appliances to provide real-time monitoring and control. Two key components constitute the HEMS of the µVPP: an embedded personal computer (EPC) was used as the central processing unit (CPU) to host the energy management software; ZigBee protocol was adopted to form the wireless-based home area network (WHAN) and facilitate bi-directional information streams. The WHAN governs the data logging and algorithmic control over the DERs inside the µVPP and it also provides interfaces to a cloud platform which enables remote monitoring and control from another location. As a safety preliminary of the electrical installation, a miniature circuit breaker (MCB) was pre-installed to isolate each apartment from the main grid during abnormal conditions and an isolator was also pre-installed to protect the ESS. The system architecture of the µVPP is presented in Fig. 6.

The home appliances within the µVPP are categorised into critical appliances (e.g. lights, TVs and refrigerators, etc.) and controllable loads (CLs) such as EVs and eHeat Pumps. The appliance demand data is collected by pre-installed smart meters and transmitted to the HEMS via the wireless network. The EVs in the µVPP are typical plug-in hybrid vehicle with battery size of 4.4kWh. A standard single-phase AC outlet is used to draw up to 3kW of power with a full charge typically taking 1.5 to 2 hours, which makes EVs energy intensive appliances in terms of consumption. Each charging outlet is equipped with a smart micro-controller that executes the ON/OFF decisions from the HEMS and determines the charging status of the connected EV for the next scheduling interval. The scheduling of the EV charging also considers the safety and the convenience of drivers by complying with a set of physical constraints. Firstly, EV should remain ON or OFF status for adequate amount of time before it can change to another status. This constraint prevents frequent interruptions to the charging process and protects the charging point from damages. Secondly, there is an upper limit of time for which EV can be turned off, guaranteeing a fully-charged EV every day. To ensure enough backup capacity for any unplanned travel, the EV will be turned ON compulsorily when it has been OFF for too long.

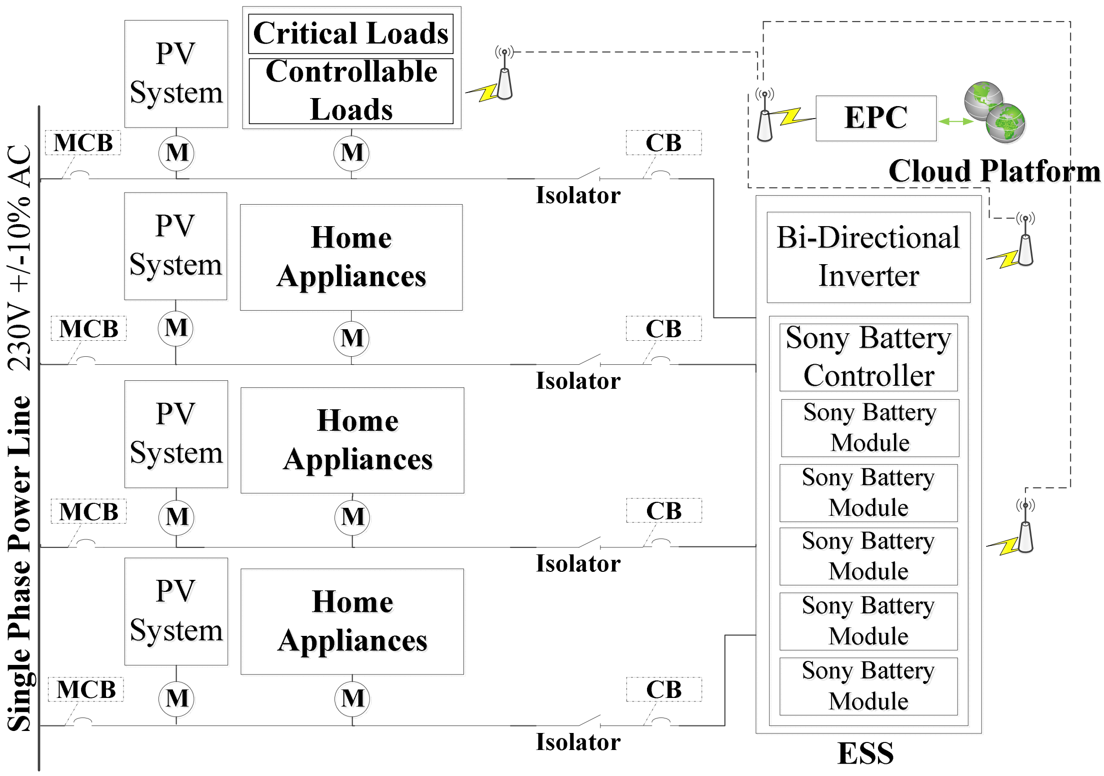


Fig. 6 System architecture of the μVPP

The eHeat Pump provides district heating and water heating to the residents, smart micro-controllers were also installed to control the eHeat Pump to be ON or OFF. During winter times the consumption power of the eHeat Pump is often higher than the other seasons due to increased demand for district heating. If left unmanaged, the eHeat Pump would be ON constantly to maintain the indoor temperature and the temperature of the water tank at a certain level. However, active management with carefully designed constraints can be equally capable of fulfilling the requirement in the heat sector while saving considerable amount of energy.

The smart meters installed at the eHeat Pump report to the HEMS about its ON/OFF status and consumption data while receiving the command to turn it ON or OFF for the following operation interval. Since the thermal information of the apartments is not yet available, the requirements on the thermal dynamics take the form of a series of time constraints. Firstly, the minimum time for which eHeat Pump should keep its ON/OFF status before shifting to another state is a mandatory requirement for the safety and continuity of the operation. The upper limit of time for which eHeat Pump can be turned off continuously utilises the thermal dynamics of the building texture to guarantee that the temperature would not drop under an undesired level. In addition, the overall OFF time limit guarantees enough heat energy and hot water for daily consumption.

The core DER component in the μVPP is the smart energy storage system (ESS). The ESS is an integrated system housed in a 19-inch rack. The components include two 4.8kW bi-directional inverters, five 1.2kWh lithium-ion battery modules with rated voltage of

51.2V, a system controller that integrates the communication circuits and their power supply electronics. The communication interfaces are embedded into the inverter and battery controller to enable two-way information logging and algorithmic control. The schematic diagram of the ESS is shown in Fig. 7 and the actual system installed on site is presented in Fig. 8.

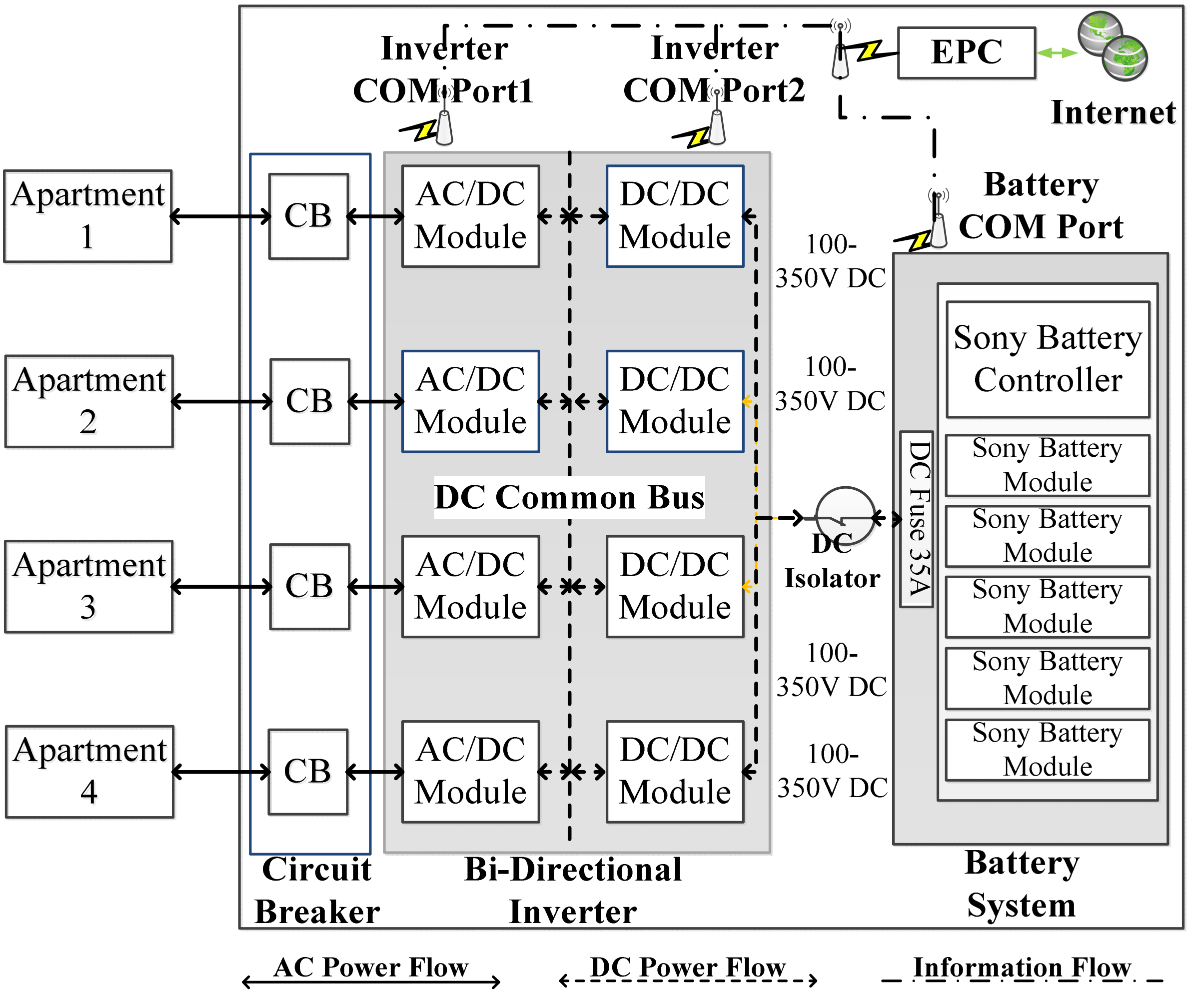


Fig. 7 Smart energy storage system schematics

One ESS is responsible to optimise the local power flow among four apartments with each apartment connecting to the four separate AC/DC modules of the bi-directional inverter respectively. Those four AC/DC modules share a common DC link which enables the internal power exchange of the four connected apartments. Any surplus power or shortage power resulting from the internal exchange will pass on the request to the other side of DC link and the request will be transferred into battery charging/discharging commands. The system controller equipped in the ESS shoulders the centralised monitoring and control over the inverter and battery system, broadcasts the collected information to the EPC and receives the charging/discharging command from the EPC. For protection purpose, the ESS is also fully equipped with fuses on both AC and DC side as well as a separate DC isolator.

Fig. 8 Smart energy storage system installed in the μVPP

The ESS complies with several physical constraints: firstly, the battery state-of-charge (SOC) should not exceed an upper limit of 85% and a lower limit of 15%. The two thresholds are set to avoid deep charge or discharge and prolong the life span of batteries; secondly, there are also upper and lower limits on the charging and discharging power; a minimum time requirement of 15 minutes should be met before the power direction can change for each inverter AC/DC module and the battery respectively. The last constraint prevents frequent change of power directions for the safety of both inverters and battery modules. Given that each operation interval takes 3 minutes, this constraint indicates that the direction of power flow should remain the same for at least 5 operation intervals until it can be changed to the opposite direction (i.e. from charging the ESS to discharging the ESS).

3.3 µVPP Business Model and Managed Energy Services

3.3.1 Nomenclature

Sets and Indices

t	Index of time in the scheduling horizon
i	Index of the apartment that is connected to the ESS
I	Set of the apartments that are connected to the ESS
NI	Number of apartments connected to the ESS
k	Index of the apartment in the power redistribution queue
K	Set of the apartments in the power redistribution queue
NK	Number of apartments in the power redistribution queue
EV	Set of parameters and variables related to the electric vehicle
HP	Set of parameters and variables related to the eHeat Pump
ESS	Set of parameters and variables related to the energy storage system
APT	Set of parameters and variables related to the individual apartment
DNO	Set of parameters and variables related to the distribution network operator

Parameters

C_{RT}	\$/kWh, real-time electricity price
η	Discount rate for end-consumers in the µVPP, the released power from the ESS is sold to end-consumers at price $\eta \times C_{RT}$
C_{FIT}	\$/kWh, feed-in tariff for the surplus RES production

C_{DNO} $/kW, network surcharge rate determined by the peak consumption rate kW

C_{ESS}^{cap} $/kWh, capital investment for each kWh of the ESS capacity

$C_{ESS}^{\Delta pv}$ $/kWh, internal electricity trading price for importing the surplus RES production from the apartments to the ESS

C_{APT}^{ESS} $/kWh, internal electricity trading price for the transactions between the apartment and the ESS

B_{ESS} kWh, rated capacity of the ESS

$\overline{SOC}_{ESS}$ Maximum state-of-charge for the ESS

$\underline{SOC}_{ESS}$ Minimum state-of-charge for the ESS

$\overline{P}_{ESS}$ kW, maximum charging/discharging power for the ESS

$\underline{P}_{ESS}$ kW, minimum charging/discharging power for the ESS

T_{EV} hours, total available time that EV can access to the charging point per day

T_{HP} hours, maximum time limit that eHeat Pump can be turned OFF per day

Variables

$S_{APT,i}^{bill}$ $, the annual electricity bill of a μVPP tenant

S_{uVPP}^{rent} $, the rent that end-consumers pay to the μVPP operator

S_{uVPP} $, the profit of μVPP operator from internal electricity trading

t_{ROI} years, the payback period of capital investment

S_{DNO} $, network surcharge paid by end-consumers to the DNO

$P_{APT,i}^{grid}$ kW, total power imported from the grid by each apartment; this variable corresponds to a single apartment

$P_{APT,i}^{fit}$ kW, surplus RES production exported by the apartment to be fed back to the grid; this variable corresponds to a single apartment

$P_{APT,i}^{\Delta pv}$ kW, surplus RES production exported by the apartment to be stored in ESS; this variable corresponds to a single apartment

$P_{APT,i}^{\Delta grid}$ kW, extra power imported by the apartment from the grid to be stored in ESS; this variable corresponds to a single apartment

$P_{APT,i}^{net}$ kW, the expected power transaction for each apartment calculated by deducting the micro-generation from total demand; positive value indicates the apartment is a demand block, negative value indicates the apartment is a supply block; this variable corresponds to a single apartment

$P_{APT,i}^{ESS}$ kW, the actual power transaction between each apartment and the ESS; positive value means the power flows from the ESS to the apartment, negative value means the power flows from the apartment to the ESS; this variable corresponds to a single apartment

P_{ESS}^{pre} kW, preliminary charging/discharging decisions for ESS derived by FLC; positive value means the ESS is going to be charged and negative value means it is going to be discharged

P_{ESS}^{fin} kW, final charging/discharging decisions considering the collective request from all connected apartments; positive value means the ESS is going to be charged and negative value means it is going to be discharged

ΔP_{APT}^{ESS} kW, the power difference between the expected and the actual transactions between the connected apartments and the ESS; this variable corresponds to the collective results of all the apartments

SOC_{ESS} State-of-charge of the ESS

λ_{EV} Fuzzy input variable, the available charging time ratio for the EV

λ_{HP} Fuzzy input variable, the available off time ratio for the eHeat Pump

λ_{ESS} Fuzzy input variable, the discharging ability ratio for the ESS

t_{EV} hours, this variable defines how much time the EV has already been plugged-in during the day (EV in the plugged-in status is not necessarily being charged)

t_{HP} hours, this variable defines how much time the eHeat Pump has already been OFF during the day

γ_{EV} Fuzzy output variable, 1 means the decision is to turn ON the EV, 0 means to turn OFF the EV

γ_{HP} Fuzzy output variable, 1 means the decision is to turn ON the eHeat Pump, 0 means to turn OFF the eHeat Pump

γ_{ESS} Fuzzy output variable, the satisfaction ratio for discharging request of the ESS

$\delta^1_{APT,i}$ Priority factor 1 when sorting the apartments in a queue, this variable corresponds to a single apartment

δ^2_{APT} Priority factor 2 when sorting the apartments in a queue, this variable corresponds to the collective of all apartments

3.3.2 μVPP Business Model and Service Types

To identify the beneficiaries and their revenue streams in the daily operation of the μVPP, the business model is presented in Fig. 9. The participants of the μVPP environment include DNO, electricity supplier company, μVPP operator and end-consumers.

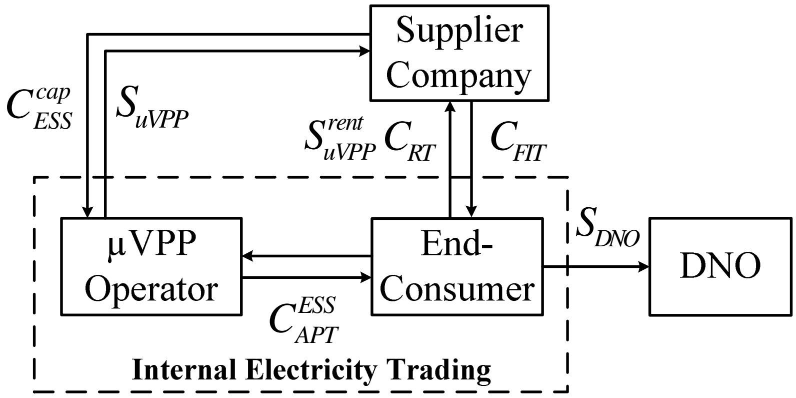


Fig. 9 Value streams between μVPP participants

Supplier Company

Supplier companies such as E. ON is the investor for the μVPP while functioning as traditional electricity suppliers. They provide the upfront cost, which mainly consists of the capital investment for the ESS at price C_{ESS}^{cap}, to construct the hardware and software infrastructure of the μVPP. End-consumers pay the supplier for the electricity consumption at real-time price C_{RT} and receive compensation for the excessive RES generation which is fed back to the grid at FIT C_{FIT}. By signing a binding contract with the supplier, end-consumers can join the μVPP and the supplier receives an annual rent S_{uVPP}^{rent} from the tenant. Also, the supplier is the recipient of the μVPP's profit S_{uVPP} from the internal electricity trading. For the supplier company, the return on investment (ROI) for the μVPP operation consists of the rent S_{uVPP}^{rent} and the profit S_{uVPP} but not its electricity retail income.

Therefore, the payback period is calculated as:

$$t_{ROI} = \frac{C_{ESS}^{cap} \times B_{ESS}}{S_{uVPP}^{rent} + S_{uVPP}} \tag{3.1}$$

where the numerator term is the total capital investment of an ESS of size B_{ESS} at price C_{ESS}^{cap} ; the denominator term is the annual ROI for the supplier and the payback period is the value of the fraction as equation (3.1) suggests.

DNO

DNO manages the local distribution network and it is not involved in the µVPP operation directly. However, end-consumers need to pay DNO a network surcharge S_{DNO} based on their highest monthly consumption level. The economic benefit of DNO is not included in the design of µVPP algorithm but the network surcharge scheme provides incentives for the µVPP to smooth its load profile and reduce peak consumption.

End-Consumer

The end-consumers in the µVPP participate in three kinds of electricity trading and they are presented as follows:

- As customers in the current electricity retail market, end-consumers pay for the electricity $P_{APT,i}^{grid}$ imported from the grid at retail price C_{RT} . In addition, their electricity bill includes the network surcharge S_{DNO} .
- As renewable energy generators, end-consumers receive compensation at FIT C_{FIT} if they feed the excessive RES production back to the main grid.
- As tenants in the µVPP community, they can participate in the bi-directional electricity

trading by actively importing power from the ESS or exporting power to the ESS. The internal power transactions are priced at C_{APT}^{ESS} .

If the RES generates more than the apartment needs, the surplus power $P_{APT,i}^{\Delta pv}$ can be stored in the ESS or transferred to be used by another apartment immediately. The end-consumer can sell their surplus RES production at price $C_{ESS}^{\Delta pv}$, which is higher than the FIT thus providing incentive for end-consumers to sell their surplus RES output to the local μVPP instead of feeding it back to the grid.

If the current retail price is very low, the ESS has the incentive to import electricity for later use. Under this circumstance, the apartment will import an extra amount of electricity $P_{APT,i}^{\Delta grid}$ from the grid, which is more than its actual consumption, to sell to the ESS. The additional import is priced at the current retail price C_{RT} .

If the RES generation can't satisfy the demand, the apartment can purchase from either the supplier at price C_{RT} or from the ESS at price C_{APT}^{ESS} . To encourage the internal trading between the end-consumers and the ESS, the selling price of the released electricity is designed to be cheaper than the supplier at a discount rate of η .

Therefore, the prices of the internal electricity trading are summarised as:

$$C_{APT}^{ESS}=\begin{cases} C_{ESS}^{\Delta pv} \quad for \quad P_{APT,i}^{\Delta PV}\ if \quad P_{APT,i}^{ESS}<0, P_{APT,i}^{\Delta PV}\neq 0 \\ C_{RT} \quad for \quad P_{APT,i}^{\Delta grid}\ if \quad P_{APT,i}^{ESS}<0, P_{APT,i}^{\Delta grid}\neq 0 \\ \eta\times C_{RT}\wedge 0<\eta<1 \quad if\ P_{APT,i}^{ESS}>0 \end{cases} \tag{3.2}$$

The annual electricity bill of the μVPP tenants is calculated as:

$$S_{APT,i}^{bill}=\sum\left(C_{RT}\times P_{APT,i}^{grid}+C_{APT}^{ESS}\times P_{APT,i}^{ESS}-C_{FIT}\times P_{APT,i}^{fit}\right)+S_{DNO} \tag{3.3}$$

where the monetary terms correspond to the three kinds of electricity transaction mentioned above.

μVPP Operator

The μVPP operator manages the μVPP system on behalf of the supplier company and earns the profit from the internal electricity transaction between ESS and each apartment. Its profit S_{uVPP} will pass on to the supplier company and is calculated as:

$$S_{uVPP} = \sum_{i=1}^{NI} \left(C_{APT}^{ESS} \times P_{APT,i}^{ESS} \right) \tag{3.4}$$

If the power flows from the ESS to the apartment, $P_{APT,i}^{ESS}$ is a positive value and μVPP operator receives the payment at price C_{APT}^{ESS} ; if the power flows the other way around, $P_{APT,i}^{ESS}$ is a negative value and μVPP operator pays the apartment at price C_{APT}^{ESS} . The settlement of the transaction price is shown in equation (3.2).

Based on the breakdown of the electricity bills paid by the end-consumers, the managed energy services aim at reducing the electricity bill and creating new revenue streams from different aspects and these approaches can be summarised as the following service types:

- ***Service 1 – Maximum self-consumption service***

Given the low level of the FIT, any surplus production from the RES is immediately redistributed within the μVPP or stored in the ESS instead of being fed back into the main grid. This service aims at utilising the RES locally as much as possible.

- ***Service 2 – Dynamic tariff service***

This service is designed to utilise the dynamics in the retail tariff and use grid imported electricity when it is at its cheapest. The ESS will import grid supplied electricity during the low tariff period and release the stored electricity during peak price period to be consumed by the apartments. CLs are not mobilised in this service.

- ***Service 3 – dynamic tariff with active load control***

In addition to all the functions of service 2, service 3 provides an add-on function of actively scheduling the CLs based on the dynamics in the retail tariff. Further bill reductions are expected compared with service 2.

- ***Service 4 – dynamic tariff with load shedding***

In addition to all the functions of service 3, service 4 provides an add-on function of smoothing the load profile by shedding the CLs during peak demand period. Further bill reductions are expected compared with service 3 due to a cheaper network surcharge.

The managed energy services described above summarise the popular operation modes in the DER applications and provide end-consumers an opportunity to customise their energy management schemes. To accommodate these different services without any re-engineering of the code, a prerequisite of the μVPP algorithm is to provide a generic architecture to support all HEMS propositions by simply adjusting the system configuration file.

3.4 μVPP HEMS Algorithmic Flow

3.4.1 Overview of the HEMS Algorithm

The proposed HEMS algorithm for μVPP produces real-time control signals every 3 minutes. At the beginning of each interval, meter readings of PV generation, critical load consumption, CLs status are gathered and fed into the algorithm as inputs. As the result, decisions including the charging/discharging command of the ESS, the power flow between each apartment and the ESS, the ON/OFF decisions for CLs are produced and transmitted to guide these DERs for the upcoming interval. Upon the successful execution of the decisions, the accumulative time variables such as the current OFF time of CLs are updated accordingly. A standardised workflow is designed for the HEMS algorithm and there are three workflow stages as shown in Fig. 10. Detailed inputs, outputs and function blocks are presented in Fig. 11.

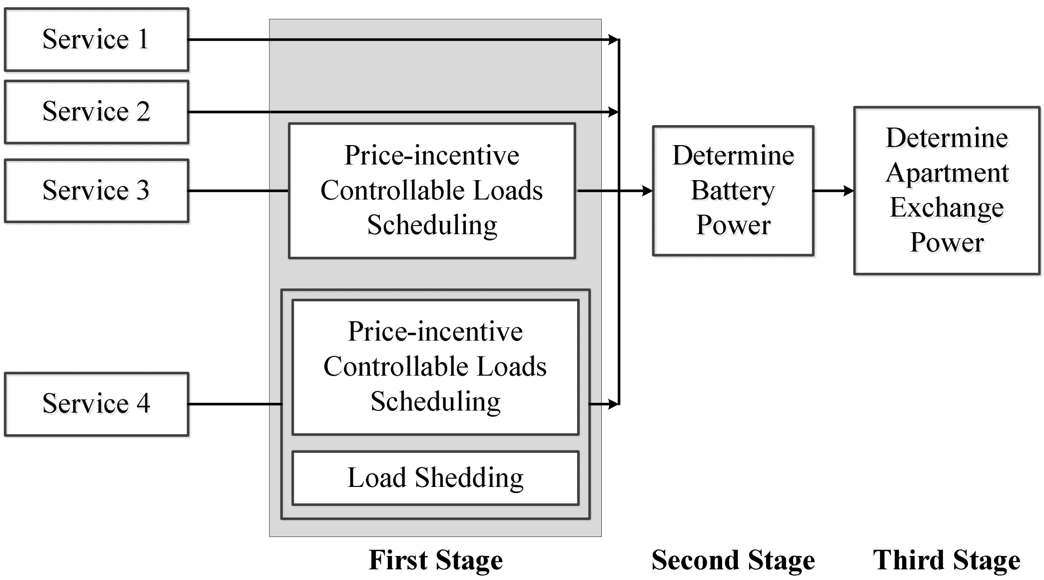


Fig. 10 HEMS algorithm architecture for different services

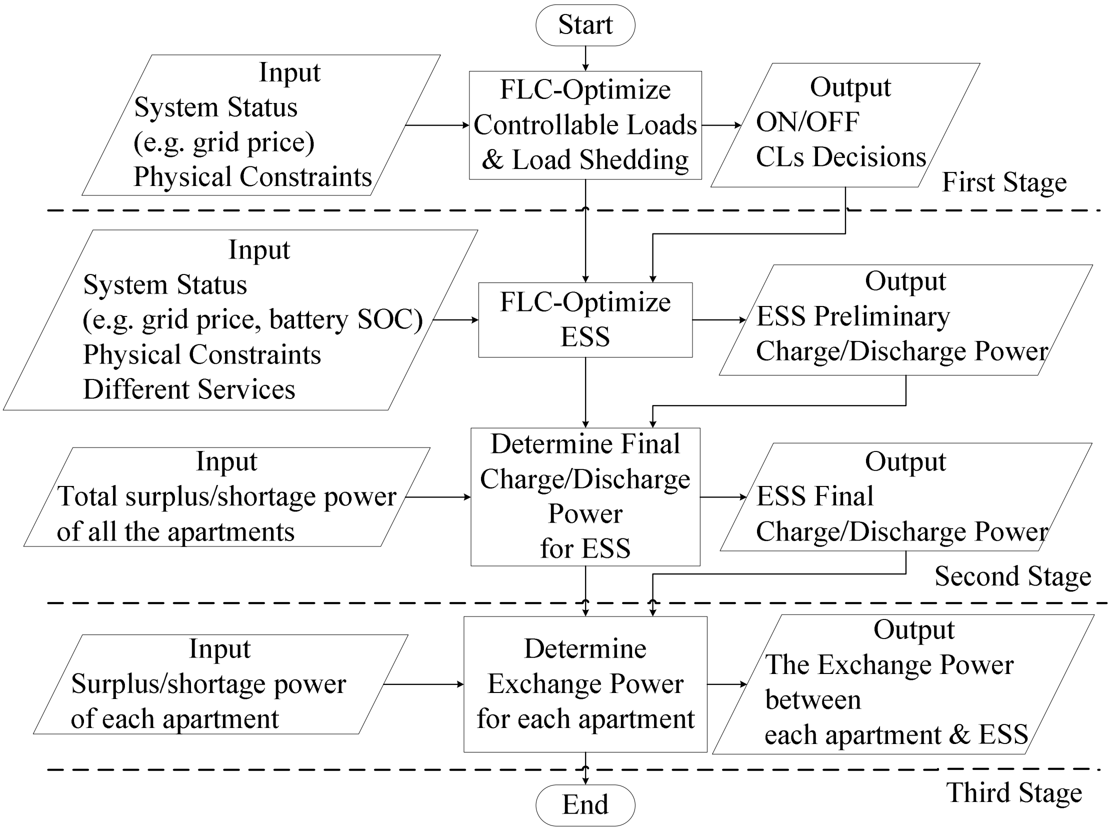


Fig. 11 Detailed HEMS algorithm workflow

The three stages are introduced as follows:

Stage 1 The first stage determines the ON/OFF decisions for CLs based on FLC. This stage only applies to service 3 and service 4, service 1 and 2 will proceed straight to the second stage. At the end of the first stage, the consumption level for all connected apartments for the next interval will be settled. Details of this stage are presented in section 3.4.2.

Stage 1.1 The fuzzified inputs of EV and eHeat Pump are processed based on inference rules and decisions γ_{EV} and γ_{HP} are obtained regarding their ON/OFF status for the next interval. By adding the rated consumption power of the CLs to the power reading of the critical loads and deducting the micro-generation power, the expected power transaction for each apartment $P_{APT,i}^{net}$ is obtained. These decisions are final for service 3 but preliminary for service 4 as additional load shedding is required.

Stage 1.2 If the apartment is a demand block and the expected power transaction $P_{APT,i}^{net}$ obtained in Stage 1.1 exceeds the load limit, the reserved capacity of ESS will be utilised first to compensate the exceeding part. If the ESS compensation is not enough, load shedding will be activated to turn OFF the CLs whose original decision is ON for the next interval. Load shedding will continue until the expected power transaction $P_{APT,i}^{net}$ falls under the limit. Stage 1.2 finalises the CL decision γ_{EV} , γ_{HP} and the expected power transaction $P_{APT,i}^{net}$ for service 4. Detailed steps of load shedding are presented in section 3.4.2.

Stage 2 The second stage firstly derives the charging/discharging power for the ESS based on FLC, which is only a preliminary decision. Then the situations of all the connected apartments are taken into consideration (whether they act as a demand block collectively or as a supply block collectively) and the ESS decisions are finalised. Details of this stage are presented in section 3.4.3.

Stage 2.1 According to the selected service type, the fuzzified inputs of ESS are processed based on inference rules to obtain preliminary decision on the ESS charge/discharge power P_{ESS}^{pre} .

Stage 2.2 The preliminary ESS decision P_{ESS}^{pre} is adjusted considering different scenarios where the request of apartments to charge or discharge is not consistent with that of ESS. Stage 2.2 produces the final ESS charge/discharge power P_{ESS}^{fin} after adjustment. Detailed description of the scenarios and the adjustment rules is presented in section 3.4.3.

Stage 3 In the third stage, the final ESS decision obtained in the second stage is decomposed into four power flow decisions between each apartment and the ESS. This is based on the actual system topology where the four apartments are connected to the ESS via four separate AC power lines. Details of this stage are presented in section 3.4.4.

Stage 3.1 This sub-stage performs queuing of the apartments to determine their sequence in receiving the allocated fraction of power to achieve the final ESS decision P_{ESS}^{fin} . The queuing strategy is presented in section 3.4.4.

Stage 3.2 This final sub-stage performs the allocation of power based on the apartment queue and finalises the exchange power $P_{APT,i}^{ESS}$ between ESS and each connected apartment. The allocation process is described in section 3.4.4.

3.4.2 First Stage in HEMS – Optimise Controllable Loads

The first stage in HEMS operation optimises CLs including EVs and eHeat Pumps, it decides whether they will be turned ON or OFF for the next scheduling interval. The FLC takes three steps of fuzzification of inputs, rule-based inference and defuzzification of outputs to derive the control signals.

Under the prerequisite that the physical constraints of the CLs should be satisfied, the optimisation of CLs aims at turning them ON when the retail electricity price is relatively low. For EVs, there are two fuzzy inputs including the real-time retail price C_{RT} and the available charging time ratio λ_{EV} . The latter input defines how much time the EV has left to carry out charging actions while it is parked in the garage and can therefore access to the charging point:

$$\lambda_{EV} = 1 - \frac{t_{EV}}{T_{EV}} \tag{3.5}$$

where the variable t_{EV} represents the time that has already passed by since EV was first plugged in for the day. Therefore, the ratio λ_{EV} stands for the remaining opportunity for EV to be charged in the daily scheduling. The smaller λ_{EV} is, the more urgent it is for EV to be charged if it needs to. With the ratio λ_{EV} ranging from 0 to 1, the EV status is fuzzified as "Very Urgent (VU)", "Urgent (U)", "Medium (M)", "Flexible (F)" and "Very Flexible (VF)". Another fuzzy input, the real-time retail price, is also fuzzified as "Very Low (VL)", "Low (L)", "Medium (M)", "High (H)" and "Very High (VH)". The output of the FLC is a linguistic variable that can be either ON or OFF, corresponding to the "turn ON" or "turn OFF" commands. To illustrate the mechanism of the FLC in scheduling the EVs, the membership functions of both inputs and output is depicted in Fig. 12 and the fuzzy inference rules are explained in the format of pseudo code.

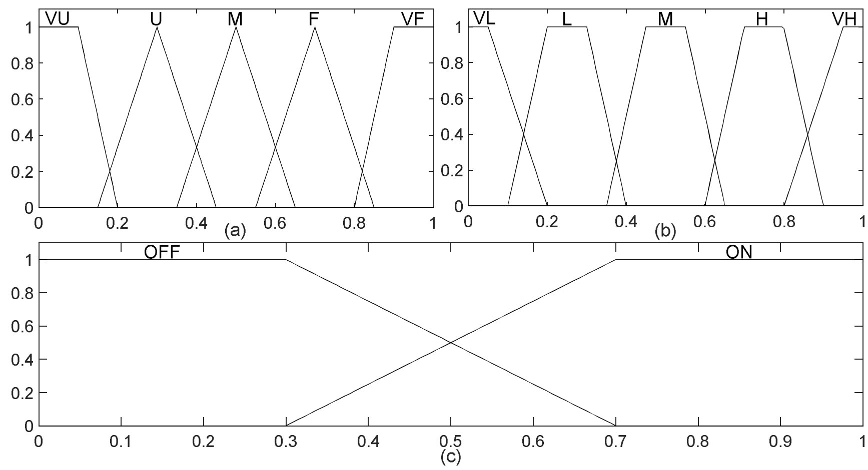


Fig. 12 Membership functions for EV FLC (a) Available charging time ratio; (b) retail price; (c) EV charging decision

The fuzzy inference rules are designed to assess the charging availability and the retail price jointly, and produce the decision based on the empirical knowledge. EV tends to be charged if it is approaching to the end of today's scheduling horizon or if the retail price is low. More sensitive responses to the input variables are designed and summarised as 25 inference rules as shown in Table I.

TABLE I FUZZY INFERENCE RULES FOR EV SCHEDULING

λ_{EV} \ C_{RT}	VL	L	M	H	VH
VU	ON	ON	ON	ON	ON
U	ON	ON	ON	ON	OFF
M	ON	ON	ON	OFF	OFF
F	ON	ON	OFF	OFF	OFF
VF	ON	OFF	OFF	OFF	OFF

The thought process of the FLC inference is presented in the following example.

IF available charging time ratio λ_{EV} indicates a flexible status (i.e. there is no rush to charge the EV immediately),

AND real-time retail electricity price C_{RT} is low,

THEN FLC decides to turn on EV charging point.

Two extreme conditions are worth highlighting:

IF available charging time ratio λ_{EV} indicates a very urgent status (i.e. the charging point will soon be unavailable in today's optimisation window),

THEN FLC decides to turn ON the charging point regardless of the price scenarios.

IF the retail price is very low,

THEN FLC decides to turn ON the charging point regardless of the availability of the charging point.

The decision-making process of eHeat Pump is carried out in the same fashion. The ON and OFF decisions obtained by FLC are the final commands sent to the micro-controllers under service 3. However, the load shedding function in service 4 requires these fuzzy decisions to be refined to level the peak monthly consumption. In service 4, the add-on function of load shedding takes the following steps:

Step 1) Calculate the expected power transaction amount $P_{APT,i}^{net}$ for each apartment by deducting the micro-generation from the demand. Positive value means the apartment is a demand block, otherwise it is a supply block;

Step 2) If the apartment is a demand block and the real-time demand value exceeds the maximum load limit, activate the reserve capacity of ESS to compensate the excess amount (i.e. 5% of the ESS capacity is reserved for compensation purpose, which is not allowed to be used in the internal trading);

Step 3) Activate load shedding if the reserved ESS capacity fails to compensate the excess load;

Step 4) Target the CLs that are scheduled to be running in the upcoming interval, check whether their decisions can be overwritten to OFF;

Step 5) If the overwriting can be authorised, shed the CLs based on the sequence of eHeat Pump first and EV second until the peak demand falls under the cap.

Three prerequisites should be met before the load shedding could be activated: firstly, the excess part of the demand is beyond the compensation ability of the ESS; secondly, at least one of the CLs are originally scheduled to be turned on for the next interval; thirdly, the overwriting of the CL decision will not violate the physical constraints of the CLs. As for the sequence of shedding, eHeat Pump comes first because of its lower consumption power. Therefore, shedding eHeat Pump alone might fulfil the task of smoothing the peak load without involving the EV. To sum up, the load shedding process is designed to reduce peak consumption and bring minimal impact on CLs' operation.

The mathematical rationale of FLC's workflow is explained as follows: firstly, conventional control algorithms such as PID control are derived from the closed-form mathematical equations that model the system. In other words, the system parameters should be known and the dynamics of the system could be accurately modelled. However, some parameters of the proposed μVPP are unavailable and some system behaviours are hard to model. For instance, the driving patterns of the EVs are difficult to obtain. While in the proposed fuzzy logic control scheme, there is no need to make unrealistic assumptions for modelling EV behaviour. Linguistic quantifications are used in the FLC to define the ambiguous status of the EV and to specify a set of rules that captures the expert's knowledge about how to control the EV charging for the benefit of the EV [133]. At the beginning of the day when the travel plan is not settled, the EV status is defined as "flexible" and the FLC decides there is no need to charge the EV. Secondly, the multiple rules used in the inference resemble the parameters of a conventional PID controller. The rules are associated with the gradient of the change in the FLC output, and the accuracy of the FLC could be improved by increasing the number of rules (i.e. the increase in rules indicates the increase in the FLC's expertise in the subject control problem). The membership functions of the FLC serve as look-up tables to convert the crisp input data to fuzzy data and to convert the fuzzy output to crisp values, in which the ambiguous linguistic result is transformed into precise numerical signal.

3.4.3 Second Stage in HEMS – Determine ESS Charging/Discharging Power

The internal electricity trading is facilitated by actively charging and discharging the ESS and the profit obtained from the internal trading is a vital source of ROI for µVPP investors. This stage determines the power level with which the ESS is charged or discharged. The decision process takes two steps: in the first step a preliminary decision is obtained based on FLC, where only the ESS' status is taken into consideration; in the second step the decision is finalised by considering the collective request from all the apartments.

The preliminary decision P_{ESS}^{pre} is obtained at the ESS' point of view, it only considers ESS' own economic interest and safety requirements including the retail electricity price, the maximum SOC and maximum power limit. A positive value of P_{ESS}^{pre} means the ESS will be charged and a negative value means the ESS will be discharged in the next interval. Also, the preliminary decisions are closely tied to the service type. Under service 1, ESS is treated as a complementary device to store the surplus RES generation and no voluntary charging/discharging actions are allowed. However, under service 2, 3 and 4, ESS becomes a responsive device to the dynamics in the retail price and performs active charging/discharging.

When the µVPP is configured to run service 1, the preliminary ESS decision is derived for the charging process and discharging process separately. Intuitively, the charging power equals to the remaining RES power after satisfying the demand to maximise self-consumption. The discharging power, on the other hand, is determined using the FLC similarly to the ones used for the CL control. There are two fuzzified inputs for the FLC under service 1: the current state-of-charge SOC_{ESS} and a discharging ability ratio λ_{ESS} which is calculated as the total expected discharging power divided by the maximum ESS power rate.

$$\lambda_{ESS} = \frac{\sum_{i=1}^{NI} P_{APT,i}^{net}}{\bar{P}_{ESS}} \tag{3.6}$$

The ratio λ_{ESS} defines the ESS' ability to satisfy the requested amount of power to be injected to the apartments. The ability is fuzzified as linguistic variables of "Low (L)", "Medium (M)" and "High (H)" which correspond to the scenarios that "the requested discharging power is low and can be handled easily by ESS", "the requested discharging power level is medium and within the ESS' capability" and "the request discharging power level is high and near to the upper limit of the capability". The other input SOC_{ESS} can be fuzzified intuitively based on its numerical readings as "Low (L)", "Medium (M)" and "High (H)".

The fuzzy output γ_{ESS} is called the satisfaction ratio for the discharging request and it has three values of "Low (L)", "Medium (M)" and "High (H)" which correspond to the scenarios that "the discharging request is poorly satisfied by the ESS", "the discharging request is half-way satisfied by the ESS" and "the discharging request is well satisfied". The fuzzy output γ_{ESS} will be defuzzified and transformed to the preliminary ESS decision under service 1:

$$P_{ESS}^{pre} = -\gamma_{ESS} \times \overline{P}_{ESS} \tag{3.7}$$

where the negative value of ESS decision P_{ESS}^{pre} represents discharging power.

The fuzzy inference rules for the preliminary decision obtained for service 1 are presented in Table II. They are derived based on an empirical anticipation of ESS' response to different discharging request submitted by the apartments: If SOC_{ESS} is low, only the apartments with low expected power request will be well satisfied. If SOC_{ESS} is medium, then both low power and medium power request will be well satisfied, leaving the request with high power level half-way satisfied. If SOC_{ESS} is high then all requests with different power levels will be well satisfied.

TABLE II FUZZY INFERENCE RULES FOR ESS PRELIMINARY DECISION UNDER SERVICE 1

γ_{ESS} \ SOC_{ESS}	L	M	H
L	H	H	H
M	M	H	H
H	L	M	H

Under service 2, 3 and 4, both charging and discharging power are derived by FLC. The fuzzy inputs include the current SOC_{ESS} and real-time retail electricity price C_{RT}. Both inputs are fuzzified as linguistic variables of "Very Low (VL)", "Low (L)", "Medium (M)", "High (H)" and "Very High (VH)". The fuzzy output is categorised based on whether they are charging decision or discharging decision and their power levels: "Charge Low (CL)", "Charge Medium (CM)", "Charge High (CH)", "Discharge Low (DL)", "Discharge Medium (DM) and "Discharge High (DH)". The membership functions for the fuzzy inputs and output are depicted in Fig. 13. There are 25 rules designed to respond to different combinations of SOC level and the price level and these rules anticipate the logical reaction of ESS: the ESS tends to be charged during the period when the price is low and the SOC is low as well; otherwise discharging action is the preferable choice. The depth of charging and discharging depends on whether the input variable is VL, L, M, H or VH. These rules are summarised in Table III.

TABLE III FUZZY INFERENCE RULES FOR ESS PRELIMINARY DECISION UNDER SERVICE 2, 3 AND 4

SOC_{ESS} \ C_{RT}	VL	L	M	H	VH
VL	CH	CH	CM	DL	DH
L	CH	CM	CL	DM	DH
M	CH	CL	DM	DM	DH
H	CH	CL	DM	DH	DH
VH	CH	CL	DH	DH	DH

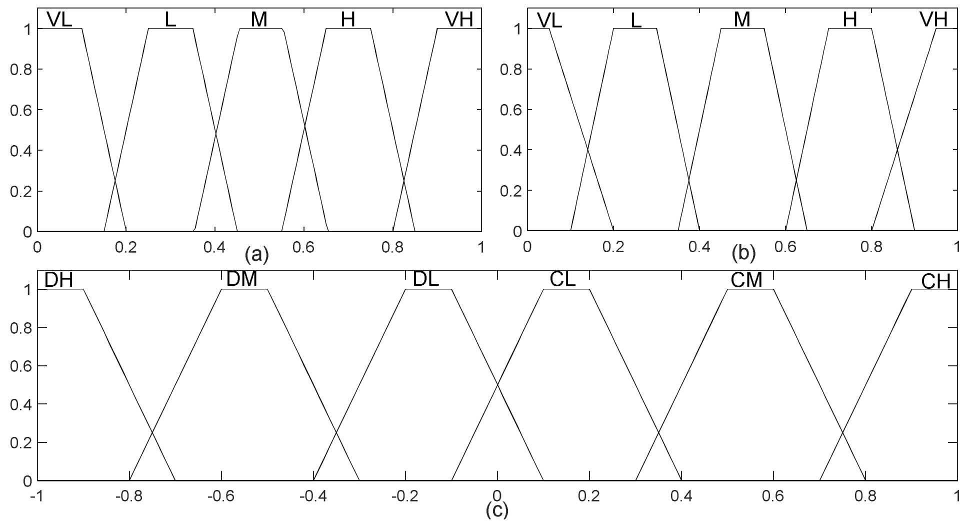


Fig. 13 Membership functions of inputs and outputs for ESS under service 2, 3 and 4
(a) SOC; (b) retail price; (c) ESS preliminary decision

Under service 1, the preliminary ESS decision is also the final decision and can be transmitted directly to control the ESS. However, under the other services, the preliminary decision only considers the real-time price and its SOC. Therefore, the preliminary decision under service 2, 3 and 4 should be adjusted based on the collective supply/demand status $\sum_{i=1}^{NI} P_{APT,i}^{net}$ of the four connected apartments. In this way, the final decision P_{ESS}^{fin} can represent the mutual benefit for both the ESS and the end-consumers. A positive value of $\sum_{i=1}^{NI} P_{APT,i}^{net}$ means the collective of four apartments behaves as a demand block thus the ESS is required to be discharged from the apartments' point of view. A negative value of $\sum_{i=1}^{NI} P_{APT,i}^{net}$ means the collective of four apartments acts as a supply block thus the ESS is required to be charged from the apartments' point of view. The adjustment rules to deliver the final decision for service 2, 3 and 4 are presented as follows:

Scenario 1 – The apartments act as a supply block collectively, FLC decision instructs ESS to be charged

$$\sum_{i=1}^{NI} P_{APT,i}^{net} < 0, \quad P_{ESS}^{pre} > 0 \tag{3.8}$$

Two independent decisions are made to charge the ESS, their charging power should be combined to deliver the final charging power as shown in equation (9):

$$P_{ESS}^{fin} = -\sum P_{APT}^{net} + P_{ESS}^{pre} \tag{3.9}$$

Scenario 2 – The apartments act as a supply block collectively, FLC decision instructs ESS to be discharged

$$\sum_{i=1}^{NI} P_{APT,i}^{net} < 0, \quad P_{ESS}^{pre} < 0 \tag{3.10}$$

Two independent decisions result in opposite directions of the power flow. However, the discharging of ESS should only be allowed when the apartments have shortage of power supply, which is not the case in this scenario. Therefore, the final ESS decision is:

$$P_{ESS}^{fin} = -\sum P_{APT}^{net} \tag{3.11}$$

Scenario 3 – The apartments are self-balancing collectively, FLC decision instructs ESS to be charged

$$\sum_{i=1}^{NI} P_{APT,i}^{net} = 0, \quad P_{ESS}^{pre} > 0 \tag{3.12}$$

When the RES generation of some apartments can balance the demand of the other apartments, ESS will agree with the preliminary charging decision to store electricity (i.e. increase the volume of the goods when spot price is low, even if there is no immediate demand).

$$P_{ESS}^{fin} = P_{ESS}^{pre} \tag{3.13}$$

Scenario 4 - The apartments are self-balancing collectively, FLC decision instructs ESS to be discharged

$$\sum_{i=1}^{NI} P_{APT,i}^{net} = 0, \quad P_{ESS}^{pre} < 0 \tag{3.14}$$

The discharging of ESS should only be allowed when the apartments have shortage of power supply, which is not the case in this scenario. Therefore, the preliminary ESS decision is overruled:

$$P_{ESS}^{fin} = 0 \tag{3.15}$$

Scenario 5 – The apartments act as a demand block collectively, FLC decision instructs

ESS to be charged

$$\sum_{i=1}^{NI} P_{APT,i}^{net} > 0, \quad P_{ESS}^{pre} > 0 \tag{3.16}$$

The FLC decides that the ESS needs to be charged due to low retail price or low SOC of the ESS, which prohibits any stored electricity to be used by apartments. On the other hand, the collective demand from all the apartments could be supplied by grid at a cheap price in this scenario. Therefore, ESS will agree to the preliminary decision and store more electricity.

$$P_{ESS}^{fin} = P_{ESS}^{pre} \tag{3.17}$$

Scenario 6 - The apartments act as a demand block collectively, FLC decision instructs ESS to be discharged

$$\sum_{i=1}^{NI} P_{APT,i}^{net} > 0, \quad P_{ESS}^{pre} < 0 \tag{3.18}$$

The apartments and the FLC in this scenario want the same thing – the ESS to be discharged and to satisfy the demand from the collective of all apartments. However, it is not necessary to discharge more than the apartments need. Therefore, the final discharging power is the smaller value of the two independent decisions:

$$P_{ESS}^{fin} = -\min\left(\left|\sum_{i=1}^{NI} P_{APT,i}^{net}\right|, \left|P_{ESS}^{pre}\right|\right) \tag{3.19}$$

Scenario 7 – The preliminary decision instructs ESS to be idle, regardless of the apartments' situation

Under this circumstance, the final decision should also be idle for the ESS to prevent any violations for the physical constraints (e.g. minimum time requirement for inverting the direction of the power flow).

$$P_{ESS}^{fin} = 0 \tag{3.20}$$

3.4.4 Third Stage in HEMS – Determining the Apartment Exchange Power

Considering that the final ESS charging/discharging power is a joint decision made by both ESS and the end-consumers, the actual power flow between these two parties may deviate from the apartments' expectation. Therefore, the third stage in HEMS is to decompose the target ESS power P_{ESS}^{fin} into four fractions and assign the specific exchange power $P_{APT,i}^{ESS}$ to each connected apartment. This redistribution stage identifies the priority of some apartments by performing a queuing process and considers the physical constraints of each AC power line that connects the apartment to the ESS. To sum up, the principle of the third stage is to guarantee that each apartment is treated equally and fairly while fulfilling the task of charging/discharging the ESS at the required power rate.

The first step is to perform queuing of the apartments to determine their sequence in receiving the allocated fraction of power. A numerical example is given as follows to illustrate the priority of apartments in the redistribution: apartment A and apartment B have surplus power of 0.5kW and 0.75kW respectively from their RES generation; apartment C and D are demand blocks with load of 0.45kW and 0.5kW respectively. Therefore, the collective of four apartments can be considered as a single supply block with 0.3kW excess power ready to be injected to the ESS. Meanwhile the final ESS decision is to put ESS in its idle state, making the 0.3kW excess power redundant and hence adjustment is needed. For apartment A and B, their power flow into the ESS should be decreased. On the other hand, apartment C and D should keep their claims on the load value as it would not be fair to ask them to increase the consumption just to accommodate the surplus power from A and B. As the result, only A and B participate in the redistribution and apartment A comes first because it has a smaller room to reduce the power injection (i.e. apartment A can reduce to a maximum of 0.5kW while B can reduce to a maximum of 0.75kW). Therefore, the final queue for power redistribution is [A, B].

This strategy is summarised in the following steps:

Step 1) Calculate the priority factors $\delta^1_{APT,i}$ for each apartment i and factor δ^2_{APT} :

$$\delta^1_{APT,i} = P^{net}_{APT,i} \times \left(\sum_{i=1}^{NI} P^{net}_{APT,i} + P^{fin}_{ESS} \right)$$

$$\delta^2_{APT} = P^{fin}_{ESS} \times \left(\sum_{i=1}^{NI} P^{net}_{APT,i} + P^{fin}_{ESS} \right) \tag{3.21}$$

Step 2) Sort apartments based on the ascending order of $\delta^1_{APT,i}$, set the queue empty if

$$\sum_{i=1}^{NI} \delta^1_{APT,i} = 0 \tag{3.22}$$

Step 3) If the queue has a non-positive factor δ^2_{APT} , remove the apartments of which $\delta^1_{APT,i} < 0$ and obtain the final redistribution queue with NK number of apartments.

The queuing strategy is summarised after examining every possible scenario in the power allocation. Although the algorithm could be designed to list every possible scenario by using "if…else…" statements, the generalised steps above provide a solution to handle large number of apartments more efficiently.

After the position of each apartment is determined, the redistribution process is carried out for the apartments $k = 1, 2 \ldots NK$ that are presented in the redistribution queue:

Step 1) Calculate the power difference ΔP_{APT}^{ESS} between the total expected transaction and the actual transaction between the ESS and the collective of all apartments:

$$\Delta P_{APT}^{ESS} = \sum_{i=1}^{NI} P_{APT,i}^{net} + P_{ESS}^{fin} \tag{3.23}$$

Step 2) Calculate the final exchange power $P_{APT,k}^{ESS}$ for apartment k, $\quad k \in K, K \subseteq I$:

$$P_{APT,k}^{ESS} = P_{APT,k}^{net} - \frac{\Delta P_{APT}^{ESS}}{NK - (k-1)} \tag{3.24}$$

Step 3) Update the remaining difference value ΔP_{APT}^{ESS} :

$$\Delta P_{APT}^{ESS} = \Delta P_{APT}^{ESS} - \left(P_{APT,k}^{net} - P_{APT,k}^{ESS} \right) \tag{3.25}$$

Step 4) Repeat step 2 and 3 until every apartment in the queue has been assigned the final exchange power. For those that are not included in the queue, their exchange power equals to their expected transaction power.

$$P_{APT,i}^{ESS} = P_{APT,i}^{net} \qquad i \in I, i \notin K \tag{3.26}$$

In the numerical example mentioned in the previous paragraphs, four apartments A, B, C, D have the following expected transaction power:

$P_{APT}^{net}(A) = -0.5kW$, $\quad P_{APT}^{net}(B) = -0.75kW$, $\quad P_{APT}^{net}(C) = 0.45kW$, $\quad P_{APT}^{net}(D) = 0.5kW$

And the final ESS decision is $P_{ESS}^{fin} = 0$ thus the power difference is calculated using equation (3.23):

$$\Delta P_{APT}^{ESS} = -0.5 - 0.75 + 0.45 + 0.5 + 0 = -0.3kW$$

Based on the queuing result [A, B], the final exchange power between apartment A and the ESS is determined first based on equation (3.24):

$$P_{APT}^{ESS}(A) = -0.5 - \frac{-0.3}{2-(1-1)} = -0.35kW$$

Then the remaining difference value is updated using equation (3.25):

$$\Delta P_{APT}^{ESS} = -0.3 - (-0.5 + 0.35) = -0.15kW$$

Then the final exchange power between apartment B and the ESS is determined based on equation (3.24):

$$P_{APT}^{ESS}(B) = -0.75 - \frac{-0.15}{2-(2-1)} = -0.6kW$$

For apartment C and D which are not included in the priority queue, their final exchange power is derived using equation (3.26):

$$P_{APT}^{ESS}(C) = 0.45kW, \quad P_{APT}^{ESS}(D) = 0.5kW$$

To sum up, the power flow before redistribution and after redistribution is presented in Table IV.

TABLE IV NUMERICAL EXAMPLE OF DETERMINING THE APARTMENT EXCHANGE POWER

Apt / ESS	A	B	C	D
Expected exchange power (kW)	-0.5	-0.75	0.45	0.5
Actual exchange power (kW)	-0.35	-0.6	0.45	0.5

As shown in the table above, the collective of all the apartments reaches self-balancing state after the redistribution process, which is required by the final ESS decision that no charging nor discharging should be allowed. Apartment A and B must curtail their RES output by 0.15kW each, but it is necessary.

3.5 Comparative Case Studies

The μVPP data including the PV generation, consumption and ESS status from January to December 2015 is recorded by the smart metering system and used for the case studies. The ESS has an installed capacity of 6kWh with an estimated lifetime of 4500 cycles. As for the price parameters, the real-time retail price is extracted from the Nord Pool data of 2015 [134], the FIT and DNO surcharge are provided by local supplier company in Sweden. To calculate the payback period, this thesis acknowledges the currently high upfront cost but it also acknowledges the fact that the initial capital for ESS will decline 20% to 30% annually and reach a more affordable level in 2020 [23]. Therefore, two payback periods are presented: one of them is calculated based on the current ESS investment and the other is based on a reduced upfront cost. The annual rent that end-consumers pay to the operator is set to be 40% of the final bill savings, which guarantees the larger half of the savings still goes to the consumers. The important price parameters are summarised in Table V.

TABLE V PRICE PARAMETERS OF μVPP BUSINESS MODEL

Parameters	C_{RT} (\$/kWh)	C_{FIT} (\$/kWh)	$C_{ESS}^{\Delta pv}$ (\$/kWh)	η	C_{ESS}^{cap} (\$/kWh)	$C_{ESS}^{cap}{}'$ (\$/kWh)	C_{DNO} (\$/kW)
Value	0.18 Avg.	0.08	0.12	90%	500	165	15

Each case in this section corresponds to one service type. One set of daily data in quarter 3, 2015 is used to demonstrate the service feature and another set of annual data of 2015 is used to perform economic analysis. The algorithm is coded in C# for the actual system and transferred to MATLAB code. The experiments run on an Intel Core-i5 2.5GHz computer.

3.5.1 Case A – Maximum Self-Consumption Service

When the µVPP is configured to run service 1, the system aims at utilising the RES generation locally as much as possible. As shown in Fig. 14, the trajectory of the SOC overlaps with the PV output throughout the day. The ESS is being charged frequently during daytime when sunlight is abundant and discharged to minimum SOC after sunset.

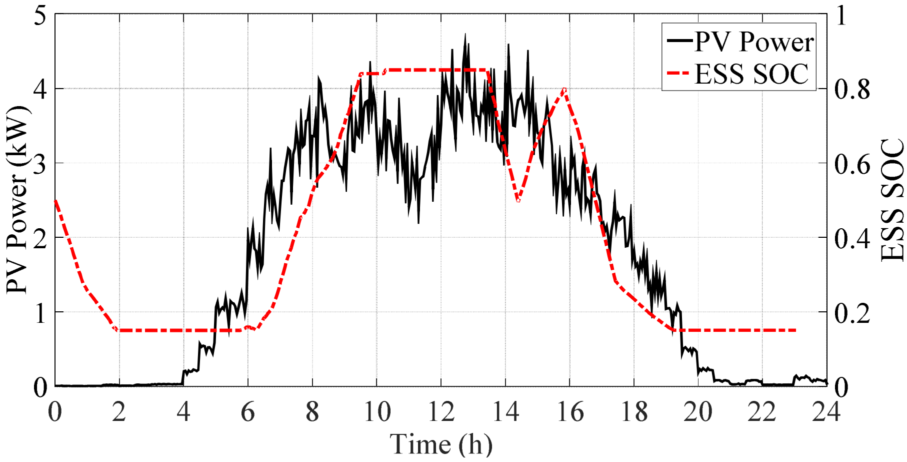


Fig. 14 ESS SOC trajectory under service 1

Considering that the µVPP operator offers a higher price than the FIT to purchase the surplus RES generation, and the stored energy is to be released later and used by the same end-consumers, a reduction of electricity bills is expected due to higher payment for the surplus RES and decreased grid import. Three key metrics are used in the economic analysis: the total bill savings, the payback period of the ESS' upfront cost and the ESS lifetime. A reference case called "No service" is used to make comparisons, where each apartment only owns PV generation but not ESS or other types of DER. Difference sizes of ESS are also included in the study to see whether it is worthwhile to rescale the ESS in the µVPP. The results of economic analysis for service 1 are displayed in Table VI.

TABLE VI SERVICE 1 PERFORMANCE WITH 1.2KW PV PRODUCTION

ESS / Results	No service	3.6kWh	6kWh	8.4kWh	12kWh
Electricity bill ($)	3639.85	3593.12	3582.13	3573.6	3563.48
Bill savings ($)	N/A	46.73	57.52	66.25	76.37
ESS charge cycle	N/A	155.68	126.76	110.04	93.86
µVPP profit ($)	N/A	25.9	28.76	29.45	27.66
Payback period (yrs)	N/A	40	57	75	103
Shortened payback period (yrs) *	N/A	13	19	24	34
ESS lifetime (yrs)	N/A	28	35	40	47

*Shortened payback period corresponds to a reduction of 67% of ESS cost

With the current PV capacity of 1.2kW, the annual saving on the electricity bill is very insignificant and there will not be much of an improvement if the ESS capacity is increased. As for the ESS charge cycle which represents the utilisation rate of the ESS asset, it takes more than two days even for the smallest ESS to complete on full charge/discharge cycle. In addition, the profit that µVPP operator receives is nearly negligible compared with the upfront cost. Economically speaking, the insignificant bill saving does not provide enough incentives to end-consumers and the negligible profit also deters investors from establishing the µVPP in the first place. Even from the perspective of a reduced capital investment, it still takes 19 years for the current ESS capacity to recoup its upfront cost. Although less charge cycles lead to a seemingly prolonged battery lifetime, the performance of battery modules will suffer from depreciation and eventually the cells fail to operate satisfactorily. To sum up, it is challenging for investors to recoup their investment if they intend to use ESS just as a complementary device to the RES. With an increasing penetration of RES generation, service 1 is not an ideal service type to be promoted.

3.5.2 Case B – Dynamic Tariff Service

When the μVPP is configured to run service 2, the charging and discharging process taps into the dynamics of the retail price and the ESS takes a more active role in the μVPP. As shown in Fig. 15, the trajectory of the ESS SOC follows the pattern of the retail price where the charging action is scheduled during low price period while the discharging action takes place during high price period.

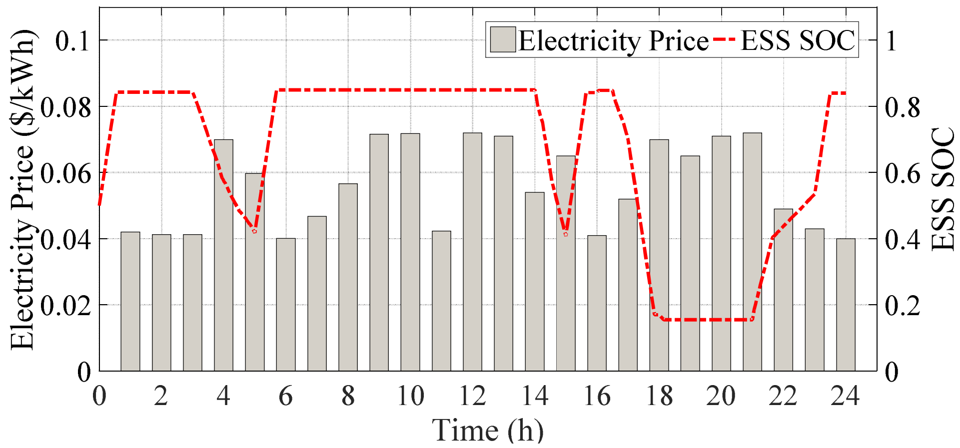


Fig. 15 ESS SOC trajectory under service 2

The price-responsive ESS in service 2 mitigates the pressure at the grid connection point during times of peak demand, when the retail price is usually high. At times of low demand, the ESS increases the electricity import from the grid by actively store the electricity. Overall, service 2 performs peak shaving and valley filling functions for the benefit of the DNO. For end-consumers, their electricity bills are reduced because they have a second option of purchasing from the internal electricity trading, at a price that is lower than the real-time retail price. For μVPP operator, the dynamics of the retail price are exploited to increase the profit in the internal trading: μVPP operator could charge the ESS when the retail price C_{RT} is low; several hours later when the system moves into a period with high retail price $C_{RT}{}'$ $\left(\eta \times C_{RT}{}' > C_{RT}\right)$, they can still make a profit by releasing the stored electricity to the end-consumers and charge them at price $\eta \times C_{RT}{}'$. The economic analysis has been performed for service 2 and the results are displayed in Table VII.

Table VII Service 2 Performance with 1.2kW PV Production

Results \ ESS	No service	3.6kWh	6kWh	8.4kWh	12kWh
Electricity bill ($)	3639.85	3551.67	3529.15	3512.45	3496.42
Bill savings ($)	N/A	88.18	110.7	127.4	143.43
ESS charge cycle	N/A	703.9	550.9	481.4	397.1
µVPP profit ($)	N/A	36.53	67.36	106.5	154.66
Payback period (yrs)	N/A	25	26	26	28
Shortened payback period (yrs) *	N/A	8	9	9	10
ESS lifetime (yrs)	N/A	6	8	9	11

*Shortened payback period corresponds to a reduction of 67% of ESS cost

Compared with service 1, the dynamic tariff service delivers better performance in bill savings, ESS utilisation rate and payback period with the same size of PV and ESS. The savings on electricity bills are nearly doubled compared with the level in service 1. The profit of the µVPP operator is also vastly increased in service 2 and the improvement is proportional to the size of the ESS: 41% improvement for a 3.6kWh ESS, 134% improvement for the current 6kWh ESS, 262% improvement for an 8.4kWh ESS and 459% improvement for a 12kWh ESS. The improvement indicates that higher profits can be obtained by upscaling the ESS within a certain range. This is due to an increased share of consumer load being supplied by the µVPP operator in the form of internal trading. However, if the capacity of the ESS increases beyond the maximum demand level within the µVPP, the upscaling will no longer generate more revenue as the internal trading market for the ESS is saturated. As for the ESS charge cycle, at least one full charge cycle is completed daily under service 2 which is regarded as an ideal utilisation level of the asset. For some sizes of the ESS such as 3.6kWh and the current 6kWh, the charging/discharging action may be too often and the maximum ESS lifetime is reached prematurely before the investment is recouped. For ESS with 8.4kWh capacity and 12kWh capacity, the investment is expected to be recouped just before the ESS exhausts its lifetime.

To sum up, the shortened payback period in service 2 falls under 10 years giving the declining upfront cost of the ESS. Supplier company and the end-consumers both benefit from an enhanced internal trading mechanism and can be both motivated to facilitate the μVPP. Service 2 is regarded as a sustainable business pattern to operate the μVPP and the major difference from service 1 is to treat ESS as an active, price-responsive DER instead of a passive, complementary DER to the RES.

3.5.3 Case C – Dynamic Tariff with Active Load Control

When the µVPP is configured to run service 3, the CLs including EVs and eHeat Pumps join the ESS to respond to the dynamics in the retail electricity price. The EV SOC trajectory is depicted in Fig. 16 to demonstrate the scheduling function of service 3.

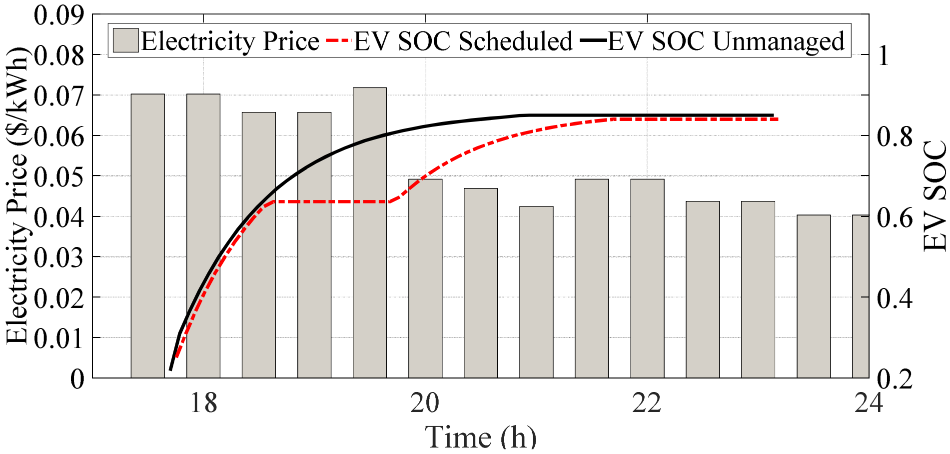


Fig. 16 EV charging responds to dynamic electricity price

As shown in Fig. 16, the EV charging process starts at 18:00 and continues until the EV is fully charged if it is unmanaged by the HEMS. However, service 3 turns EV OFF during 19:00 to 20:00 when the retail electricity price is high and turns EV back ON when the retail price drops. Under the prerequisite that the EV should be charged fully every day, the charging action should be allocated to low price periods which will lead to further reduction on electricity bills. Economic analysis has been performed for service 3 and the results are shown in Table VIII.

EVs and eHeat Pump are energy-intensive appliances and they often account for the largest percentage of the domestic consumption. Therefore, a significant reduction of the electricity bills can be observed in service 3 – the end-consumers can save up to 8% of their "No service" bills. Based on the agreement that end-consumers should pay an annual rent that equals to 40% of their bill savings, the rent in service 3 is more than that in service 2. A higher rent in this service is acceptable as end-consumers now enjoy an add-on function of active load control. In the economic analysis for service 2, conclusion has been drawn that the profit of µVPP operator from the internal electricity trading is determined mostly by the size of the ESS. Hence, the results displayed in Table VIII show a similar value of µVPP profit. In total, the investor receives higher ROI in service 3 and the payback period is slashed further. As for the utilisation rate of the ESS, service 3 is also capable to complete one charge cycle within one day.

TABLE VIII SERVICE 3 PERFORMANCE WITH 1.2KW PV PRODUCTION

Results \ ESS	No service	3.6kWh	6kWh	8.4kWh	12kWh
Electricity bill ($)	3639.85	3404.33	3383.08	3367.73	3351.73
Bill savings ($)	N/A	235.52	256.77	272.12	288.12
ESS charge cycle	N/A	686.6	536.2	462.3	383.13
µVPP profit ($)	N/A	35.7	66.47	105.23	152.63
Payback period (yrs)	N/A	13	18	19	22
Shortened payback period (yrs) *	N/A	5	6	7	8
ESS lifetime (yrs)	N/A	6	8	9	11

*Shortened payback period corresponds to a reduction of 67% of ESS cost

To sum up, the inclusion of CLs in the service 3 brings benefits for both parties. More savings on the electricity bill are achieved by simply plugging their EVs and eHeat Pumps in the HEMS. For µVPP investors, they become more confident in making the decisions because the payback period for all sizes of ESS has been reduced by another 2-3 years and the investment is guaranteed to be recouped before ESS reaches its lifetime.

3.5.4 Case D – Dynamic Tariff with Load Shedding

When µVPP is configured to run service 4, an add-on function of load shedding is included in the control scheme in addition to the price-responsive load scheduling. Given that the DNO surcharge is calculated based on the peak consumption power rate, this service aims at reducing the electricity bill by shaving the peak demand for each apartment. The EV SOC trajectories under service 3 and 4 are presented in the following figure to address the load shedding function.

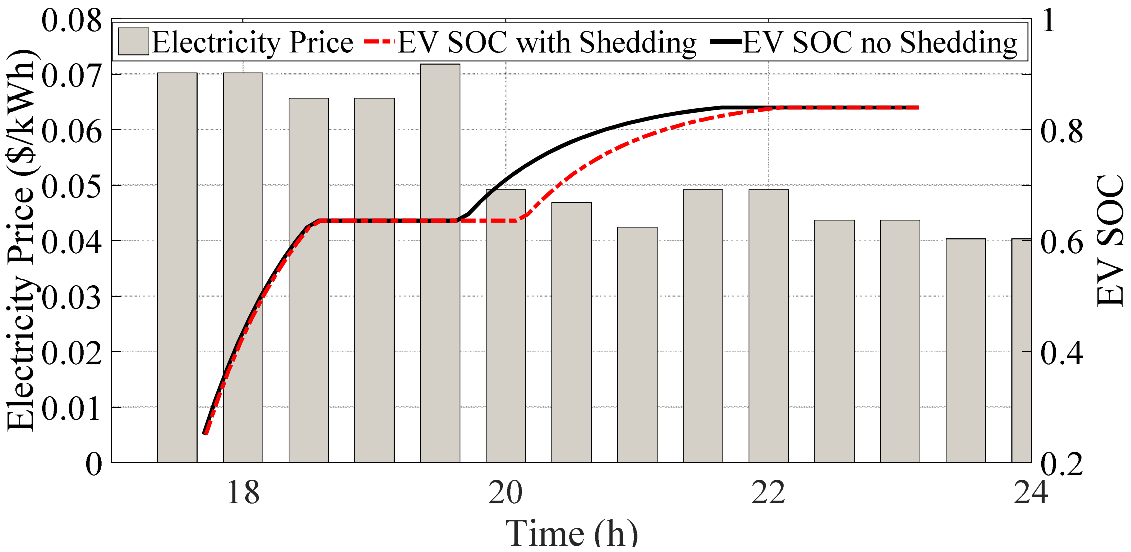


Fig. 17 EV charging with and without shedding function

As shown in Fig. 17, EV is turned OFF during 19:00 to 20:00 under both service 3 and service 4. However, in service 4 the OFF state is kept for another half an hour due to high demand level. In other words, EV is originally scheduled to be charged during 20:00 to 20:30 but it has been shed to keep the consumption level under the cap value. Both service 3 and service 4 charge the EV to the required capacity within the day, but service 4 yields a lower DNO surcharge for end-consumers. The results of the economic analysis are shown in Table IX.

TABLE IX SERVICE 4 PERFORMANCE WITH 1.2KW PV PRODUCTION

Results \ ESS	No service	3.6kWh	6kWh	8.4kWh	12kWh
Electricity bill ($)	3639.85	3277.28	3256.17	3241.46	3225.93
Bill savings ($)	N/A	362.57	383.68	398.4	413.92
ESS charge cycle	N/A	715.06	553.56	472.33	389.17
µVPP profit ($)	N/A	24.23	55.43	92.08	137.15
Payback period (yrs)	N/A	10	14	16	20
Shortened payback period (yrs) *	N/A	4	5	6	7
ESS lifetime (yrs)	N/A	6	8	9	11

*Shortened payback period corresponds to a reduction of 67% of ESS cost

Service 4 is by far the most comprehensive energy service for the µVPP, all the DER assets including the RES, ESS and DR programs are considered in the HEMS optimisation scheme. Service 4 derives the largest savings on the electricity bill and end-consumers pay 11% less than their former bills. A small-size ESS with 3.6kWh capacity can bring $362.57 saving in service 4 while a 12kWh ESS in service 3 brings only $288.12 bill reduction. Even with the currently high upfront cost, the payback period has already dropped under 10 years. For µVPP operator, the economic rationale is the same as that of service 3: a higher reduction on consumer bills means more income from the rent; the profit from the internal electricity trading remains in a steady level once the capacity of the ESS is determined. In total, service 4 has the highest ROI for investors and the fastest track to recoup their investment. For DNO, the µVPP's ability to perform peak shaving and valley filling is enhanced compared with service 2 and 3.

3.6 Summary

This chapter has presented an exemplar micro virtual power prosumer (μVPP) where the downstream DER assets including RES, ESS and DR are actively managed to reduce electricity bills, generate revenue streams for investors and provide load smoothing services to the DNO. The effectiveness of the WHAN and the HEMS has been validated by a pilot μVPP community. A μVPP business model has been proposed to explain elaborately the incentives and the economic rationale for the participants. Four energy services have been designed based on the types of DER that are utilised in the system and the different control strategies applied to them. Considering the scalability of the μVPP and the diversity of the consumer groups, the HEMS algorithm has been designed using a generic architecture to accommodate all energy services and facilitate easy switching between them. By examining the optimisation effect of each energy service in the μVPP, service 4 has been demonstrated as the optimal service type to bring maximum bill savings, fastest return on investment and active utilisation of the ESS capacity. However, the other services have also offered the opportunity for end-consumers to customise their energy mix and choose the suitable service considering the consumers' differences in geographic location, DER types and incomes. Moreover, the impact of different sizes of ESS on the economic benefit has been analysed and the result provides valuable insight into investment decision-making. It has now come to a point in the DER applications where the return on investment does not rely on compensations but on new trading agreements and new revenue streams.

CHAPTER 4 CONTRIBUTING TO THE ENERGY-RESERVE POOL: A CHANCE-CONSTRAINED TWO-STAGE μVPP BIDDING STRATEGY

4.1 Introduction

The μVPP presented in Chapter 3 has demonstrated a sustainable business pattern to generate substantial return on the initial investment for DER assets. The ICT infrastructure of the μVPP, which is already capable of real-time monitoring and control in both generation and consumption sectors, has given rise to the opportunity of entering the distribution level energy-reserve pool market. Once the dispatchable generators (DGs) are introduced to the μVPP energy portfolio, μVPP would have enough generation capacity and ramping capability to contribute energy and reserve power to the retail markets. This chapter is the second step towards the design of market-oriented μVPPs where μVPPs are permitted to participate in the distribution pool market by actively submitting quantity bids/offers. New revenue streams generated from the market trading can help accelerate the payback and ultimately bring net profit for investors. On the other hand, risks associated with the volatility of the RES production and the demand level also create barriers for μVPP entry to the market and might endanger the security of supply. Therefore, a chance-constrained μVPP bidding strategy is presented in this chapter to facilitate a safe transition for μVPPs.

4.2 μVPP Business Model in Local Energy-Reserve Pool

4.2.1 Nomenclature

Sets and Indices

t	Index of time in the scheduling horizon for each stage
i	Index of the dispatchable generators in the μVPP
s	Index of the scenarios in the real-time stage
Ω	Set of original portfolio scenarios, there are three components in each scenario including wind generation, load level and real-time electricity price
J	Set of the deleted portfolio scenarios, there are three components in each scenario including wind generation, load level and real-time electricity price
S	Set of the selected portfolio scenarios, there are three components in each scenario including wind generation, load level and real-time electricity price
NT	Number of hours in each of the two scheduling stages
NG	Number of dispatchable generators in the μVPP
$N\Omega$	Number of the original portfolio scenarios generated by the Monte Carlo method
NS	Number of the selected scenarios to represent the real-time portfolio
I_1	DER index which represents the ratio of on-site DER capacity over the maximum load level
I_2	RES index which represents the ratio of on-site RES capacity over the DER

capacity

DA Set of parameters and variables related to day-ahead scheduling stage

RT Set of parameters and variables related to real-time scheduling stage

Parameters

$C_t^{E,DA}$ £/kWh, day-ahead energy retail price during time t

C_{DA}^{R} £/kWh, day-ahead reserve energy retail price

C_i^{Gen} £/kWh, variable production cost of dispatchable generator i

C_i^{SU} £, start-up cost of dispatchable generator i

C_i^{SD} £, shut-down cost of dispatchable generator i

C_{loss} £/kWh, penalty price for involuntary disconnection of the load within the μVPP

η price coefficient determined by the maximum transaction limit at the grid connection point, a higher transaction limit corresponds to more expensive tariff

ω discount rate of electricity price to motivate end-consumers to join the μVPP

$SIG_{s,t}^{up}$ real-time binary call up signals for upward reserve offers in scenario s during time t ; “1” represents the offer is called up to produce, “0” represents the offer is not called up to produce

$SIG_{s,t}^{dw}$ real-time binary call up signals for downward reserve offers in scenario s during time t ; “1” represents the offer is called up to produce, “0” represents the offer is not called up to produce

$EXCH_{\max}$	kW, the transaction limit at the μVPP grid connection point
$P_t^{W,DA}$	kW, day-ahead forecasted power of wind generation of the μVPP
$P_t^{L,DA}$	kW, day-ahead forecasted power of load level of the μVPP
$\overline{P}_i^{Gen}$	kW, maximum output power of dispatchable generator i
$\underline{P}_i^{Gen}$	kW, minimum output power of dispatchable generator i
$\underline{T}_{on}^{Gen}$	hour, minimum time the dispatchable generator should be up per day
$\underline{T}_{off}^{Gen}$	hour, minimum time the dispatchable generator should be down per day
RU_i	kW/h, maximum power limit for dispatchable generator i to ramp up
RD_i	kW/h, maximum power limit for dispatchable generator i to ramp down
ρ_{up}	upper limit of the available upward spinning reserve power
ρ_{dw}	upper limit of the available downward spinning reserve power
ε_{LOLP}	loss of load probability, represents the chance of involuntary disconnection of the consumer loads
ξ	maximum load loss percentage that is tolerable in the μVPP

Variables

π_s	the probability of each scenario in the original portfolio scenario set
π_s^*	the probability of each scenario in the selected portfolio scenario set
D	the distance between any two scenario points of the original portfolio set after mapping the scenario values into a three-dimensional coordinate space
KD_s	the Kantorovich distance of scenario s in the original portfolio scenario set
$C_{s,t}^{E,RT}$	£/kWh, real-time energy retail price in scenario s during time t

$P_{s,t}^{W,RT}$ kW, real-time wind generation in scenario s during time t

$P_{s,t}^{L,RT}$ kW, real-time load level in scenario s during time t

σ_{CE} £/kWh, standard deviation of real-time retail energy price from day-ahead prediction

σ_{W} kW, standard deviation of real-time wind generation from day-ahead prediction

σ_{L} kW, standard deviation of real-time load level from day-ahead prediction

$P_{DA,t}^{E}$ kW, day-ahead energy bid/offer quantity submitted by the μVPP; positive value corresponds to energy bid, negative value corresponds to energy offer

$P_{up,t}^{R}$ kW, day-ahead upward reserve offer quantity submitted by the μVPP; this variable has positive values which correspond to offers

$P_{dw,t}^{R}$ kW, day-ahead downward reserve offer quantity submitted by the μVPP; this variable has positive values which correspond to offers

$\Delta P_{s,t}^{E+}$ kW, real-time upward variation to the energy bids/offers

$\Delta P_{s,t}^{E-}$ kW, real-time downward variation to the energy bids/offers

$P_{i,t}^{Gen}$ kW, day-ahead output power of dispatchable generator i during time t

$o_{i,t}$ day-ahead binary variable which represents the operation status of dispatchable generator i during time t

$u_{i,t}$ day-ahead binary variable which represents the start-up decision of dispatchable generator i during time t

$v_{i,t}$ day-ahead binary variable which represents the shut-down decision of dispatchable generator i during time t

$\Delta P_{s,i,t}^{Gen}$ kW, real-time variation of the output power of dispatchable generator i in scenario s during time t

$P_t^{W,S}$ kW, day-ahead variable which represents the scheduled usage of the forecasted wind generation power

$P_t^{W,A}$ kW, real-time variable which represents the actual usage of the real-time wind generation power

$r_{i,t}^{Gen,up}$ kW, available upward reserve capacity sourced from dispatchable generator i during time t

$r_{i,t}^{Gen,dw}$ kW, available downward reserve capacity sourced from dispatchable generator i during time t

$P_{s,t}^{Loss}$ kW, real-time consumption power of load loss in scenario s during time t

S_{uVPP}^{DSO} £, total income of the μVPP from the two-stage distribution system market

S_{DA}^{E} £, income/expense of the μVPP from day-ahead energy market; positive value corresponds to expense, negative value corresponds to income

S_{DA}^{R} £, income of the μVPP from day-ahead reserve market

S_{RT}^{E} £, income/expense variation of the μVPP from real-time energy market

S_{RT}^{R} £, income variation of the μVPP from real-time reserve market

S_{DA}^{Gen} £, day-ahead generation cost of all the dispatchable generators

S_{RT}^{Gen} £, real-time generation cost variation of all the dispatchable generators

S_{DA}^{Load} £, day-ahead income of the μVPP from supplying energy to end-consumers

S_{RT}^{Loss} £, real-time expense of the μVPP for compensating the load loss

4.2.2 µVPP Business Model in the Local Energy-Reserve Pool

By pooling the energy and reserve capacities resourced from both local DERs and traditional suppliers, a market is established in the distribution system as shown in Fig. 18. The participants in the market including µVPPs and energy suppliers are managed by a Distribution System Operator (DSO). The dual role of µVPP as both producer and consumer enables a submission of either energy offer or energy bid to the market, depending on the capacity of DER and the demand level inside the µVPP. The energy suppliers submit only energy offers to sell the capacity purchased from wholesale market. The proposed distribution system pool introduces more competition to the retail energy market and provides µVPPs with the liberty to switch between producer and consumer in the daily operation.

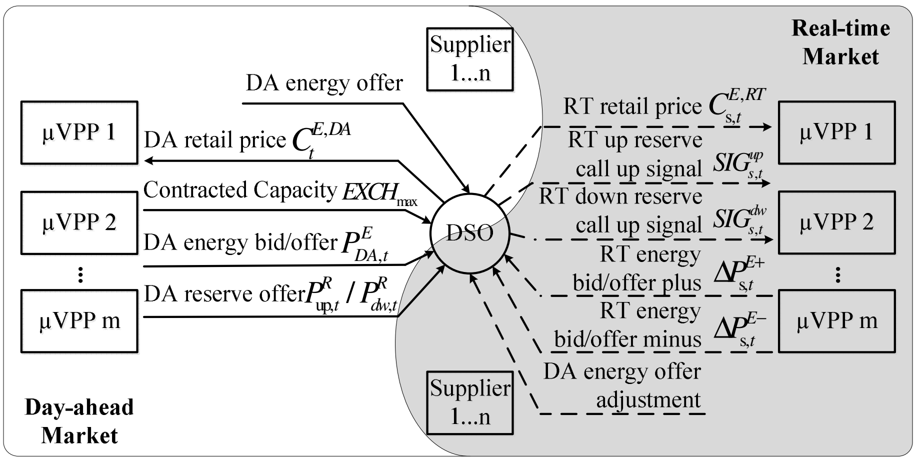


Fig. 18 Energy-reserve pool market in the distribution system

In the day-ahead (DA) market, the DA retail energy price $C_t^{E,DA}$ (£/kWh) is broadcasted by the DSO to the market participants. Based on the price signals, µVPPs submit two sets of hourly quantity bid/offer: the energy bid or offer $P_{DA,t}^{E}$ (kW) to purchase or sell energy and the upward or downward reserve offer $P_{up,t}^{R}$ / $P_{dw,t}^{R}$ (kW) to provide regulating service. In the real-time (RT) market, the retail energy price is updated to $C_{s,t}^{E,RT}$ (£/kWh). Thus, changes are made to the energy bid/offer as the μVPP needs to purchase/sell more energy $\Delta P_{s,t}^{E+}$ (kW) or less $\Delta P_{s,t}^{E-}$ (kW). Should the need arise for the provision of reserve capacity, call up signals $SIG_{s,t}^{up}$ / $SIG_{s,t}^{dw}$ will be issued by the DSO and the μVPPs that are called up will produce the exact amount of regulating power as they offered in the DA market. To sum up, DA market matches the electricity demand bids and supply offers from pool participants and RT market settles the imbalanced power to achieve real-time equation of supply and demand. This thesis focuses on the behaviour of a price-taking μVPP when pursuing its individual profit in the local pool market. As a prerequisite, the decisions made by DSO including DA and RT retail price as well as the call up signals are assumed to be known.

To illustrate the context and beneficiaries of the energy-reserve pool in the distribution system, the μVPP business model should be developed addressing the roles and value transactions between players including DSO, μVPP and end-users as presented in Fig. 19.

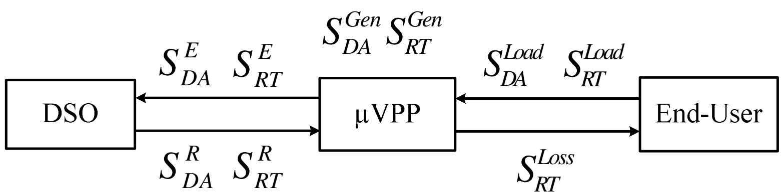


Fig. 19 Value transactions between participants in the distribution system market

μVPP - DSO

DSO manages the pool market and channels the value stream between participants from energy and reserve capacity transactions. Based on the Common Distribution Charging

Methodology issued by Ofgem, a capacity charge determined by the highest kW power flow at the grid connection point will be included in the energy tariff. Thus, the DA energy bid/offer $P_{DA,t}^{E}$ (kW) is priced at $\eta \times C_{t}^{E,DA}$ (£/kWh), where the ratio η implies that a higher transaction limit corresponds to more expensive tariff. Also in the DA market, DSO pays each µVPP for the submission of upward or downward reserve offer $P_{up,t}^{R}$ / $P_{dw,t}^{R}$ (kW) at price C_{DA}^{R} (£/kWh). Later in the RT market, µVPP's payment/income from DA energy bid/offer could be affected by two sources: the upward or downward changes to the DA energy bid/offer and the difference between RT energy tariff $C_{s,t}^{E,RT}$ (£/kWh) and the DA energy tariff. Another RT income for µVPP comes from the provision of reserve capacity if its DA reserve offer is called up to produce. The income of µVPP from participating in the distribution system market is calculated as:

$$\begin{aligned} S_{uVPP}^{DSO} &= S_{DA}^{R} + S_{RT}^{R} - S_{DA}^{E} - S_{RT}^{E} \\ &= C_{DA}^{R} \times \sum_{t=1}^{NT} \left(P_{up,t}^{R} + P_{dw,t}^{R} \right) + C_{RT}^{R} \times \pi_s^{*} \sum_{s=1}^{NS} \sum_{t=1}^{NT} \left(P_{up,t}^{R} \times SIG_{s,t}^{up} + P_{dw,t}^{R} \times SIG_{s,t}^{dw} \right) \\ &- \sum_{t=1}^{NT} \eta \times C_{t}^{E,DA} \times P_{DA,t}^{E} - \pi_s^{*} \sum_{s=1}^{NS} \sum_{t=1}^{NT} \eta \times C_{s,t}^{E,RT} \left(\Delta P_{s,t}^{E+} - \Delta P_{s,t}^{E-} \right) \\ &- \pi_s^{*} \sum_{s=1}^{NS} \sum_{t=1}^{NT} \eta \times \left(C_{s,t}^{E,RT} - C_{t}^{E,DA} \right) \times P_{DA,t}^{E} \qquad \forall s, \forall t \end{aligned} \tag{4.1}$$

where the first term of equation represents the revenue of µVPP S_{DA}^{R} (£) for the provision of reserve offers in the DA market. This income is obtained whether the offers are called up or not. The second term stands for the payment S_{RT}^{R} (£) in the RT market when the reserve capacity is called up to produce. The third term is the expense S_{DA}^{E} (£) of purchasing energy or the income of selling energy in the DA market. The last two terms constitute the RT expense/income variation S_{RT}^{E} (£), which is the result of changes of the energy capacity being traded in the RT market and the difference between DA and RT energy price. In equation (4.1), the RT value stream S_{RT}^{R} and S_{RT}^{E} under each scenario s are assigned with a specific probability π_s^* derived from scenario reduction process presented in section 4.3.

µVPP Generation Cost

The DER located in the proposed µVPP includes small or medium scale wind turbines and diesel generators. The operation cost of wind turbines is assumed to be zero, leaving the inherent cost to be the operation cost of dispatchable generators (DG):

$$S_{DA}^{Gen} = \sum_{t=1}^{NT}\sum_{i=1}^{NG}\left(C_i^{Gen} \times P_{i,t}^{Gen} + C_i^{SU} \times u_{i,t} + C_i^{SD} \times v_{i,t}\right) \qquad \forall i, \forall t \tag{4.2}$$

where the price parameters include fuel cost C_i^{Gen} (£/kWh) for hourly power output $P_{i,t}^{Gen}$ (kW), start-up cost C_i^{SU} (£) associated with start-up decision $u_{i,t}$ and shut-down cost C_i^{SD} (£) associated with shut-down decision $v_{i,t}$. While in the RT market, the diesel generators must ramp up or ramp down their output power $\Delta P_{s,i,t}^{Gen}$ (kW) to accommodate the changes in demand level and fulfil the task to produce reserve capacity. The variation of operation cost is therefore calculated as:

$$S_{RT}^{Gen} = \pi_s^* \sum_{s=1}^{NS}\sum_{t=1}^{NT}\sum_{i=1}^{NG} C_i^{Gen} \times \Delta P_{s,i,t}^{Gen} \qquad \forall s, \forall i, \forall t \tag{4.3}$$

µVPP – End-Consumer

To encourage end-users to join the µVPP community, a discount rate ω is applied for retail energy price. Based on the DA prediction of load, μVPP estimates a retail income S_{DA}^{Load} (£) from end-users:

$$S_{DA}^{Load} = \sum_{t=1}^{NT} \omega \times \eta \times C_t^{E,DA} \times P_t^{L,DA} \qquad \forall t \tag{4.4}$$

where $\omega \times \eta \times C_t^{E,DA}$ is the DA energy price with discount for the end-users in the μVPP and $P_t^{L,DA}$ (kW) is the forecasted load level. In the RT market scenarios, both the retail energy price and the actual demand vary from DA forecasted value, the variation of retail income is calculated as:

$$S_{RT}^{Load} = \pi_s^* \sum_{s=1}^{NS} \sum_{t=1}^{NT} \omega \times \eta \times C_{s,t}^{E,RT} \times \left(P_{s,t}^{L,RT} - P_t^{L,DA} \right) \qquad \forall s, \forall t \tag{4.5}$$

where $\omega \times \eta \times C_{s,t}^{E,RT}$ is the RT energy price with discount for the μVPP end-consumers and $P_{s,t}^{L,RT}$ (kW) is the RT load level in each scenario. Additionally, a small level of load loss $P_{s,t}^{Loss}$ (kW) is tolerable in the μVPP supply commitment but the end-consumers should be well compensated at the penalty price C_{loss} (£/kWh) as equation (4.6) shows.

$$S_{RT}^{Loss} = \pi_s^* \sum_{s=1}^{NS} \sum_{t=1}^{NT} C_{loss} \times P_{s,t}^{loss} \qquad \forall s, \forall t \tag{4.6}$$

4.3 Modelling of the Uncertainties in the µVPP

The uncertain components in the µVPP include wind power output, load level, RT energy price and RT call up signals for reserve offers. A truncated normal distribution is used to mimic the DA forecast error of the first three components. The truncated normal distribution is one of the straightforward interpretations of the forecast errors in predicting the renewable generation, demand and electricity price because the characteristic parameters of mean and standard deviation could be readily derived by analysing the historical data [135]. In theory, the values of a normally distributed parameter can range from $-\infty$ to $+\infty$ and could lead to significant computational errors if the sample number is not enough. Therefore, the normally distributed data is "truncated" to preserve the realistic probability range [135]. In practice, the truncated normal distribution is already used by California Independent System Operator (ISO) to establish the forecast model for renewable resources and load [136].

$$P_{s,t}^{W,RT} \sim TN\left(P_t^{W,DA}, \sigma_W^2\right) \qquad \forall s, \forall t \tag{4.7}$$

$$P_{s,t}^{L,RT} \sim TN\left(P_t^{L,DA}, \sigma_L^2\right) \qquad \forall s, \forall t \tag{4.8}$$

$$C_{s,t}^{E,RT} \sim TN\left(C_t^{E,DA}, \sigma_{CE}^2\right) \qquad \forall s, \forall t \tag{4.9}$$

where the DA forecasted values $P_t^{W,DA}$, $P_t^{L,DA}$ and $C_t^{E,DA}$ are used as the mean value in equation (4.7) - (4.9) and the forecast error is represented by the standard deviation of each component. A truncated normal distribution is like a normal distribution but differs in its bounded or truncated extremities, which corresponds to the fact that forecasting error would not exceed certain limits for the uncertainties involved in the µVPP. As for the RT call up signals for reserve offers, they are generated as random binary signals with a low probability of signal "1" ("1" represents the offer is being called up). This is because the reserve capacity is only required to be produced during emergency period when there is an unexpected disruption to the supply. The Monte Carlo method is applied to generate scenarios for the uncertain components in μVPP based on repeated sampling following the truncated normally probability distribution. As a computational approach, the complexity for solving stochastic programs gets worse when increasing the number of scenarios. In this case, scenario reduction technique is introduced in the following as a tradeoff between data accuracy and computational efficiency.

Scenario reduction techniques including forward selection algorithm and backward reduction algorithm have been widely utilised in [137-139] to deal with individual stochastic data. Through eliminating scenarios with very low probability and aggregating close scenarios based on the distance of probability distributions, a subset of the original scenario set is derived to be the best approximation. This section aims at capturing all the stochastic components concurrently thus the scenario reduction should be executed for three stochastic variables simultaneously. A novel three-dimension forward selection algorithm is therefore proposed to produce an optimal subset of scenarios with an updated probability distribution. Each scenario contains a wind generation power, load consumption power and RT electricity price.

Step 1) Generate the initial scenario set Ω, each scenario $s \in \Omega$ contains three uncertain components $\left(P_{s,t}^{W,RT}, P_{s,t}^{L,RT}, C_{s,t}^{E,RT}\right)$; perform mapping of the components onto a three-dimensional coordinate space with $P_{s,t}^{W,RT}$ as X coordinate, $P_{s,t}^{L,RT}$ as Y coordinate and $C_{s,t}^{E,RT}$ as Z coordinate.

Step 2) Calculate the distance between any two scenario points:

$$D(s,s') = \sum_{t=1}^{NT} \sqrt{\left(X(s_t) - X(s_t')\right)^2 + \left(Y(s_t) - Y(s_t')\right)^2 + \left(Z(s_t) - Z(s_t')\right)^2} \quad \forall s,s' \in \Omega \tag{4.10}$$

Step 3) Calculate the Kantorovich distance of each point s:

$$KD_s = \sum_{s'=1}^{N\Omega} \pi_{s'} \times D(s,s') \qquad \forall s,s' \in \Omega \tag{4.11}$$

Choose $s_1 \in \arg\min_{s\in\Omega} KD_s$

Update the deleted scenario set $J \leftarrow \Omega \setminus \{S_1\}$

Step i) Calculate the distance between any two scenario points left in J:

$$D^i(s,s') = \min\left\{D^{i-1}(s,s'), D^{i-1}(s,s_{i-1})\right\} \qquad \forall s,s' \in J^{i-1} \tag{4.12}$$

Calculate the Kantorovich distance of the scenario point:

$$KD_s^i = \sum_{s'\in J^{i-1}\setminus s} \pi_{s'} D^{i-1}(s',s) \quad \forall s \in J^{i-1} \tag{4.13}$$

Choose $s_i \in \arg\min_{s\in\Omega} KD_s^i$

Update the deleted scenario set $J^i \leftarrow J^{i-1} \setminus \{S_i\}$

Step i+1) Repeat Step I until the required number of scenarios have been deleted then update the following set:

$$J^* = J^{i+1} \qquad S = \Omega \setminus J^*$$

Calculate the probability of each selected scenario in the set S:

$$\pi_s^* = \pi_s + \sum\nolimits_{s' \in J(s)} \pi_{s'} \quad \text{where}$$

$$J(s) = \left\{ s' \in J^* \mid s = j(s'), j(s') \in \arg\min\nolimits_{s'' \in S} D(s'', s') \right\} \tag{4.14}$$

The initial scenario set generated in step 1 has a large scenario number $N\Omega$ and an equal probability of $1/N\Omega$ for each scenario. By mapping each scenario as a point in the three-dimensional coordinate space, the distance between any two scenarios could be calculated using equation (4.10) in Step 2 and later in Step 3 a probability metric called Kantorovich distance is obtained using equation (4.11). Intuitively, if each scenario distributed in the three-dimensional space is viewed as a unit amount of “earth” pile, then the scenario point s_1 with minimum Kantorovich distance represents the minimum “cost” of transferring all earth piles to a single point in the given space. Therefore s_1 is selected as the first scenario to represent the stochastic profile. This iterative process in Step i continues to select representative scenarios s_i by updating the distance in equation (4.12) and Kantorovich distance in equation (4.13), leaving fewer and fewer scenarios in the deleted set J . Finally, the process terminates when required number of scenarios have been selected. Equation (4.14) assigns the new probability π_s^* to each selected scenario by adding its former probability and all probabilities of the deleted scenarios that are closest to it with respect to distance. The following figure Fig. 20 displays how the three-dimensional forward selection algorithm delivers a best possible approximation of the initial stochastic data. In the 3D domain where the scenarios $\left(P_{s,t}^{W,RT}, P_{s,t}^{L,RT}, C_{s,t}^{E,RT}\right)$ are mapped onto, the selected scenarios after reduction are distributed uniformly while the deleted scenario points are concentrated near the edges of the domain. This phenomenon proves the effectiveness of the scenario reduction algorithm because the scenarios distributed uniformly in the centre of the domain have minimum distances from the rest of the points and therefore the selected scenarios can better represent the original data sample.

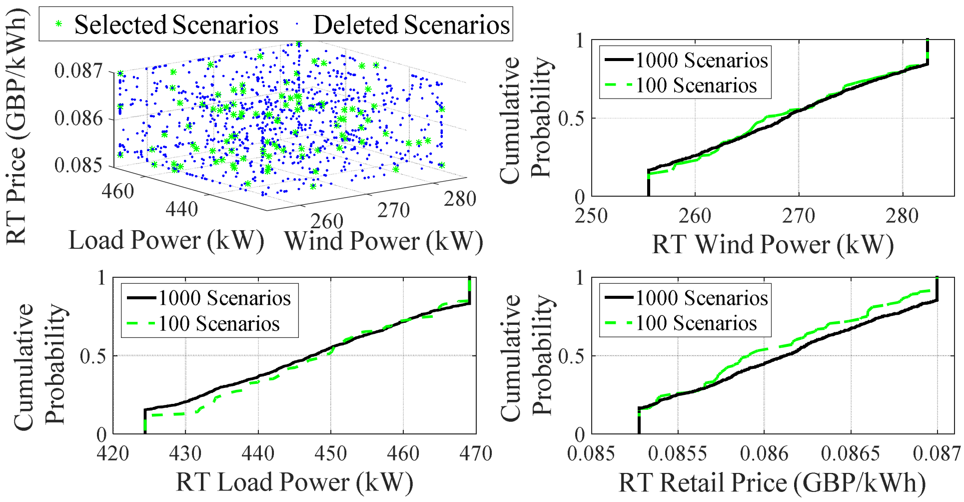


Fig. 20 Three-dimensional forward selection algorithm performance

From the probability distribution point of view, the cumulative probability curves of the selected scenarios for $\left(P_{s,t}^{W,RT}, P_{s,t}^{L,RT}, C_{s,t}^{E,RT}\right)$ are derived from their RT value and new probability π_s^*. The new cumulative probability curves nearly overlap with the original curve formed by 1000 scenarios, which verifies the close resemblance between the selected set S and initial set Ω in terms of data distribution. In addition, both cumulative probability curves are only continuous against a limited range of X-axis, which proves that the obtained uncertain data complies with the truncated normal distribution and unrealistic data values are not included in the sample.

4.4 Chance-Constrained Two-Stage Stochastic µVPP Bidding Strategy Formulation

In this section, a chance-constrained two-stage stochastic formulation is utilised to devise the bidding strategy for a µVPP. In the first stage, the objective is to maximise µVPP's expected net profit by adding up its income from the DA energy-reserve market and deducting the operation cost of generators. The decision variables determined in the first stage include: 1) the energy bid/offer submitted to the DA market; 2) the reserve bid submitted to the DA market; 3) the operation schedule and output power for each generator and 4) the scheduled usage of wind power based on the forecasted output.

The objective function of the first stage is formed as follows:

$$\begin{aligned} \max \quad & S_{DA}^{R} + S_{DA}^{Load} - S_{DA}^{E} - S_{DA}^{Gen} \\ & = \sum_{t=1}^{NT} \Big\{ C_{DA}^{R} \times \left(P_{up,t}^{R} + P_{dw,t}^{R} \right) + \omega \times \eta \times C_{t}^{E,DA} \times P_{t}^{L,DA} \\ & -\eta \times C_{t}^{E,DA} \times P_{DA,t}^{E} - \sum_{i=1}^{NG} \left(C_{i}^{Gen} \times P_{i,t}^{Gen} + C_{i}^{SU} \times u_{i,t} + C_{i}^{SD} \times v_{i,t} \right) \Big\} \end{aligned} \tag{4.15}$$

where the DA revenue comes from submitting reserve offers S_{DA}^{R} and energy retail S_{DA}^{Load}. The DA cost includes expected payment for energy bid S_{DA}^{E} (if the energy offer instead of bid is submitted in the DA market, S_{DA}^{E} is another source of revenue) and operation cost S_{DA}^{Gen} of generators.

Subject to the following constraints:

$$-EXCH_{\max} \le P_{DA,t}^{E} \le EXCH_{\max} \tag{4.16}$$

$$\underline{P}_i^{Gen} \le P_{i,t}^{Gen} o_{i,t} \le \overline{P}_i^{Gen} \qquad \forall i, \forall t \tag{4.17}$$

$$-o_{i,t-1} + o_{i,t} - o_{i,k} \le 0, 1 \le k - (t-1) \le \underline{T}_{on}^{Gen} \qquad \forall i, \forall t \tag{4.18}$$

$$o_{i,t-1} - o_{i,t} + o_{i,k} \le 1, 1 \le k - (t-1) \le \underline{T}_{off}^{Gen} \qquad \forall i, \forall t \tag{4.19}$$

$$-o_{i,t-1} + o_{i,t} - u_{i,t} \le 0 \qquad \forall i, \forall t \tag{4.20}$$

$$o_{i,t-1} - o_{i,t} - v_{i,t} \le 0 \qquad \forall i, \forall t \tag{4.21}$$

$$P_{i,t}^{Gen} - P_{i,t-1}^{Gen} \le \left(2 - o_{i,t-1} - o_{i,t}\right) \underline{P}_i^{Gen} + \left(1 + o_{i,t-1} - o_{i,t}\right) RU_i \qquad \forall i, \forall t \tag{4.22}$$

$$P_{i,t-1}^{Gen} - P_{i,t}^{Gen} \le \left(2 - o_{i,t-1} - o_{i,t}\right) \underline{P}_i^{Gen} + \left(1 - o_{i,t-1} + o_{i,t}\right) RD_i \qquad \forall i, \forall t \tag{4.23}$$

$$0 \le P_t^{W,S} \le P_t^{W,DA} \qquad \forall t \tag{4.24}$$

$$P_{DA,t}^{E} + \sum_{i=1}^{NG} P_{i,t}^{Gen} + P_t^{W,S} = P_t^{L,DA} \qquad \forall i, \forall t \tag{4.25}$$

$$0 \le r_{i,t}^{Gen,up} \le \rho_{up} \overline{P}_i^{Gen} \qquad \forall i, \forall t \tag{4.26}$$

$$0 \le r_{i,t}^{Gen,\mathrm{dw}} \le \rho_{dw} \overline{P}_i^{Gen} \qquad \forall i, \forall t \tag{4.27}$$

$$P_{i,t}^{Gen} + r_{i,t}^{Gen,up} \le \overline{P}_i^{Gen} o_{i,t} \qquad \forall i, \forall t \tag{4.28}$$

$$P_{i,t}^{Gen} - r_{i,t}^{Gen,dw} \ge \underline{P}_i^{Gen} o_{i,t} \qquad \forall i, \forall t \tag{4.29}$$

$$P_{i,t}^{Gen} - P_{i,t-1}^{Gen} + r_{i,t}^{Gen,up} \le \left(2 - o_{i,t-1} - o_{i,t}\right) \underline{P}_i^{Gen} + \left(1 + o_{i,t-1} - o_{i,t}\right) RU_i \qquad \forall i, \forall t \tag{4.30}$$

$$P_{i,t-1}^{Gen} - P_{i,t}^{Gen} + r_{i,t}^{Gen,dw} \le \left(2 - o_{i,t-1} - o_{i,t}\right) \underline{P}_i^{Gen} + \left(1 - o_{i,t-1} + o_{i,t}\right) RD_i \qquad \forall i, \forall t \tag{4.31}$$

$$0 \le P_{up,t}^{R} \le P_t^{L,DA} \qquad \forall t \tag{4.32}$$

$$0 \le P_{up,t}^{R} \le \sum_{i=1}^{NG} r_{i,t}^{Gen,up} \qquad \forall i, \forall t \tag{4.33}$$

$$0 \le P_{dw,t}^{R} \le P_t^{L,DA} \qquad \forall t \tag{4.34}$$

$$0 \le P_{dw,t}^{R} \le \sum_{i=1}^{NG} r_{i,t}^{Gen,dw} \qquad \forall i, \forall t \tag{4.35}$$

$$\Pr\left\{\sum_{i=1}^{NG} P_{i,t}^{Gen} + EXCH_{\max} + \sum_{i=1}^{NG} r_{i,t}^{Gen,up} \geq P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right\} \geq 1-\varepsilon_{LOLP} \qquad \forall t \tag{4.36}$$

$$\Pr\left\{\sum_{i=1}^{NG} P_{i,t}^{Gen} + P_{DA,t}^{E} - P_{up,t}^{R} + \sum_{i=1}^{NG} r_{i,t}^{Gen,up} \geq P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right\} \geq 1-\varepsilon_{LOLP} \qquad \forall t \tag{4.37}$$

The objective function (4.15) aims at maximising the expected DA profit of μVPP while considering the limits of its generators and guaranteeing a small probability of load loss. Equation (4.16) defines the upper and lower limits of the DA energy bid/offer. Equation (4.17) ensures the power output of each generator is within its capacity. Equation (4.18) and (4.19) are the minimum on time and minimum off time constraints for generators respectively. Equation (4.20) and (4.21) define the start-up and shut-down variables. Equation (4.22) and (4.23) apply the ramping rate limits on the speed of each generator to increase or decrease its power output. Equation (4.24) represents the fact that the scheduled wind power will not exceed the forecasted value. Equation (4.25) is the power balance constraint between supply and demand inside the μVPP. Should the DA reserve offer be called up to produce, equation (4.26) and (4.27) set the upper limit of upward and downward spinning reserve that are available from each generator. However, the production of upward or downward spinning reserve capacity should also abide by the output power limit and ramping limit as indicated by (4.28) - (4.29) and (4.30) - (4.31) respectively. Equation (4.32) indicates that the upward reserve capacity offered by μVPP should not exceed its demand level since satisfying the load is the priority of DER production. Equation (4.33) explains that the upward reserve capacity offer is originated from ramping up the generator output. Similar constraints (4.34) and (4.35) apply the same rules to the downward reserve offer. Equation (4.36) is the chance constraint for LOLP if upward reserve offer is not called up to produce. Equation (4.37) is the chance constraint for LOLP if upward reserve offer is called up to produce. In this case the power flows from the μVPP to the distribution pool and the upward reserve capacity will be deducted from the upward spinning reserves. The remainder of the power supply should guarantee a low probability of load loss.

The chance constraints (4.36) and (4.37) are converted into their equivalent deterministic formulation as follows:

$$\begin{aligned}&\sum_{i=1}^{NG} P_{i,t}^{Gen} + EXCH_{\max} + \sum_{i=1}^{NG} r_{i,t}^{Gen,up} \\ &\geq E\left(P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right) + \phi^{-1}\left(1-\varepsilon_{LOLP}\right)\sigma\left(P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right) \quad \forall s, \forall t\end{aligned} \tag{4.38}$$

$$\begin{aligned}&\sum_{i=1}^{NG} P_{i,t}^{Gen} + P_{DA,t}^{E} - P_{up,t}^{R} + \sum_{i=1}^{NG} r_{i,t}^{Gen,up} \\ &\geq E\left(P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right) + \phi^{-1}\left(1-\varepsilon_{LOLP}\right)\sigma\left(P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right) \quad \forall s, \forall t\end{aligned} \tag{4.39}$$

where the mean of the RT net load (i.e. net load is obtained by deducing the wind power from load) is calculated as:

$$E\left(P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right) = P_{t}^{L,DA} - P_{t}^{W,DA} \qquad \forall t \tag{4.40}$$

And the standard deviation of the stochastic net load is calculated as:

$$\sigma\left(P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right) = \sqrt{\pi_s^* \sum_{s=1}^{NS}\left(P_{s,t}^{L,RT} - P_{s,t}^{W,RT} - E\left(P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right)\right)^2} \qquad \forall t \tag{4.41}$$

In the second stage, the objective is to maximise the gains (or minimise the losses) of μVPP profit brought by RT uncertainties. The second stage objective function is presented in equation (4.42):

$$
\begin{aligned}
&\max S_{RT}^{R}+S_{RT}^{Load}-S_{RT}^{E}-S_{RT}^{Gen}-S_{RT}^{Loss} \\
&=\sum_{s=1}^{NS}\sum_{t=1}^{NT}\Big\{\pi_s^*\Big\{C_{RT}^{R}\times\left(P_{up,t}^{R}\times SIG_{s,t}^{up}+P_{dw,t}^{R}\times SIG_{s,t}^{dw}\right) \\
&+\omega\eta C_{s,t}^{E,RT}\times\left(P_{s,t}^{L,RT}-P_{t}^{L,DA}\right)-\eta C_{s,t}^{E,RT}\times\left(\Delta P_{s,t}^{E+}-\Delta P_{s,t}^{E-}\right) \\
&-\eta\left(C_{s,t}^{E,RT}-C_{t}^{E,DA}\right)\times P_{DA,\mathrm{t}}^{E}-\sum_{i=1}^{NG}C_{i}^{Gen}\times\Delta P_{s,i,t}^{Gen}-C_{loss}\times P_{s,t}^{Loss}\Big\}\Big\}
\end{aligned}
\tag{4.42}
$$

Subject to the following constraints:

$$-r_{i,t}^{Gen,dw}\leq\Delta P_{s,i,t}^{Gen}\leq r_{i,t}^{Gen,up}\qquad\forall s,\forall i,\forall t \tag{4.43}$$

$$0\leq\Delta P_{s,t}^{E+}\leq EXCH_{\max},0\leq\Delta P_{s,t}^{E-}\leq EXCH_{\max}\qquad\forall s,\forall t \tag{4.44}$$

$$-EXCH_{\max}\leq P_{DA,t}^{E}+\Delta P_{s,t}^{E+}-\Delta P_{s,t}^{E-}\leq EXCH_{\max}\qquad\forall s,\forall t \tag{4.45}$$

$$0\leq P_{s,t}^{W,A}\leq P_{s,t}^{W,RT}\qquad\forall s,\forall t \tag{4.46}$$

$$0\leq P_{s,t}^{Loss}\leq\zeta P_{s,t}^{L,RT}\qquad\forall s,\forall t \tag{4.47}$$

$$\left(P_{DA,t}^{E}+\Delta P_{s,t}^{E+}-\Delta P_{s,t}^{E-}\right)+\sum_{i=1}^{NG}\left(P_{i,t}^{Gen}+\Delta P_{s,i,t}^{Gen}\right)+P_{s,t}^{W,A}=P_{s,t}^{L,RT}-P_{s,t}^{Loss}\qquad\forall s,\forall t \tag{4.48}$$

$$-P_{up,t}^{R}SIG_{s,t}^{up}+P_{dw,t}^{R}SIG_{s,t}^{dw}=\Delta P_{s,t}^{E+}-\Delta P_{s,t}^{E-}\qquad\forall s,\forall t \tag{4.49}$$

The second stage objective function (4.42) aims at maximising the increment (or equally minimising the decrement) of expected μVPP profit in different scenarios with specified probability. The first term represents the RT income S_{RT}^{R} from delivering the offered reserve capacity. The second term refers to the income variation S_{RT}^{Load} caused by uncertain RT load. The third and fourth terms of function (4.42) stand for cost variation S_{RT}^{E} which settles the RT payment for any upward or downward changes to energy bid and for the price difference between the DA market and the RT market. The fifth term is the cost variation S_{RT}^{Gen} for the increment or decrement in output power for all generators. The last term $C_{loss}P_{s,t}^{Loss}$ is the compensation cost S_{RT}^{Loss} to end-consumers for possible load loss in certain scenarios. The first stage decision variables $P_{DA,t}^{E}$, $P_{up,t}^{R}$, $P_{dw,t}^{R}$, $P_{i,t}^{Gen}$, $r_{i,t}^{Gen,up}$ and $r_{i,t}^{Gen,dw}$ are still involved in the second stage formulation. Additional decision variables include: 1) the upward change $\Delta P_{s,t}^{E+}$ or downward change $\Delta P_{s,t}^{E-}$ to the DA energy quantity bid/offer; 2) the change to the ith scheduled generator output power $\Delta P_{s,i,t}^{Gen}$; 3) the actual wind power usage $P_{s,t}^{W,A}$ according to the RT wind power production and 4) the load loss power $P_{s,t}^{Loss}$.

As for constraints, equation (4.43) ensures that the adjustment to the generator output lies within the limits of upward and downward spinning reserve. Equation (4.44) and (4.45) address that the transaction limit should not be exceeded when changing the energy bid/offer capacity in the RT market. Equation (4.46) represents the constraint for actual wind power usage in different scenarios. The chance constraints (4.36) - (4.37) guarantee a low probability of load loss event, however, the capacity of load loss should be confined to a small portion ζ of load as equation (4.47) indicates. Equation (4.48) is the power balance constraint between supply and demand for the μVPP in the RT market. Finally, the power flow relationship at the distribution network connection point is described in an equality constraint (4.49).

To sum up, the two-stage stochastic bidding strategy is formulated as a mixed-integer linear programming (MILP) problem with the first stage objective (4.15) subjected to the first stage constraints (4.16) - (4.37) and the second stage objective (4.42) subjected to the second stage constraints (4.43) - (4.49). The two-stage objective functions are combined and the problem is solved concurrently with state-of-the-art solvers such as CPLEX.

4.5 Comparative Case Studies

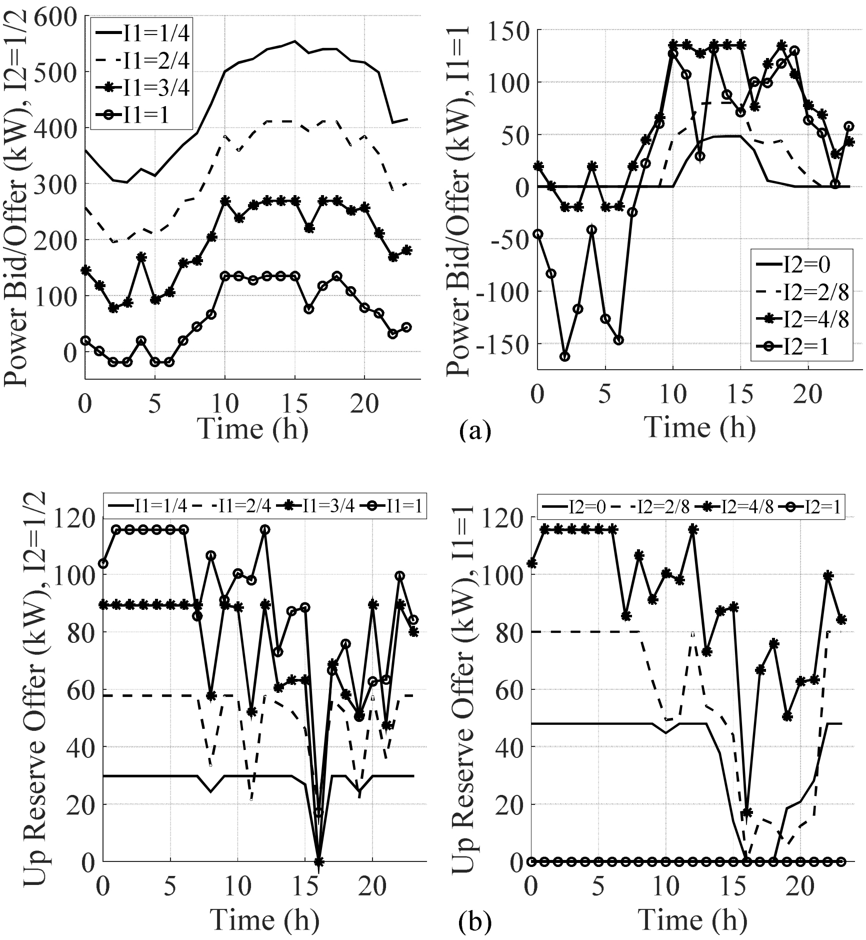
In the comparative performance study, the interrelation between the μVPP design and its projected profit are addressed. Two parametric indexes are introduced: the DER index that represents the ratio of on-site DER capacity over the value of maximum load level and the RES index that is defined as the ratio of RES capacity over the total DER capacity. The first case is set up with fixed uncertainty level for volatile parameters, where μVPPs with different DER indexes and RES indexes are studied. The second case studies the impact of wind power uncertainty, load uncertainty and LOLP level individually. The third case compares the proposed chance-constrained formulation with the classical Monte Carlo RT recourse approach. The fourth case analyses the impact of the congestion on the μVPP bidding behaviours. Considering the decarbonisation strategy promoted by the UK government, the last case investigates the impact on μVPPs' profit brought by the introduction of carbon tax.

The UK DA forecasted retail electricity price is extracted from Nord Pool price data 2016 [134], while the carbon tax rates are calculated according to the UK government's policy on carbon pricing [140]. The μVPP candidate, a residential community located in West Midlands County, has around 200 households with an average of 533kW daily consumption power. End-consumers of the community are subject to a 10% discount on retail price and 200% compensation for load loss. To provide guidance to deploy DERs in this community, different sizes of dispatchable generators from 165kW to 660kW and wind turbines from

20kW to 660kW are studied. All case studies are coded with YALMIP and CPLEX 12.1.4 is utilised as the solver. The program runs on an Intel Core-i5 2.5-GHz computer and the run time for the algorithm is around 80 seconds.

4.5.1 Case A – Impact of DER Index and RES Index

In this case, four DER indexes of 1/4, 1/2, 3/4 and 1 are studied. Nine RES indexes from 0 to 1 with a gradient of 1/8 are also introduced. Firstly, the bidding behaviour in DA energy-reserve market for different combinations of DER index (I1) and RES index (I2) is depicted in Fig. 21.



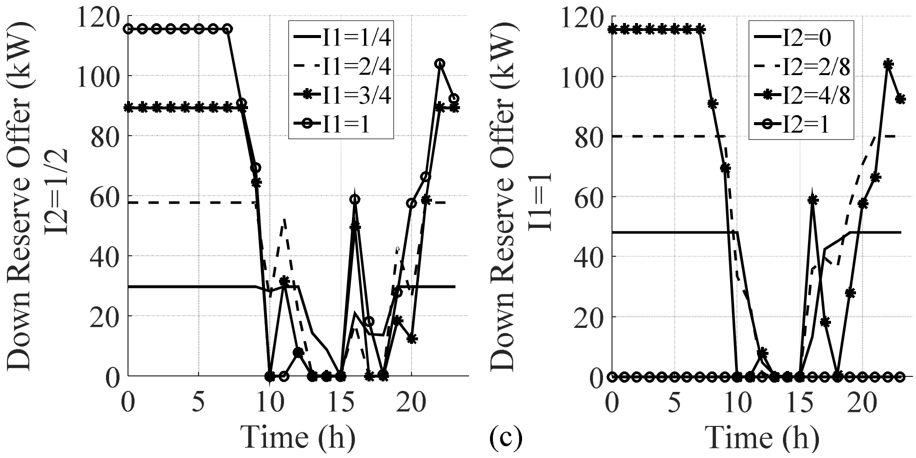


Fig. 21 μVPP bidding behaviour: (a) energy market bidding;
(b) upward reserve offering; (c) downward reserve offering

The diagram on the left-hand side of Fig. 21(a) shows a similar pattern of bidding behaviour for μVPPs with the same RES index and different DER index: the peak and valley bidding curves overlap with peak and valley load. When the DER capacity equals to the value of maximum load, μVPP can make energy offers to the pool during low demand period of 3-4 a.m. and 6-7 a.m. The diagram on the right-hand side of Fig. 21(a) demonstrates how the RES index impacts the bidding behaviour under a fixed DER capacity: with a low RES penetration level of 0 and 1/4 Index value, μVPP is more inclined to an autonomy state from the grid and will only make energy bid during energy intensive period of the day. The capacity of the bid is also lower with low RES indexes since dispatchable generators, which account for the larger half of the DER, can provide more upward spinning reserve to be used inside μVPP. For higher RES index of 1/2 and 1, the bidding/offering pattern becomes more volatile. Although μVPP is capable of producing energy offers during low consumption period, it also needs to purchase large capacity of energy during energy intensive hours. Such a volatile bidding/offering behaviour leads to heavy reliance on the utility grid, which increases μVPP's vulnerability to fault events.

In the left diagram of Fig. 21(b), the upward reserve offers submitted by μVPPs with different DER indexes share the same pattern. Intuitively, a larger DER capacity means a higher offer capacity from dispatchable generators. When the DER is made up entirely of wind generation, μVPP becomes incapable of providing upward reserve offer.

The provision of downward reserve offer as indicated in Fig. 21(c) shares similarities with upward reserve offering except for the energy intensive period of 10 a.m. to 18 p.m., when μVPP rarely submits downward reserve offers. This is because the submission of downward reserve offers during the high demand period is only driven by lower energy price. If the cost of dispatchable generation is lower than the RT energy price, μVPP will not provide downward reserve service for economic concerns.

Secondly in Case A, the daily profit of μVPP of different DER index and RES index is presented in Fig. 22.

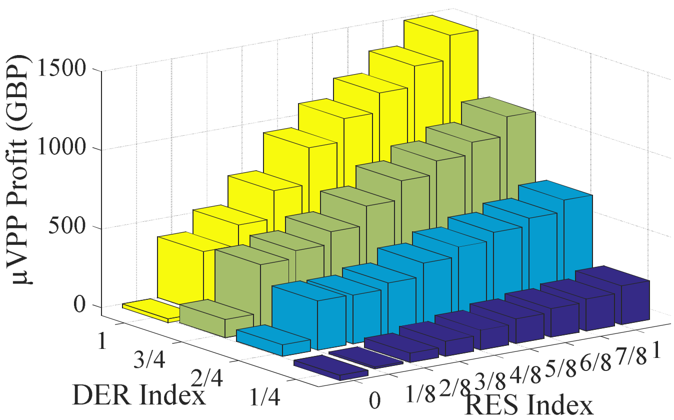


Fig. 22 μVPP profit for different DER and RES indexes

The profit of μVPP increases with a rising DER index and RES index, this is due to the assumption that wind turbine has zero operation cost. When the DER index is fixed and the RES index increases gradually, the net load will gradually decrease and therefore the expected profit will increase with a gradually reduced grid import. When the RES index is fixed, the increase of the profit with a rising DER index has two reasons: firstly, the reduction of net load still increases with the same gradient as the RES capacity increases. Secondly the rise in DG capacity brings more revenue from offering in the energy and reserve markets. However, high penetration of RES requires major initial investment followed by regular expenses on maintenance and repair. A μVPP with a seemingly high daily profit could also risk being put on a slow lane to recoup its capital investment. The profit for RES-dominated μVPP calculated based on the optimistic assumption may seem tempting for investors. However, the limitation of Case A is that the maximum capacity of RES does not exceed the peak demand. If the installed capacity of the RES is higher than the demand and μVPP expects to earn more by transforming itself into RES plant, the expectation will be challenged by non-profitable curtailment of the RES output due to supplier market saturation. Therefore, it is expected that the increase of profit will slow down and eventually stop if the RES capacity continues to rise. Thus, the financial viability of entering the distribution market relies heavily on the allocation of DER capacities. A poorly organised μVPP such as the one with the DER index 1 and RES index 0 has a negative projected profit and the decision to enter distribution market will not be optimal.

4.5.2 Case B – Impact of Uncertainties and LOLP

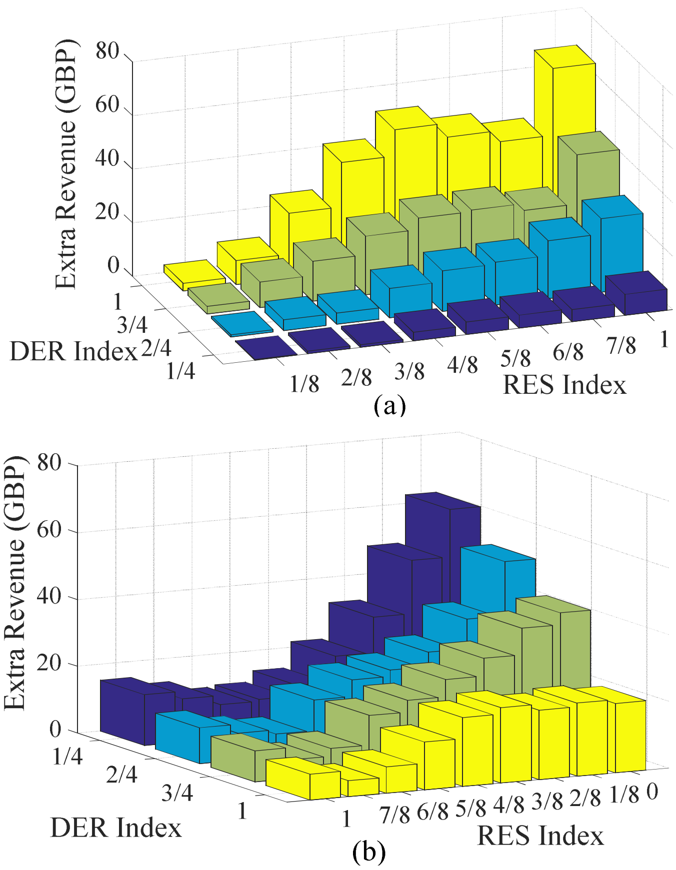


Fig. 23 Extra revenue obtained by (a) eliminating 20% wind forecast error;
(b) eliminating 5% load forecast error

In this case, the impact of narrowing down the parameter uncertainties of wind power and load level is demonstrated in Fig. 23. It is pointed out that extra revenue can be generated by acquiring more accurate forecast information during the DA bidding stage. This figure depicts the increment of the revenue instead of the revenue itself, therefore the positive values of the bars still indicate a continuous increase in the profit as the DER index and the RES index rise. However, the extra revenue (or the increment of the revenue) demonstrates a fluctuating characteristic: the increment from more accurate wind forecast drops a bit and then rises again with the RES index gradually increasing. The fluctuation grows even more severe for the extra revenue from more accurate load forecast. The fluctuation profile can be explained by examining the chance constraints (4.38) and (4.39) in section 4.4. When one of the forecast error is fixed and the other is changing gradually, the mean value of the net load $E\left(P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right)$ changes at the same speed. But the change of the standard deviation $\sigma\left(P_{s,t}^{L,RT} - P_{s,t}^{W,RT}\right)$ does not follow a fixed pattern which causes the fluctuation. Ultimately the fluctuation passes to the left-hand side of the chance constraints and leads to fluctuating patterns of bidding behaviours. Since the load level is higher than the wind power for most indexes, the change in revenue increment brought by altering load forecast accuracy is expected to be more dramatic. Fig. 23(a) shows how much extra revenue can be obtained by narrowing down the wind forecast error from 20% to 0. The revenue rises with an increasing capacity of DER and the increasing share of RES, but the additional income barely achieves 5% increase in percentage terms for all possible configurations. This phenomenon also results from the relatively small capacity of the wind generation. Therefore, a small level of wind power forecast error is tolerable for µVPPs under the current configurations but an accurate forecast system will be beneficial to those with large wind turbine assets. Fig. 23(b) displays the extra revenue generated by slashing the load forecast error from 5% to 0. Unlike wind power uncertainty, an accurate load forecast information proves to be crucial for µVPPs with all configurations because of the relatively large capacity of the load compared with the RES. The maximum profit increments in percentage terms are 71.28%, 36.88% and 86.66% for µVPP with DER index 1/2, 3/4 and 1 respectively. For µVPP with DER index 1/4, the forecast error reduction of load could even recover a losing business back to a break-even point. To sum up, accurate load forecast system is mandatory for profit-seeking μVPPs, especially for those with small wind turbine assets because a more volatile load would cost more energy bidding variations and more spinning reserves to be consumed inside μVPP.

The second result presented in this case is the impact of LOLP level on the profit and upward reserve offering behaviour. The European Parliament has issued a regulation on risk-preparedness in the electricity sector, in which the security of power supply requires that 95% to 99% of the time no one should be involuntarily disconnected. Consequently, the value of LOLP could be set as 0.01, 0.02 and 0.05. The result of an example μVPP with DER index 1/4 is given in Table X. Theoretically speaking, a strict LOLP level requires more upward spinning reserve to be ready for domestic consumption inside the μVPP instead of being submitted to the market. By relaxing the LOLP level from 0.01 to 0.02, there is an increase in the upward reserve capacity being submitted to the market for almost all configurations and by relaxing the LOLP from 0.01 to 0.05 the increase in the upward reserve offer can be doubled. For μVPP with higher share of dispatchable generators (represented by lower RES index I2), the reserve offer increment becomes more significant with LOLP relaxation and so does the extra revenue. An inconsistency is spotted in the results presented in Table X: the increase in the profit of a full-dispatchable μVPP is not as significant as the μVPP with 1/8 of RES share. This phenomenon results from the optimistic assumption that the operation cost of RES in this study is zero. The profit increment of the full -dispatchable μVPP could be shadowed by the cost savings of RES output.

TABLE X IMPACT OF LOLP ON PROFIT AND UPWARD RESERVE OFFERING FOR DER INDEX 1/4

I2 \ Result	$P^{R}_{up,t}$ kW 0.01	$P^{R}_{up,t}$ kW 0.02	$P^{R}_{up,t}$ kW 0.05	$\Delta P^{R}_{up,t}(\%)$ (0.01→0.02)	$\Delta P^{R}_{up,t}(\%)$ (0.01→0.05)	$\Delta S_{uVPP}(\%)$ (0.01→0.05)
0	290.37	415.04	602.03	42.93%↑	107.33%↑	36.86%↑
1/8	404.69	532.68	723.01	31.63%↑	78.66%↑	186.11%↑
2/8	581.77	638.54	788.39	9.76%↑	35.52%↑	38.60%↑
3/8	627.97	697.67	782.41	11.10%↑	24.59%↑	18.38%↑
4/8	607.25	649.63	674.00	6.98%↑	10.99%↑	9.63%↑
5/8	509.23	517.89	520.85	1.70%↑	2.28%↑	6.17%↑
6/8	358.75	362.92	372.21	1.16%↑	3.75%↑	4.58%↑
7/8	192.50	192.50	192.50	0	0	3.66%↑
1	0	0	0	0	0	3.33%↑

Four specific configurations are worth highlighting: for μVPPs with extremely high share of dispatchable generators in their energy mix (represented by low RES index 0 and 1/8), the LOLP setting has a tremendous impact on the upward reserve offer behaviour and a LOLP relaxation from 0.05 to 0.01 could potentially recover a losing μVPP operation to the break-even point. To achieve the trade-off between supply security (guaranteed by low LOLP) and economic viability (financially sound under higher LOLP), these μVPPs with low RES index should consider the deployment of controllable loads to actively shed the lost load. On the other hand, some μVPPs have extremely low capacity of dispatchable generators (represented by high RES index 7/8 and 1) and the upward spinning reserve is not enough to be submitted as reserve offers. Thus, it is not necessary for these μVPPs to participate in the reserve market. Also, the insignificant rise in extra revenue makes them less motivated to secure low LOLP.

4.5.3 Case C – Comparison of Risk-Hedging Methods

To address the competitiveness of the proposed chance-constrained formulation, a reference case is derived by solving a deterministic DA problem and applying the Monte Carlo recourse method in RT stage to obtain the best approximation of µVPP profit. The DA objective (4.15) subjected to constraints (4.16) - (4.35) is solved independently as a deterministic problem, with chance constraints (4.36) - (4.37) replaced by the following limits (4.50) - (4.51):

$$-EXCH_{\max} \le P^{E}_{DA,t} - P^{R}_{up,t} \le EXCH_{\max} \qquad \forall t \tag{4.50}$$

$$-EXCH_{\max} \le P^{E}_{DA,t} + P^{R}_{dw,t} \le EXCH_{\max} \qquad \forall t \tag{4.51}$$

where the provision of upward and downward reserve strictly obeys the transaction limit at the grid connection point, regardless of any RT stochastic parameters. Then the already derived bid/offer capacities and the dispatchable generation schedule are utilised in RT recourse with objective (4.42) subjected to constraints (4.43) - (4.49). Both risk-hedging methods are applied in an example µVPP with DER index 1 and RES index 1/2. The result is displayed in Table XI.

Based entirely from DA forecasted knowledge, the capacity of energy bid in the reference case (Monte Carlo recourse method) is closer to the forecasted consumption level and there is larger headroom to purchase more energy from the pool to provide downward reserve. Also, the deterministic formulation requires the forecasted load to be satisfied without any tolerance to loss, thus µVPP becomes more conservative in terms of providing upward reserve services. Although the RT recourse has made every effort to accommodate the uncertainties and achieved 97.3% of the proposed profit, it still yields a staggering 69% probability of load loss event and a daily penalty that is more than 100 times of the proposed method. The deterministic & Monte Carlo recourse method utilises Monte Carlo sampling to realise the uncertainties in the RT operations given the DA schedules. The purpose of the method is to approximate the projected profit from the two-stage market and evaluate physical requirement such as the loss of load probability. Therefore, the DA schedules from the separate deterministic formulation could be assessed and modified accordingly. Chance-constrained formulation, on the other hand, incorporates the risk management in the DA scheduling and solves the two-stage bidding problem concurrently. This consideration gives chance-constrained method more confidence in purchases and sales of larger quantities and yields a higher expected profit.

TABLE XI COMPARISON BETWEEN TWO RISK-HEDGING METHODS IN THE BIDDING STRATEGY

Results \ Methods	Chance-Constrained	Deterministic & Monte Carlo Recourse
Total Power bid/offer in energy market (kW)	1547.11	960.09
Total Up reserve offer (kW)	2161.95	1889.46
Total Down reserve offer (kW)	1517.59	1582.29
Loss of Load Probability	5%	69%
Total energy payment in DA and RT market (£)	125.44	109.80
Total reserve income in DA and RT market (£)	202.00	178.56
Avg. Load Loss Penalty (£)	0.05	5.13
µVPP Profit (£)	926.15	900.94
Computation time (s)	80.1	104.0

To sum up, the reference case represents a conservative business pattern for µVPP to participate in the energy-reserve distribution market. Although the RT recourse method does perform satisfactorily in pursuing maximum daily profit, the security of supply would be a major hazard unless controllable loads are introduced. On the other hand, the proposed method excels in terms of accurate control of load loss, higher daily profit and computational efficiency.

4.5.4 Case D – Rival's Impact on Bidding Behaviours

The bidding behaviours of the µVPP is influenced by rivals located in its nearby buses. For price-taking µVPPs, such impact takes place in the event of distribution line congestion when the feeders are heavily loaded. A three bus DC network model is utilised in this case and presented in Fig. 24: two rival µVPPs are represented by two adjacent nodes (node 1 and node 2) while node 3 is the energy-reserve pool managed by the DSO.

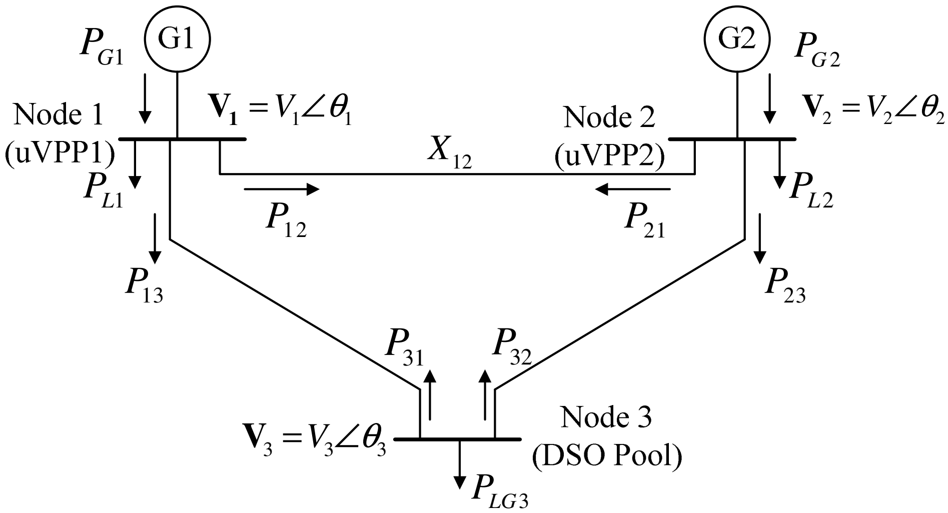


Fig. 24 Three bus DC network model for µVPPs

With the following additional constraints of the DC power flow model:

$$P_{G1} - P_{L1} - (\frac{1}{X_{12}} + \frac{1}{X_{13}})\theta_1 + \frac{1}{X_{12}}\theta_2 + \frac{1}{X_{13}}\theta_3 = 0 \tag{4.52}$$

$$P_{G2} - P_{L2} - (\frac{1}{X_{12}} + \frac{1}{X_{23}})\theta_2 + \frac{1}{X_{12}}\theta_1 + \frac{1}{X_{23}}\theta_3 = 0 \tag{4.53}$$

$$0 - P_{LG3} - (\frac{1}{X_{13}} + \frac{1}{X_{23}})\theta_3 + \frac{1}{X_{13}}\theta_1 + \frac{1}{X_{23}}\theta_2 = 0 \tag{4.54}$$

where the parameter P_{LG3} represents the net load or the net surplus of the pool market.

And the following additional constrains of the line limits:

$$-P_{12}^{\max} \le P_{12} \le P_{12}^{\max} \tag{4.55}$$

$$-P_{13}^{\max} \le P_{13} \le P_{13}^{\max} \tag{4.56}$$

$$-P_{23}^{\max} \le P_{23} \le P_{23}^{\max} \tag{4.57}$$

And the constraints for state variables:

$$0 \le \theta_1 \le 0 \tag{4.58}$$

$$-\infty \le \theta_2 \le \infty \tag{4.59}$$

$$-\infty \le \theta_3 \le \infty \tag{4.60}$$

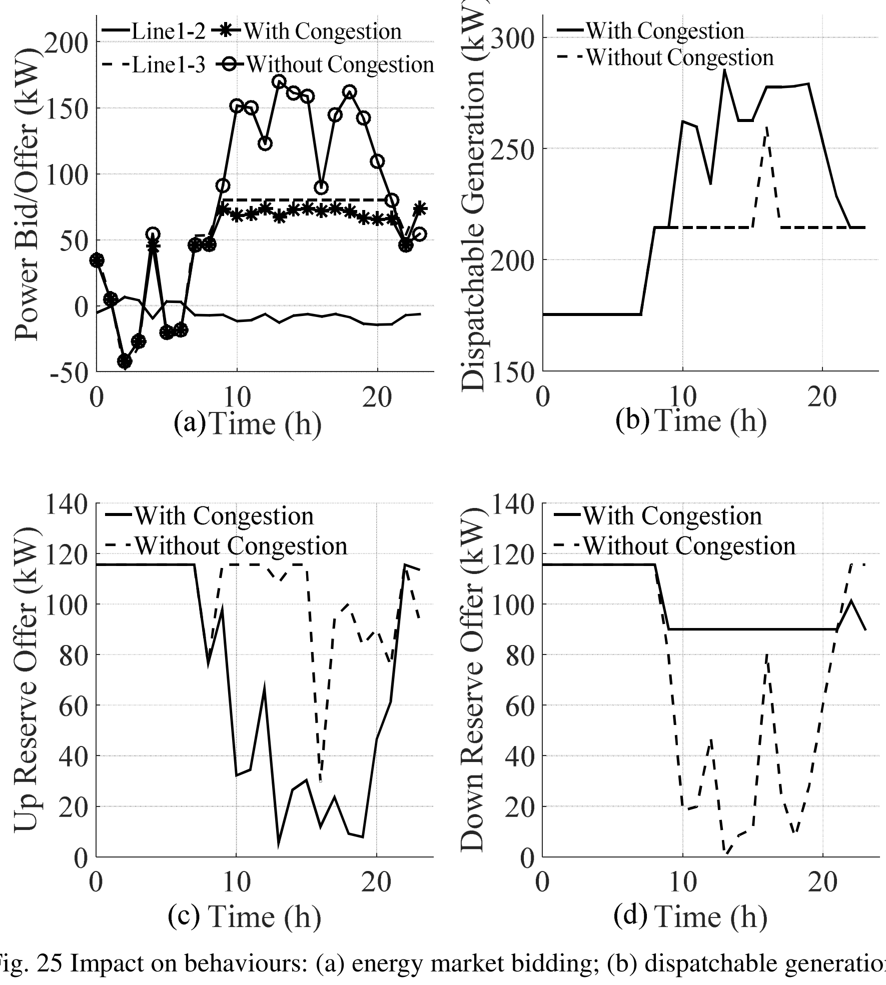


Fig. 25 Impact on behaviours: (a) energy market bidding; (b) dispatchable generation; (c) upward reserve offering; (d) downward reserve offering

If network congestion is not considered, the bidding quantity of individual μVPP in the energy market is limited only by the overall transaction limit. However, the distribution line between node 1 and node 3 is congested during peak load period from 09:00 to 21:00 since the power flow requested by the μVPP exceeds the thermal limit of the distribution line. As shown in Fig. 25(a), the energy bidding trajectory becomes flat during the same congestion period. To satisfy the demand within μVPP that has encountered congestion, the dispatchable generators must ramp up and produce more power as Fig. 25(b) indicates. Consequently, the dispatchable generators would have reduced room to ramp up and increased room to ramp down if they enter the reserve market. Fig. 25(c) and Fig. 25(d) show the decreased ability to provide upward reserve offer and the increased ability to provide downward reserve offer during the congestion period.

4.5.5 Case E – Impact of Implementing Carbon Tax

To promote the decarbonisation of electricity supply and reduce greenhouse gas emissions, the UK government has introduced a carbon tax levied on the electricity produced by generators using fossil fuels. From previous case studies, it has been demonstrated that dispatchable generators play a vital role in mitigating the RES volatility, load forecast error and providing regulating services. However, high penetration of fuel-fired dispatchable generators will compromise the 2020 emission targets and carbon tax is introduced to prevent harmful and unfavourable application of the dispatchable generators. The carbon tax ranges from 1.3p/kWh to 3.9p/kWh and it will be added to the variable unit cost for the dispatchable generators in the proposed μVPP. This case investigates how μVPPs, with their different shares of dispatchable generators, are affected by the implementation of carbon tax in terms of economic profit.

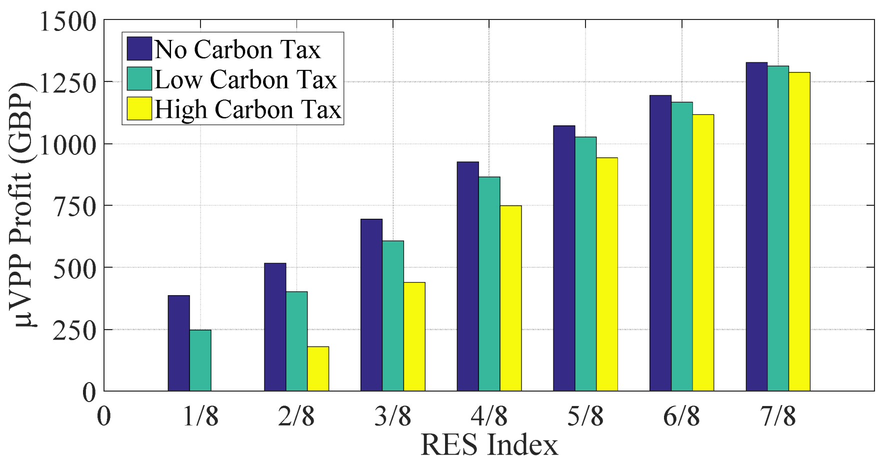


Fig. 26 Impact of carbon tax on μVPPs with different RES indexes

In Fig. 26, the bars in dark shade represent μVPPs' profit without the consideration of carbon tax, where the variable unit cost is the actual production cost of dispatchable generators. The medium bars and bars in light shade depict μVPPs' profits with a low carbon tax rate of 1.3p/kWh and a high rate of 3.9p/kWh respectively. The introduction of carbon tax decreases μVPPs' profit due to an increased operation cost of dispatchable generators and the reduction grows more significant with a higher tax rate. For those μVPPs with extremely high share of dispatchable generators (characterised by low RES index of 1/8), the profit even drops to zero in the presence of a high carbon tax rate of 3.9p/kWh. Secondly, with the RES index increases from 1/8 to 7/8, the electricity supply of the μVPP becomes more decarbonised and the reduction on profit brought by carbon tax becomes less obvious. With the implementation of carbon tax, the μVPP would purchase more from the energy market and sell less to the market because of a reduced margin in energy transactions. Similarly, it would become less active in the provision of reserve capacities. Although the carbon tax deters many investors, especially the small-scale ones, from installing dispatchable generators in their μVPPs, it is still crucial to have adequate number of dispatchable generation assets in the distribution network if DSO wants to meet the reserve requirement locally and avoid catastrophic loss of load. This case study reveals the disadvantage of the price-taker model of the μVPP: the investment decision-making and the projected revenue of the μVPP are heavily influenced by the current policies and pricing mechanisms because μVPP as a prosumer does not have a say in the price-making process. By submitting price bids/offers along with the quantity bids/offers, those μVPPs with large dispatchable generators could still obtain a considerable margin after the implementation of carbon tax.

4.6 Summary

This chapter has presented the bidding strategy formulation for price-taking micro Virtual Power Prosumers (µVPPs) to gain competitive advantage in the upcoming deployment of the distribution system market. Beside active bidding and offering in the energy pool, the µVPP also has its asset value stretched to provide ancillary services. In a foreseeable future, the energy-reserve equilibrium will be achieved locally by the interworking of multiple µVPPs. The increasing revenue for µVPPs will encourage the distribution system pool to become a highly competitive market. End-users will have a greater choice of energy suppliers which may yield retail electricity price reductions. µVPPs, recognised as full-dependent, semi-autonomous and full-autonomous in terms of DER coverage and full-dispatchable, semi-renewable and full-renewable in terms of RES share, have been shown to have significant differences in bidding behaviours and projected daily profits. The numerical tests have shown that accurate wind power and load forecasting bring additional revenue to the µVPP. The extra income can also be obtained by relaxing the required LOLP level due to increased DG availability to make higher offer in the reserve market. As a computationally efficient and technically secure method, the proposed chance-constrained two-stage µVPP optimisation has provided valuable guidance to investors in the determination of DER and RES capacities and the mitigation of risks brought by uncertainties. The deployment of such µVPPs in the distribution network could be a potential solution to better integrate DERs into the existing networks.

CHAPTER 5 MARKET EQUILIBRIUM IN ACTIVE DISTRIBUTION SYSTEM WITH μVPPS: A COEVOLUTIONARY APPROACH

5.1 Introduction

The price-taking μVPP presented in Chapter 4 has demonstrated its ability to actively utilise the DERs and earn considerable profit as a new entry to the distribution system market. The bidding strategy derived from Chapter 4 is suitable for a type of market where the μVPP has perfect knowledge of the rivals' information and market demand. Therefore, the μVPP is not exposed to market risks but only to the risks associated with the uncertainties within the μVPP itself. Consequently, the bidding strategy derived from the chance-constrained two-stage stochastic formulation is a rational decision under the market assumption. However, it is hard to find examples of industries which fit the criteria of "perfect knowledge". In a more practical market setting, market players submit sealed bids to the system operator simultaneously so that no bidder knows the price and the quantity of the others. In such a non-cooperative market environment, players submit various quantities of the goods and price them differently to compete with rivals and maintain profit margin. This chapter investigates the equilibrium model of the distribution system market, where multiple μVPPs participate in the energy-reserve auction by submitting price-quantity bids/offers. A novel coevolutionary approach is proposed to obtain pure strategy Nash Equilibrium.

5.2 Three Market Frameworks in the Distribution System

5.2.1 Nomenclature

Sets and Indices

t Index of time in the scheduling horizon

i Index of the μVPPs in the market, index of the species in the ecosystem

$-i$ Set of the rival μVPPs of the μVPP i

s Index of the individual in the population of the species

k Index of the iteration

I Set of the μVPPs in the market, set of the species in the ecosystem

T Set of the scheduling periods

NI Number of the μVPPs, number of the species

NT Number of hours in the scheduling horizon

NS The population size of the species, number of the individuals in the population

NK Number of the iterations in the coevolution

$Ind_{k,s}^{i}$ the individual in the s position of the population of species i in the kth iteration

$\left(Ind_{k,s}^{i}\right)^{*}$ pure strategy Nash Equilibrium individual of species i found at the s position of the population and in the kth iteration

Pop_{k}^{i} the population of species i in the kth iteration

f_{i}^{UL} upper-level objective function: the profit of μVPP i

f^{LL} lower-level objective function: the social welfare of the market

Parameters

λ_t^{RE}	£/kWh, energy price of traditional retailer during time t
λ_t^{RR}	£/kWh, reserve price of traditional retailer during time t
λ_t^{FIT}	£/kWh, feed-in tariff for µVPPs' surplus RES generation
C_i^{Gen}	£/kWh, variable production cost of the dispatchable generator in µVPP i
C_i^{SU}	£, start-up cost of the dispatchable generator in µVPP i
C_i^{SD}	£, shut-down cost of the dispatchable generator in µVPP i
$EXCH_{\max}$	kW, the transaction limit at the µVPP grid connection point
$P_{i,t}^{W}$	kW, power of wind generation of the µVPP i during time t
$P_{i,t}^{L}$	kW, power of load level of the µVPP i during time t
$\overline{P}_i^{Gen}$	kW, maximum output power of the dispatchable generator in µVPP i
$\underline{P}_i^{Gen}$	kW, minimum output power of the dispatchable generator in µVPP i
$\underline{T}_{on}^{Gen}$	hour, minimum time the dispatchable generator should be up per day
$\underline{T}_{off}^{Gen}$	hour, minimum time the dispatchable generator should be down per day
RU_i	kW/h, ramping up limit for the dispatchable generator in µVPP i
RD_i	kW/h, ramping down limit for the dispatchable generator in µVPP i
ω_{up}	upper limit of the available upward spinning reserve power
ω_{dw}	upper limit of the available downward spinning reserve power
$\overline{\lambda}_t^{E}$	£/kWh, upper limit of the energy bid price during time t
$\underline{\lambda}_t^{E}$	£/kWh, lower limit of the energy bid price during time t
$\overline{\lambda}_t^{R}$	£/kWh, upper limit of the reserve offer price during time t

$\underline{\lambda}_t^R$ £/kWh, lower limit of the reserve offer price during time t

δ_{RU} total amount of upward spinning reserve required as a percentage of the total load

δ_{RD} total amount of downward spinning reserve required as a percentage of the total load

Variables

P_t^{RE} kW, the energy offer quantity of the traditional supplier to satisfy demand blocks in the distribution system

P_t^{RRU} kW, the upward reserve offer quantity of the traditional supplier

P_t^{RRD} kW, the downward reserve offer quantity of the traditional supplier

$P_{i,t}^{E}$ kW, the energy bid quantity submitted by μVPP i during time t ; positive value corresponds to bid quantity, negative value corresponds to offer quantity

$P_{i,t}^{RU}$ kW, the upward reserve offer quantity submitted by μVPP i during time t

$P_{i,t}^{RU}$ kW, the downward reserve offer quantity submitted by μVPP i during time t

$\lambda_{i,t}^{E}$ £/kWh, the energy bid price submitted by μVPP i during time t

$\lambda_{i,t}^{R}$ £/kWh, the reserve offer price submitted by μVPP i during time t

C_t^{E} £/kWh, market clearing price for energy bids/offers

C_t^{RU} £/kWh, market clearing price for upward reserve offers

C_t^{RD} £/kWh, market clearing price for downward reserve offers

$C_{i,t}^{ULOC}$ £/kWh, the lost-opportunity-cost of μVPP i during time t for submitting upward reserve offer

$C_{i,t}^{DLOC}$ £/kWh, the lost-opportunity-cost of μVPP i during time t for submitting downward reserve offer

q_t^{RE} kW, the accepted quantity of the energy offer submitted by the traditional supplier during time t

q_t^{RRU} kW, the accepted quantity of the upward reserve offer submitted by the traditional supplier during time t

q_t^{RRD} kW, the accepted quantity of the downward reserve offer submitted by the traditional supplier during time t

$q_{i,t}^{E}$ kW, the accepted quantity of the energy bid/offer submitted by μVPP i during time t

$q_{i,t}^{RU}$ kW, the accepted quantity of the upward reserve offer submitted by μVPP i during time t

$q_{i,t}^{RD}$ kW, the accepted quantity of the downward reserve offer submitted by μVPP i during time t

$o_{i,t}$ binary variable which represents the operation status of dispatchable generator in μVPP i during time t

$u_{i,t}$ binary variable which represents the start-up decision of dispatchable generator in μVPP i during time t

$v_{i,t}$ binary variable which represents the shut-down decision of dispatchable generator in μVPP i during time t

$P_{i,t}^{Gen}$ kW, the scheduled generation power of dispatchable generator in μVPP i during time t

$r_{i,t}^{Gen,up}$ kW, available upward reserve capacity sourced from the dispatchable generator in μVPP i during time t

$r_{i,t}^{Gen,dw}$ kW, available downward reserve capacity sourced from the dispatchable generator in μVPP i during time t

$P_{s,t}^{Loss}$ kW, real-time consumption power of load loss in scenario s during time t

5.2.2 The Current, A Passive and An Active Distribution System Market

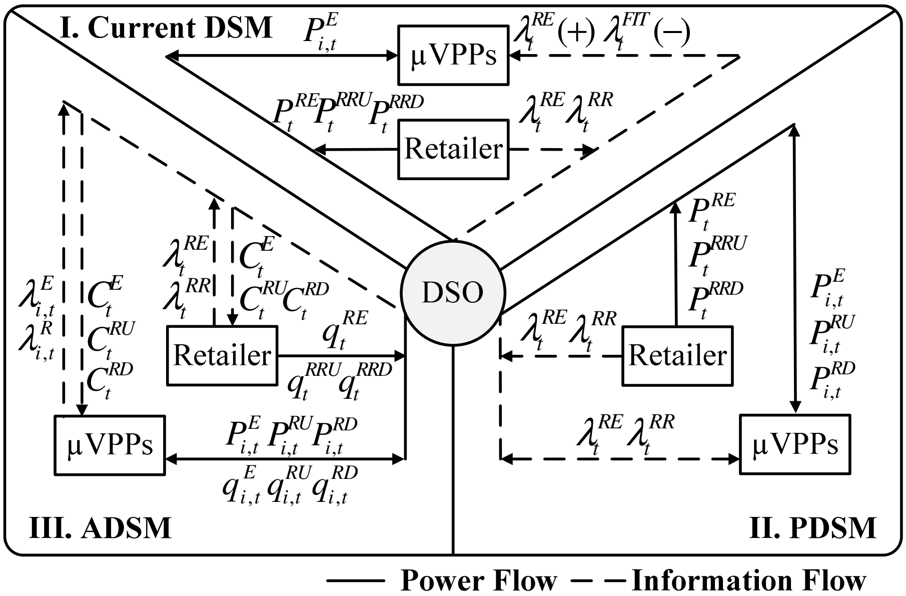


Fig. 27 Three types of markets in the distribution system

Fig. 27 illustrates the proposed active distribution system market (ADSM) structure. To highlight its novelties, the frameworks of the current distribution system market (DSM) and a passive distribution system market (PDSM) are also included. The participants in three types of distribution markets include μVPPs and traditional retailers and the markets are managed by a DSO. The differences between market types lie in the role of μVPPs, type of the bids/offers and market status as Table XII shows.

TABLE XII THE DIFFERENCES BETWEEN THREE TYPES OF DISTRIBUTION SYSTEM MARKETS

Properties / Types	Role of μVPPs	Type of Bids	Type of Competition
Current DSM	Consumer	N/A	Retailer-dominant
PDSM	Price-taking Prosumer	Quantity Bids/Offers	Close-to-Perfect Competition
ADSM	Price-making Prosumer	Price-Quantity Bids/Offers	Oligopolistic Competition

Current DSM

The section "I. Current DSM" in Fig. 27 illustrates the power flow and the information flow between market participants and the DSO in the current electricity retail market. For an individual μVPP, the DERs generate electricity only to satisfy its own demand during the periods when the operation cost is lower than retail energy price. Otherwise the μVPP submits the quantity $P_{i,t}^{E}$ (kW) it intends to buy from retailers at the retail energy price λ_t^{RE} (£/kWh). The DSO then sums up the demand from μVPPs and request the total amount of P_t^{RE} (kW) from the retailers. There are times when renewable energy sources (RES) generate more than the demand needs, μVPP will export the excess power back to grid at feed-in tariff λ_t^{FIT} (£/kWh). As for reserve capacities required in the distribution system, the upward reserve demand P_t^{RRU} (kW) and downward reserve demand P_t^{RRD} (kW) are completely supplied by retailers at retail reserve price λ_t^{RR} (£/kWh). To sum up, the current distribution system market is dominated by retailers. The capacities of DERs are restricted to be consumed inside μVPPs, thus the function of μVPPs is degraded into MGs and the role of μVPPs is limited as pure consumers despite their insignificant renewable export.

PDSM

The section "II. PDSM" in Fig. 27 depicts the transaction of power and information between market participants and the DSO in a PDSM. In a PDSM, the transactions of power in energy market and reserve market are priced at retail price λ_t^{RE} and λ_t^{RR} respectively. Based on the price signals, μVPPs submit two sets of hourly quantity bids/offers: the energy bid or offer $P_{i,t}^{E}$ (kW) to purchase or sell energy and the upward/downward reserve offer P_{t}^{RRU} / P_{t}^{RRD} (kW) to provide regulating service. Then DSO clears the energy and reserve markets for each hour by matching the quantity in supply offers to the quantity in demand bids. The dual role of both producer and consumer defines μVPPs as prosumers. As price-takers, μVPPs and traditional retailers provide a homogeneous product at the same price which leads the market towards perfect competition. However, the volatility and small-scale capacities of DERs' generation make μVPPs an imperfect substitution for traditional retailers therefore the PDSM can be described as "close-to-perfect".

ADSM

The proposed ADSM is shown in section "III. ADSM" in Fig. 27 μVPPs participate in the ADSM as price-making prosumers by submitting two sets of hourly price-quantity bids/offers: the energy bid or offer $P_{i,t}^{E}$ (kW) at price $\lambda_{i,t}^{E}$ (£/kWh) to purchase or sell energy; the upward/downward reserve offer $P_{i,t}^{RU}$ / $P_{i,t}^{RD}$ (kW) at price $\lambda_{i,t}^{R}$ (£/kWh). Traditional retailers, on the other hand, offer ADSM with quantities that are large enough to cover all the energy demand and reserve demand inside the distribution system at their retail prices. Then DSO clears the energy and reserve markets for each hour and produce the clearing price and clearing quantity for both markets aiming at maximising social welfare. DSO informs μVPPs of their clearing quantity $q_{i,t}^{E}$ (kW) and clearing price C_{t}^{E} (£/kWh) after clearing the energy market; the clearing quantity $q_{i,t}^{RU}$ / $q_{i,t}^{RD}$ (kW) and clearing price C_{t}^{RU} / C_{t}^{RD} (£/kWh) after clearing the upward/downward reserve market. The same clearing prices

$C_t^E / C_t^{RU} / C_t^{RD}$ (£/kWh) also apply to traditional retailers for their clearing quantity $q_t^{RE} / q_t^{RRU} / q_t^{RRD}$ (kW) in the energy market, upward reserve market and downward reserve market respectively.

The market frameworks of the current DSM and PDSM are used in this thesis as reference cases to demonstrate the advantages of ADSM. The maximisation of μVPPs' profit (or equally the minimisation of their cost) in the current DSM and PDSM can be easily formulated as mixed-integer linear problem (MILP) and solved by commercial solvers. The results are utilised to investigate the operation strategies of μVPPs under different market setups in case studies.

5.3 Bilevel EPEC Formulation of Active Distribution System Market

This section concentrates on formulating the proposed ADSM equilibrium model as a bilevel EPEC. The upper-level (UL) problem aims at maximising the economic profit of each μVPP and the lower-level (LL) problem aims at maximising the social welfare of the market clearing process. The objective functions and constraints of the bilevel EPEC are presented as follows.

5.3.1 Upper-Level Problem - μVPP Profit Maximisation

The objection function of the UL problems is formed as:

$$\begin{aligned}&\max_{i\in I}\sum_{t=1}^{NT}\Big\{C_t^{RU}\times P_{i,t}^{RU}+C_t^{RD}\times P_{i,t}^{RD}-C_t^{E}\times P_{i,t}^{E}+C_t^{E}\times P_{i,t}^{L}\\&-\left(C_i^{Gen}\times P_{i,t}^{Gen}+C_i^{SU}\times u_{i,t}+C_i^{SD}\times v_{i,t}\right)\Big\}\end{aligned}\tag{5.1}$$

where the first two terms $C_t^{RU}\times P_{i,t}^{RU}+C_t^{RD}\times P_{i,t}^{RD}$ represent the revenue received from upward and downward reserve markets. The third term $C_t^{E}\times P_{i,t}^{E}$ is the cost for energy bid. If μVPP offers energy to the market, the term $-C_t^{E}\times P_{i,t}^{E}$ is another source of revenue. The fourth term $C_t^{E}\times P_{i,t}^{L}$ is the income from supplying μVPPs' end-consumers. The income and payment of the transactions between μVPPs and ADSM are calculated by multiplying the offering/bidding quantities by the clearing prices. The last term $C_i^{Gen}\times P_{i,t}^{Gen}+C_i^{SU}\times u_{i,t}+C_i^{SD}\times v_{i,t}$ is the generation cost of dispatchable generators (DG) owned by μVPPs.

Subject to the following constraints:

$$-o_{i,t-1}+o_{i,t}-o_{i,k}\le 0,1\le k-(t-1)\le \underline{T}_{on}^{Gen} \quad \forall i,\forall t \tag{5.2}$$

$$o_{i,t-1}-o_{i,t}+o_{i,k}\le 1,1\le k-(t-1)\le \underline{T}_{off}^{Gen} \quad \forall i,\forall t \tag{5.3}$$

$$-o_{i,t-1}+o_{i,t}-u_{i,t}\le 0 \quad \forall i,\forall t \tag{5.4}$$

$$o_{i,t-1}-o_{i,t}-v_{i,t}\le 0 \quad \forall i,\forall t \tag{5.5}$$

$$u_{i,t}-v_{i,t}-o_{i,t}+o_{i,t-1}=0 \quad \forall i,\forall t \tag{5.6}$$

$$\underline{P}_i^{Gen}\le P_{i,t}^{Gen}o_{i,t}\le \overline{P}_i^{Gen} \quad \forall i,\forall t \tag{5.7}$$

$$P_{i,t}^{Gen}-P_{i,t-1}^{Gen}\le \left(2-o_{i,t-1}-o_{i,t}\right)\underline{P}_i^{Gen}+\left(1+o_{i,t-1}-o_{i,t}\right)RU_i \quad \forall i,\forall t \tag{5.8}$$

$$P_{i,t-1}^{Gen}-P_{i,t}^{Gen}\le \left(2-o_{i,t-1}-o_{i,t}\right)\underline{P}_i^{Gen}+\left(1-o_{i,t-1}+o_{i,t}\right)RD_i \quad \forall i,\forall t \tag{5.9}$$

$$-EXCH_{\max}\le P_{i,t}^{E}\le EXCH_{\max} \quad \forall i,\forall t \tag{5.10}$$

$$P_{i,t}^{E}+P_{i,t}^{Gen}+P_{i,t}^{W}=P_{i,t}^{L} \quad \forall i,\forall t \tag{5.11}$$

$$0\le r_{i,t}^{Gen,up}\le \omega_{up}\overline{P}_i^{Gen} \quad \forall i,\forall t \tag{5.12}$$

$$0\le r_{i,t}^{Gen,\mathrm{dw}}\le \omega_{dw}\overline{P}_i^{Gen} \quad \forall i,\forall t \tag{5.13}$$

$$P_{i,t}^{Gen}+r_{i,t}^{Gen,up}\le \overline{P}_i^{Gen}o_{i,t} \quad \forall i,\forall t \tag{5.14}$$

$$P_{i,t}^{Gen}-r_{i,t}^{Gen,dw}\ge \underline{P}_i^{Gen}o_{i,t} \quad \forall i,\forall t \tag{5.15}$$

$$P_{i,t}^{Gen}-P_{i,t-1}^{Gen}+r_{i,t}^{Gen,up}\le \left(2-o_{i,t-1}-o_{i,t}\right)\underline{P}_i^{Gen}+\left(1+o_{i,t-1}-o_{i,t}\right)RU_i \quad \forall i,\forall t \tag{5.16}$$

$$P_{i,t-1}^{Gen}-P_{i,t}^{Gen}+r_{i,t}^{Gen,dw}\le \left(2-o_{i,t-1}-o_{i,t}\right)\underline{P}_i^{Gen}+\left(1-o_{i,t-1}+o_{i,t}\right)RD_i \quad \forall i,\forall t \tag{5.17}$$

$$0\le P_{i,t}^{RU}\le r_{i,t}^{Gen,up} \quad \forall i,\forall t \tag{5.18}$$

$$0\le P_{i,t}^{RD}\le r_{i,t}^{Gen,dw} \quad \forall i,\forall t \tag{5.19}$$

Equation (5.2) and (5.3) are the minimum on time and minimum off time constraints for generators respectively. Equation (5.4) - (5.6) define the start-up and shut-down variables.

Equation (5.7) ensures the power output of each generator is within its capacity. Equation (5.8) and (5.9) apply the ramping rate limits on the speed of each generator to increase or decrease its power output. Equation (5.10) defines the upper and lower limits of the energy bid/offer quantity. Equation (5.11) is the power balance constraint between supply and demand for each μVPP. Equation (5.12) and (5.13) set the upper limit of upward and downward spinning reserve that are available from each generator. In addition, the production of upward or downward spinning reserve capacity should also abide by the output power limit and ramping limit as indicated by (5.14) - (5.15) and (5.16) - (5.17) respectively. Equation (5.18) explains that the upward reserve capacity offer is originated from ramping up the generator output. Similarly, constraints (5.19) explains that the downward reserve offer is sourced from ramping down the generator output.

5.3.2 Lower-Level Problem – DSO Social Welfare Maximisation

The objective function of the LL problem is formulated as:

$$\underset{t\in T}{Max}\left\{\sum_{i=1}^{NI}\left[\lambda_{i,t}^{E}\times q_{i,t}^{E}-\left(\lambda_{i,t}^{R}+C_{i,t}^{ULOC}\right)\times q_{i,t}^{RU}-\left(\lambda_{i,t}^{R}+C_{i,t}^{DLOC}\right)\times q_{i,t}^{RD}\right]\right.$$
$$\left.-\lambda_{t}^{RE}\times q_{t}^{RE}-\lambda_{t}^{RR}\times\left(q_{t}^{RRU}+q_{t}^{RRD}\right)\right\} \tag{5.20}$$

where the term $\lambda_{i,t}^{E}\times q_{i,t}^{E}$ stands for the consumer benefit if the ith µVPP acts as consumer in the energy market during period t (the value of clearing quantity $q_{i,t}^{E}$ is positive for consumer µVPP). If the µVPP acts as producer, the term $-\lambda_{i,t}^{E}\times q_{i,t}^{E}$ represents the production cost (the value of clearing quantity $q_{i,t}^{E}$ is negative for producer µVPP). The term $\left(\lambda_{i,t}^{R}+C_{i,t}^{ULOC}\right)\times q_{i,t}^{RU}$ is the production cost of the ith µVPP in the upward reserve market, in which the marginal cost consists of the reserve offer price $\lambda_{i,t}^{R}$ and lost opportunity cost $C_{i,t}^{ULOC}$. Similarly, the term $\left(\lambda_{i,t}^{R}+C_{i,t}^{DLOC}\right)\times q_{i,t}^{RD}$ is the production cost of the ith µVPP in the downward reserve market. The production costs of traditional retailer in both energy and reserve market are also included and they are calculated as $\lambda_{t}^{RE}q_{t}^{RE}$ and $\lambda_{t}^{RR}\times\left(q_{t}^{RRU}+q_{t}^{RRD}\right)$ respectively. The social welfare of the market clearing process is then derived by deducting the overall production cost from the total consumer benefit.

The LL objective function (5.20) subjects to the following constraints:

$$\underline{\lambda}_{t}^{E}\leq\lambda_{i,t}^{E}\leq\overline{\lambda}_{t}^{E}\qquad\forall i,\forall t \tag{5.21}$$

$$\underline{\lambda}_{t}^{R}\leq\lambda_{i,t}^{R}\leq\overline{\lambda}_{t}^{R}\qquad\forall i,\forall t \tag{5.22}$$

$$\begin{cases}P_{i,t}^{E}\leq q_{i,t}^{E}\leq 0, & if\ P_{i,t}^{E}<0\quad\forall i,\forall t\\ q_{i,t}^{E}=P_{i,t}^{E}, & if\ P_{i,t}^{E}\geq 0\quad\forall i,\forall t\end{cases} \tag{5.23}$$

$$0 \le q_{i,t}^{RU} \le P_{i,t}^{RU} \qquad \forall i, \forall t \tag{5.24}$$

$$0 \le q_{i,t}^{RD} \le P_{i,t}^{RD} \qquad \forall i, \forall t \tag{5.25}$$

$$q_t^{RE} \ge 0, q_t^{RRU} \ge 0, q_t^{RRD} \ge 0 \quad \forall t \tag{5.26}$$

$$-q_t^{RE} + \sum_{i=1}^{NI} q_{i,t}^{E} = 0 \qquad \forall i, \forall t \tag{5.27}$$

$$q_t^{RRU} + \sum_{i=1}^{NI} q_{i,t}^{RU} = \delta_{RU} \sum_{i=1}^{NI} P_{i,t}^{L} \qquad \forall i, \forall t \tag{5.28}$$

$$q_t^{RRD} + \sum_{i=1}^{NI} q_{i,t}^{RD} = \delta_{RD} \sum_{i=1}^{NI} P_{i,t}^{L} \qquad \forall i, \forall t \tag{5.29}$$

$$\begin{cases} C_{i,t}^{ULOC} = C_t^E - \lambda_{i,t}^E, & if\ P_{i,t}^{RU} \ne 0, \lambda_{i,t}^E < C_t^E \quad \forall i, \forall t \\ C_{i,t}^{DLOC} = \lambda_{i,t}^E - C_t^E, & if\ P_{i,t}^{RD} \ne 0, \lambda_{i,t}^E > C_t^E \quad \forall i, \forall t \end{cases} \tag{5.30}$$

As for constraints, equation (5.21) - (5.22) define the upper and lower limits of the bid/offer prices in the energy market and reserve market respectively. Equation (5.23) describes the relationship between clearing quantity and bid/offer quantity for the ith µVPP in the energy market: if the µVPP acts as energy producer during period *t*, it is possible that its offer quantity will be not accepted, partially accepted or fully accepted. If the µVPP acts as energy consumer during period *t*, then its bid quantity will be fully satisfied under any condition. The same rules apply for the reserve offer quantities submitted by the ith µVPP during period *t* as equation (5.24) - (5.25) indicate. If the energy and reserve capacities produced by µVPPs can't meet the demand, the rest will be provided by traditional retailers as equation (5.26) - (5.29) describe. The concept of lost opportunity cost is included in equality constraint (5.30). It is defined as the difference in net compensation for µVPPs between what their DERs receive when providing regulation services and what the DERs would have received for providing energy only [141]. For those µVPPs who decide to reserve some of their capacities for upward regulation service during the period when energy market clearing price C_t^E (£/kWh) is higher than the energy offer price $\lambda_{i,t}^E$ (£), they would have received an added revenue at price $C_{i,t}^{ULOC}$ (£/kWh) if the reserved capacities were sold as energy offers. Similarly, if the energy market clearing price C_t^E (£/kWh) is lower than the energy offer price $\lambda_{i,t}^E$ (£) and the µVPPs' output is still raised uneconomically to provide downward regulation, they should receive compensation at price $C_{i,t}^{DLOC}$ (£/kWh) for the extra energy output that will not bring any profit given the low market clearing price.

The bilevel EPEC formulation above demonstrates a highly-coupled nature of the decision-making process for both market participants and the DSO: In UL problem, µVPPs derive their optimal bidding/offering strategies and schedule their DERs' generation based on the maximisation of individual profit, in which the quantities of energy/reserve transactions are priced at the clearing prices determined in LL problem. In LL problem, the DSO derives the clearing prices and quantities based on the maximisation of social welfare, in which the clearing quantities of energy/reserve transactions are priced at the original bid/offer prices from UL problem. The highly-coupled nature requires the UL problem and LL problem to be solved simultaneously. However, due to the pessimistic assumption that µVPPs do not have any knowledge of the acceptance for their bids/offers, it is hard to utilise KKT conditions and transform the bilevel EPEC problem into a single-level problem [142]. To solve this conundrum, a novel coevolutionary approach is proposed in the next section.

5.4 Finding Market Equilibrium using A Coevolutionary Approach

To solve the bilevel EPEC formulated in Section 5.3, this section proposes a bilevel coevolutionary algorithm with real-coded Genetic Algorithm (GA) Operators including selection, crossover and mutation. Under the coevolutionary framework, a μVPP is represented by a "species" i in the ecosystem and the total number of species NI corresponds to the total number of μVPPs participating in ADSM. The "individual" of the species i is defined as the operation strategy set $\left\{\lambda_{i,t}^{E},\lambda_{i,t}^{R},P_{i,t}^{E},P_{i,t}^{RU},P_{i,t}^{RD},P_{i,t}^{Gen},o_{i,t},u_{i,t},v_{i,t},r_{i,t}^{Gen,up},r_{i,t}^{Gen,dw}\right\}$ of the ith μVPP for a scheduling period of 24 hours. For species i in the kth iteration, there are NS number of individuals $Ind_{k,s}^{i}$ which constitute a "population" Pop_{k}^{i}. The UL and LL objective functions are utilised as two separate fitness functions to assess the quality of the operation strategy set represented by individuals $Ind_{k,s}^{i}$. While the UL fitness function determines the fittest individual that brings the maximum profit for species i among the entire population, the LL fitness function provides a shared domain for all species to interact with one another. After NK number of iterations, the coevolutionary algorithm aims at finding the pure strategy NE set $\left(Ind_{k,s}^{i}\right)^{*},\forall i$ for all species. The pure strategy NE satisfy the following conditions:

$$f_{i}^{UL}\left(\left(Ind_{k,s}^{i}\right)^{*}\right)\geq f_{i}^{UL}\left(Ind_{k,s}^{i}\right)\qquad\forall i \tag{5.31}$$

$$f^{LL}\left(\left(Ind_{k,s}^{i}\right)^{*}\mid\left(Ind_{k,s}^{-i}\right)^{*}\right)\geq f^{LL}\left(Ind_{k,s}^{i}\mid\left(Ind_{k,s}^{-i}\right)^{*}\right)\qquad\forall i \tag{5.32}$$

For all species i inside the ecosystem, condition (5.31) describes the UL optimality of the pure strategy NE set $\left(Ind_{k,s}^{i}\right)^{*}, \forall i$. It is the fittest individual among the entire population that brings the maximum profit. Condition (5.32) states the LL optimality of the pure strategy NE: if the rest of the species $-i$ find their UL optimal strategy set $\left(Ind_{k,s}^{-i}\right)^{*}, \forall -i$, the pure strategy NE $\left(Ind_{k,s}^{i}\right)^{*}, \forall i$ is the best response for species i. No single μVPP can obtain a higher margin by deviating unilaterally from its pure strategy NE profile without decreasing the social welfare of the ADSM.

5.4.1 Building Blocks of the Coevolutionary Algorithm

Initialisation

At the beginning of the iterative process, all elements in the individual strategy string $Ind_{0,s}^{i}$ are initialised with their real value to form the initial population Pop_{0}^{i}. The randomly generated value should comply with its upper and lower limits defined in constraints (5.2) - (5.19) and (5.21) - (5.22). Firstly, the binary variables $o_{i,t}, u_{i,t}, v_{i,t}$ are initialised subject to constraints (5.2) - (5.6). Based on the derived operation variable $o_{i,t}$ and constraints (5.7) - (5.9), the DG output $P_{i,t}^{Gen}$ is initialised. Then the value of energy bid/offer quantity $P_{i,t}^{E}$ can be derived based on constraints (5.10) - (5.11). After $P_{i,t}^{Gen}$ is settled, constraints (5.12) - (5.17) and (5.18) - (5.19) initialise the value of available reserve capacities $r_{i,t}^{Gen,up} / r_{i,t}^{Gen,dw}$ and reserve offer quantities $P_{i,t}^{RU} / P_{i,t}^{RD}$ respectively. Finally, the bid/offer prices for energy $\lambda_{i,t}^{E}$ and for reserve $\lambda_{i,t}^{R}$ are initialised based on constraints (5.21) - (5.22).

Selection

The aim of selection in the coevolution paradigm is to form a mating pool of individuals for reproduction. Fitter individuals have a higher chance to pass on their profile to the succeeding iteration and the offspring will in turn have even higher fitness. The proposed coevolutionary algorithm uses an elitism-based tournament selection method in which some of the fittest individuals could transfer their unaltered profile to their offspring [126]. In addition to the computationally efficient tournament selection method, elitism concept is applied in this thesis to improve the performance of the algorithm by preventing loss of good solutions. To select fitter individuals for species i, firstly the rest of the species $-i$ must choose their best individual set $\left(Ind_{k,s}^{-i}\right)^*, \forall -i$ based on UL optimality. Then the individual $Ind_{k,s}^{i}$ from current population Pop_k^i can be evaluated with LL optimality as criterion. The elite individuals of species i are those with high LL fitness value, in other words, they represent the best response of the ith μVPP given the strategies of the others. The selection process will then run several "tournaments" among the non-elite individuals, after which the non-elites with low LL fitness value are removed from the mating pool.

Crossover

For the selected individuals in the mating pool, crossover operation randomly chooses a position and the parts of two parent individuals at the position are exchanged to form two offspring. In the proposed coevolutionary algorithm, every individual has 24 points in its strategy string which corresponds to the scheduling horizon of 24 hours. A multi-point crossover scheme is applied in this thesis which means every hour is a potential point for crossover to take place. When crossover happens at hour t, all elements included in the strategy string $\left\{\lambda_{i,t}^{E},\lambda_{i,t}^{R},P_{i,t}^{E},P_{i,t}^{RU},P_{i,t}^{RD},P_{i,t}^{Gen},o_{i,t},u_{i,t},v_{i,t},r_{i,t}^{Gen,up},r_{i,t}^{Gen,dw}\right\}$ of both parents will be exchanged. However, the crossover operation may be disruptive to the parents' genetic profile because the new strategy string at hour *t* may conflict with the original strings at hour *t-1* and *t+1*. Therefore, the crossover operation should be supervised by constraints (5.2) - (5.19).

Mutation

After crossover operation updates the individuals in the mating pool, there is a small probability for the algorithm to perform mutation operation on updated individuals. This GA operator will randomly choose a position of the individual and change the value of the string to another value within its feasible region. The probability of mutation is small but the operation itself is indispensable because it helps the search evade local optimums and prevents premature convergence [143]. When mutation happens at hour *t*, an element will be chosen randomly from the strategy string $\left\{\lambda_{i,t}^{E},\lambda_{i,t}^{R},P_{i,t}^{E},P_{i,t}^{RU},P_{i,t}^{RD},P_{i,t}^{Gen},o_{i,t},u_{i,t},v_{i,t},r_{i,t}^{Gen,up},r_{i,t}^{Gen,dw}\right\}$ and changed to another feasible value. Similarly, the mutation process should also be supervised by constraints (5.2) - (5.19).

Energy and Reserve Market Clearing

The process of energy and reserve market clearing determines the market clearing price, at which the transactions of energy/reserve capacities are priced; and the market clearing quantities, which are assigned to producers to dispatch their generation resources. The offers from suppliers including producer μVPPs and retailers are aggregated as a monotonically increasing supply curve and the bids from consumer μVPPs are aggregated as a monotonically decreasing demand curve. At each hour, the energy market is cleared first by finding the intersection of supply and demand curves. The price at the intersection is defined as energy market clearing price C_t^E . Then the lost opportunity cost $C_{i,t}^{ULOC} / C_{i,t}^{DLOC}$ are obtained based on equation (5.30). By matching the supply quantity to the demand quantity as constraints (5.23) and (5.27) suggest, the market clearing quantities $q_{i,t}^E / q_t^{RE}$ are derived for μVPPs and retailers respectively. The DSO then clears the reserve market following the same procedure and derives the following results: reserve market clearing prices C_t^{RU} / C_t^{RD}, market clearing quantities $q_{i,t}^{RU} / q_{i,t}^{RD}$ for μVPPs and q_t^{RRU} / q_t^{RRD} for retailers. The only difference between energy market clearing and reserve market clearing is that the reserve demand is a fixed level in every scheduling period, which is represented by a straight line perpendicular to the price axis. The market clearing process represents the LL problem and the maximum social welfare is achieved at the intersection of supply and demand curves. The results obtained in this algorithmic block facilitate the calculation of LL fitness value.

5.4.2 Procedure of the Coevolutionary Algorithm

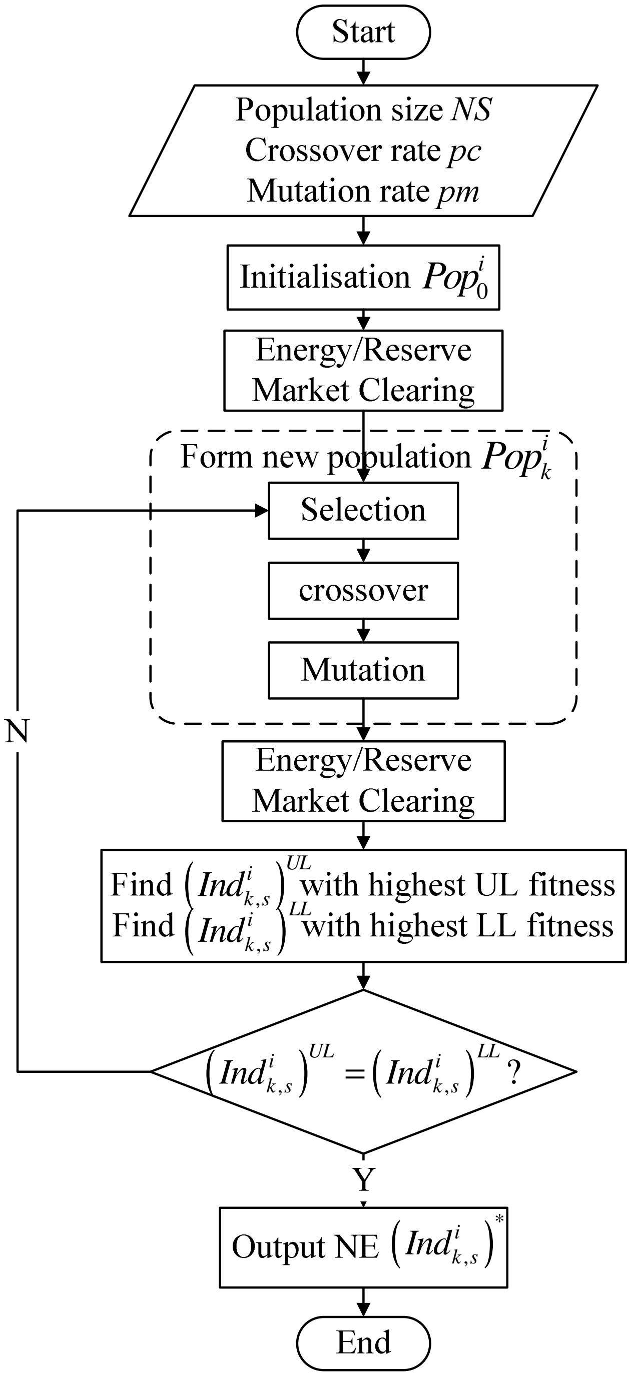


Fig. 28 Coevolutionary algorithm workflow

The workflow of coevolutionary algorithm in this thesis is shown in Fig. 28. Detailed procedure is described as follows:

Step 1) Initialise the first population for each species i. There are NI number of populations and each population Pop_k^i contains NS number of individuals;

Step 2) Perform energy/reserve market clearing, obtain UL and LL fitness value of the individuals in the first population;

Step 3) Based on the UL and LL fitness value of the individuals in the previous iteration, perform selection, crossover and mutation to form new population Pop_k^i;

Step 4) Perform energy/reserve market clearing, obtain UL and LL fitness value of the individuals in the current population;

Step 5) For each species i, compare the individual $\left(Ind_{k,s}^i\right)^{UL}$ with the highest UL fitness and the individual $\left(Ind_{k,s}^i\right)^{LL}$ with the highest LL fitness;

Step 6) Repeat Step 3) to Step 5) until $\left(Ind_{k,s}^i\right)^{UL} = \left(Ind_{k,s}^i\right)^{LL}$ is achieved for every species simultaneously, output pure strategy NE $\left(Ind_{k,s}^i\right)^*, \forall i$. The strict equality of the convergence criteria is relaxed by a very small tolerance of 0.02. It means that for the two strategy sets which achieve UL and LL optimality respectively, they can be regarded as the same strategy and the convergence is achieved when the difference between them does not exceed 2%. The criterion is derived based on the pure strategy NE conditions described in (5.31) and (5.32).

5.5 Comparative Case Studies

In the comparative performance study, the effectiveness of the proposed coevolutionary approach in finding the equilibrium is investigated and demonstrated. Also, the operation behaviours of a single μVPP under different market structures are analysed, addressing the advantages of the proposed ADSM over the current DSM and PDSM. The UK retail energy price and reserve price are extracted from Nord Pool price data 2016 [134]. A modified IEEE 33 bus distribution system is used and presented in Fig. 29. the supply and demand nodes of the example system are aggregated into four μVPPs to form the oligopolistic ADSM.

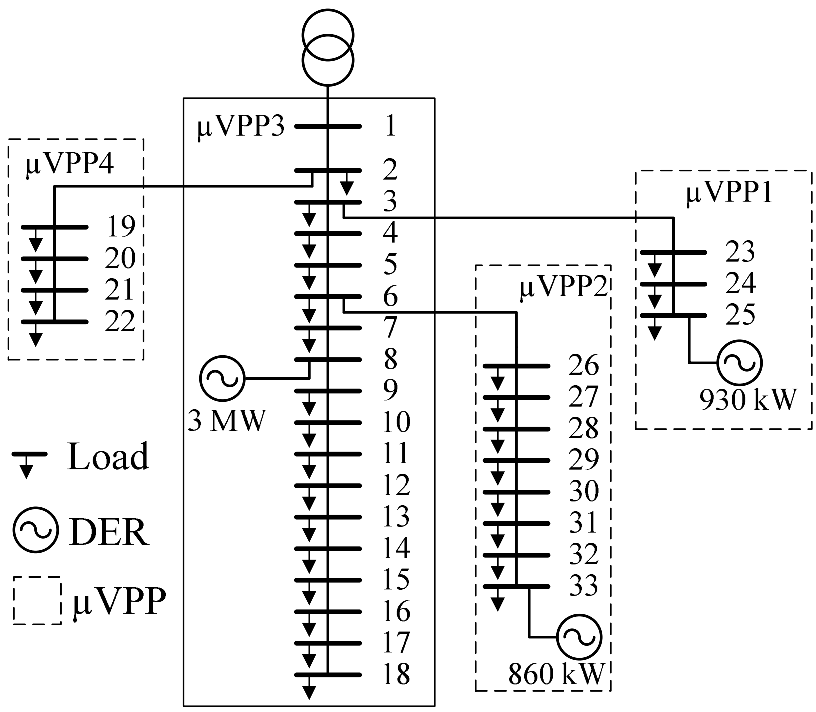


Fig. 29 Modified IEEE 33 bus distribution system model with aggregated μVPPs

μVPP1 (node 23 to 25) has an average hourly demand of 930kW and DER capacity of 930kW, of which RES capacity accounts for 70% of the DER capacity. μVPP2 (node 26 to node 33) has a similar hourly demand of 860kW and DER capacity of 860kW, but its RES capacity accounts for only 30% of the DER. µVPP3 (node 1 to node 18) has the highest hourly demand of 1445kW, the highest RES capacity of 1500kW and the highest DG capacity of 1500kW. µVPP4 (node 19 to node 22) has a small demand level of 360kW and no DER assets. The four µVPPs presented in the case studies represent the typical types of DER resource allocation: µVPP1 and µVPP2 can be viewed as prosumers, one is equipped with more RES than DG and the other has more DG than RES. µVPP3 is a major producer in the market and a main competitor for the traditional suppliers. µVPP4 is a pure consumer but it can participate in the market by pricing its demand strategically. By assigning different profiles to the participating µVPPs, this thesis studies the impact on µVPPs' bidding strategies brought by DER and RES penetration level.

For the parameters of the coevolutionary approach, the population size, crossover rate and mutation rate are set as 60, 0.8 and 0.1 respectively. Although the correlation between the population size and the solution speed remains debatable, references [127-131] showed that convergence of the coevolutionary algorithm could be achieved relatively fast if the population size is set to be 5 to 10 times the number of decision variables. The high crossover rate is chosen to give more genetic diversity within the population, promoting the search for new feasible solutions. The low mutation rate prevents the coevolutionary process from degrading to random search and improve the computation efficiency [143]. The operation problems in the current DSM and PDSM are formulated as MILP and solved using commercial solver CPLEX 12.1.4. The proposed coevolutionary algorithm for ADSM is coded in MATLAB and solved using embedded solvers. The equilibrium of ADSM is found after executing 253 coevolutionary iterations for 14 hours, however, the proposed method delivers pure strategy NE under strict convergence criteria described in section 5.4.

5.5.1 Case A – Consumer μVPP in the Current DSM

Under the market structure of the current DSM, any μVPP is a pure consumer regardless of their DER portfolio. The DG assets are forbidden to actively offer energy nor reserve capacity to the distribution system market. The surplus RES outputs can be fed into the main grid at FIT. In the current DSM, an optimal energy dispatch is performed for μVPP3 which aims at minimising the energy cost and the operation strategy is depicted in Fig. 30.

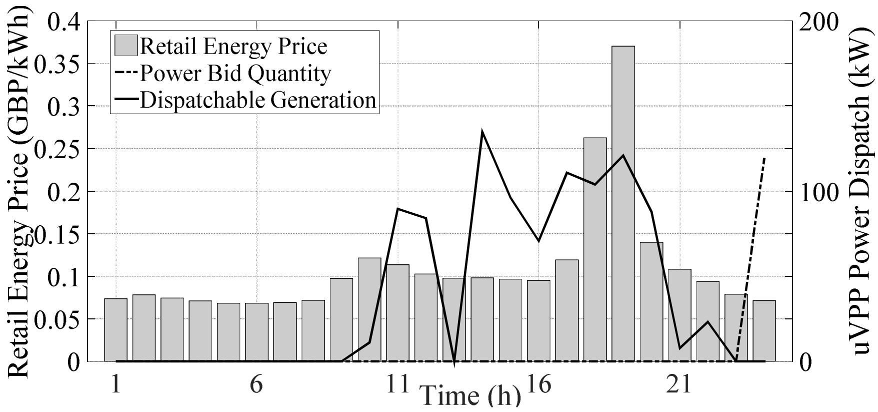


Fig. 30 Operation strategy of μVPP3 in current DSM

As shown in Fig. 30, μVPP3 submits nearly no energy bid to the market. This μVPP is operated autonomously from the grid due to its large DER capacity and it is degraded to a MG. During the period of 9 a.m. to 23 p.m., the demand inside μVPP3 is satisfied by the combined output of RES and DG since the generation cost is lower than the retail energy price. However, the peak output power of DG barely exceeds 125kW compared with the rated value of 1500kW, showing a poor utilisation of the DER capacity. This is because DER generation is restricted to be consumed inside µVPP under the current DSM instead of exported for extra revenue.

5.5.2 Case B – Price-taking Prosumer µVPP in PDSM

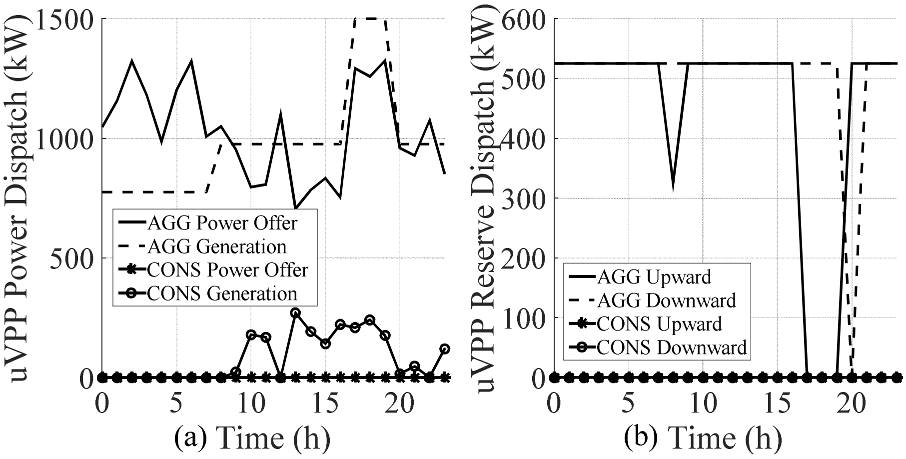


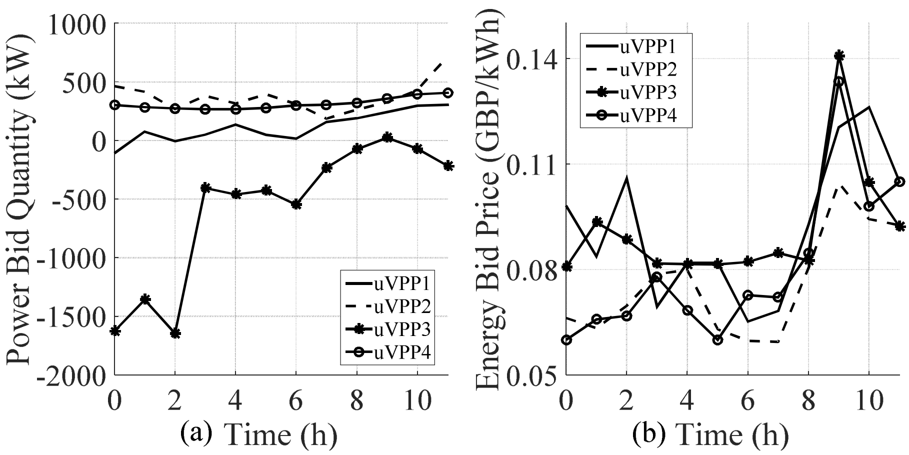
Fig. 31 Offering strategy of µVPP in PDSM: (a) energy market; (b) reserve market

Under the market structure of PDSM, µVPP is permitted to submit quantity bids/offers to the market for revenue. However, they do not participate in settling the clearing prices of both energy and reserve markets. The bidding/offering strategy of µVPP3 in PDSM is shown in Fig. 31.

As a price-taker, one market player (µVPP or retailer) has no strategic advantage over the others because they provide a homogenous product. For DSO, it makes no difference to accept the offer from a µVPP or from a traditional retailer. Consequently, the offering strategy of a producer µVPP can be characterised as "aggressive" (AGG) or "conservative" (CONS). In Fig. 31(a), µVPP3 can submit aggressive energy offers to the market by keeping its DG running all day, hoping for the acceptance of all the submitted quantities and high profit. Alternatively, μVPP3 operates conservatively and submits no energy offers. The DG is utilised only for the demand inside μVPP3 thus the operation cost can be reduced to minimum. Fig. 31(b) demonstrates similar behaviours in the reserve market: aggressive μVPP would use the ramping capability of its DG to make upward and downward reserve offers to the market while conservative μVPP would offer nothing. In a non-cooperative PDSM environment, price-taking prosumer μVPPs have a hard time determining their optimal offering strategies because they lack the market power to influence the market outcome. Consequently, their revenue from the market would vary significantly from the anticipation.

5.5.3 Case C – Price-making μVPP in ADSM

Under the framework of ADSM, μVPPs are permitted to submit price-quantity bids/offers to the markets. The proposed coevolutionary approach achieves pure strategy NE for all participants in the market. No single μVPP can obtain a higher margin by deviating unilaterally from its pure strategy NE profile without decreasing the social welfare of the ADSM. Their bidding/offering behaviours in the energy market are depicted in Fig. 32.



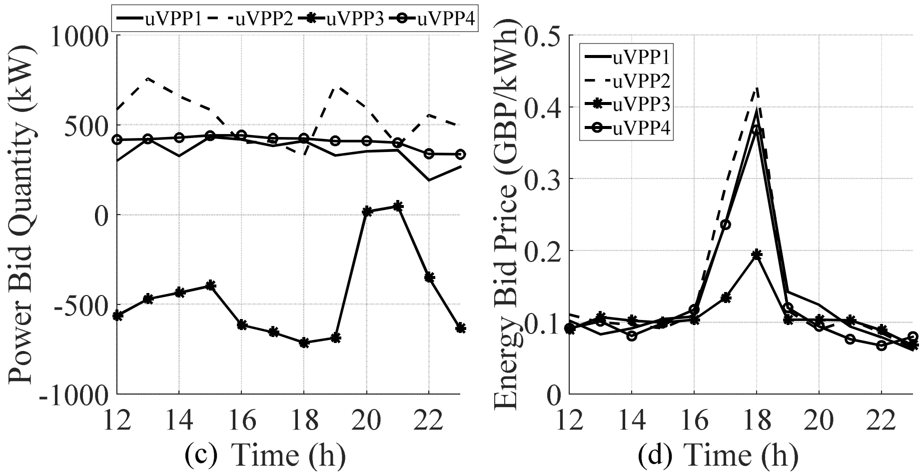


Fig. 32 Energy bidding/offering strategies in ADSM: (a) bid quantity a.m.; (b) bid price a.m.; (c) bid quantity p.m.; (d) bid price p.m.

µVPPs' behaviours in terms of bid price are analysed together with their bid quantities. µVPP1 and µVPP2 have similar DER capacity and they both act as energy consumers for the first half of the day as Fig. 32(a) indicates. However, µVPP2 has a larger percentage of DG capacity in its DER which results in lesser dependence on the imported energy. Therefore Fig. 32(b) shows that µVPP2 tends to bid a lower price for its energy import compared with µVPP1 knowing it can always produce its own energy even the bid is rejected. µVPP3 acts as a pure producer in the ADSM to compete with traditional retailers. To gain strategic advantage, Fig. 32(b) shows high bid price at 9 a.m. when µVPP3 exports low volume and low bid price during 0 a.m. to 8 a.m. when it exports high volume. µVPP4 is a pure consumer in the ADSM and has similar load level with µVPP2 as Fig. 32(a) shows. However, the lack of self-generation assets forces µVPP4 to bid a higher price than µVPP2 as Fig. 32(b) depicts. Fig. 32(c) and Fig. 32(d) describe the energy bidding/offering behaviours for the second half of the day. A peak point of energy bid price trajectories is spotted at 18 p.m. in Fig. 32(d) and it can be explained from the viewpoint of energy market clearing process. At 18 p.m., the aggregated demand of µVPP1, µVPP2 and µVPP4 exceeds the supply quantity offered by µVPP3. In this case, traditional retailers must supply some or all the demand at its peak retail price £0.37/kWh. For consumer µVPPs, they tend to submit higher bid price to guarantee the acceptance of their demand bids; for producer µVPP3, it needs to submit a lower bid price £0.2/kWh to occupy some of the supplier market share. For DSO who aims at maximising social welfare, the bidding/offering strategies at 18 p.m. produce the highest consumer benefit and the lowest production cost. To sum up, the bidding/offering strategies obtained by the coevolutionary approach have achieved UL and LL optimality simultaneously.

Fig. 33(a) and Fig. 33Fig. 33(b) display µVPPs' offering strategies of upward reserve capacity while Fig. 33(c) and Fig. 33(d) show µVPPs' offering strategies of downward reserve capacity. For upward reserve market, only µVPP2 and µVPP3 have the DG large enough to provide upward ramping resources. Their bid prices in Fig. 33(b) follows the economic rationale to compete with traditional retailers: bid high price when the reserve production is low and bid low price when the reserve production is high. The same rule applies to determining the downward reserve offer price shown in Fig. 33(d) as µVPP1-3 offer different volumes of downward reserve based on their DG capacities.

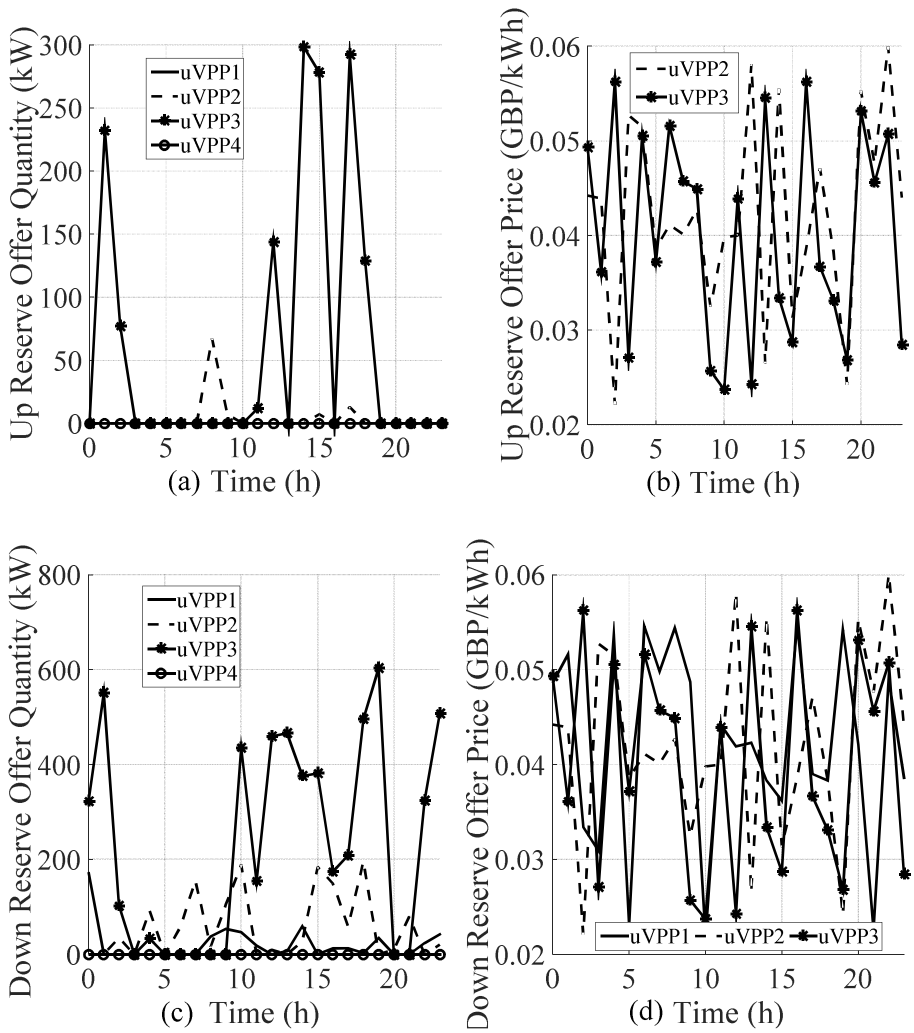


Fig. 33 Reserve offering strategies in ADSM: (a) upward offer quantity; (b) upward offer price; (d) downward offer quantity; (d) downward offer price

To address the advantage of deploying an ADSM in the distribution system, the impact of different market structures on μVPP operation is demonstrated in Table XIII. Six criterions are used to characterise μVPP3 in the current DSM, PDSM and the proposed ADSM respectively: DG utilisation rate is calculated as the ratio of the average DG output power over its rated power; Energy market income is the revenue received from μVPP's energy offers which are settled at market clearing price; Reserve market income is the revenue received from μVPP's reserve offers which are settled at market clearing price; End-consumer income represents the payment received from μVPP's end-consumers for energy consumption; DG cost calculates the operation cost of μVPP's self-generation assets; finally total profit is the net revenue of μVPP from market activities.

TABLE XIII IMPACT OF MARKET STRUCTURES ON μVPP3'S OPERATION AND PROFIT

Framework / Result	Current DSM	PDSM	ADSM
DG utilisation (%)	5%	5% - 65%	31%
Energy market income (£)	114.36	114.36 – 2800.86	1360.75
Reserve market income (£)	0	0 – 12508	282.33
End-consumer income (£)	4012.9	4012.9	3960.7
DG cost (£)	390.53	390.53 – 1955	1339.4
Total profit (£)	3736.73	3736.73 – 17366.76	4264.38

Under the current DSM structure, consumer μVPP only receives an insignificant payment for exporting its excessive RES generation back to grid at feed-in tariff. The DER assets within μVPP are utilised poorly and their capacities are not exploited to generate extra revenue. The energy market income of the μVPP comes entirely from feeding the surplus RES back to the grid and it is the lowest (£114.36) of all three market types. The reserve market income is zero because the ramping capability of the DG is not exploited to provide regulation services. The optimal energy dispatch strategy for the μVPP under the current DSM does yield a minimum DG cost, however, it is still not favourable for such a large DG capacity installed in the μVPP3. The PDSM structure shows a promising range of DG utilisation rate up to 65% and a profit that could be four times higher than that of the current DSM. However, these improvements are based on an optimistic anticipation that all the aggressive offers will be accepted by the DSO. As price-takers, μVPP under PDSM has no market power to influence the market clearing result thus its actual profit from the energy market may deviate considerably from the anticipation (from £114.36 to £2800.86). The uncertainty grows even severe in the reserve market in which the projected profit of an aggressive strategy yields £12508 and the profit of a conservative strategy is zero. Therefore, the market structure of PDSM is impractical for µVPP to make a reliable decision if the rivals' information is shielded from each participant. On the other hand, the framework of ADSM gives µVPP market power to obtain reliable bidding/offering strategies that lead to secured net profit. Compared with the current DSM, µVPP3's offering strategy at the NE point shows a good DG utilisation rate of 31% and a considerable 14% increase (from £114.36 to £4264.38) in the total profit. Above all, the projected return on investment will be delivered as promised.

5.6 Summary

This chapter has established a novel application of an active distribution system market (ADSM) which allows μVPPs to submit price-quantity bids/offers of both energy and reserve resources. Market power has been granted to the DER assets by involving their owners in the price-making process of the retail electricity market. A bilevel EPEC formulation has been presented to model the operation of both energy and reserve market at the distribution level, addressing the maximisation of all μVPPs' profit and the maximisation of social welfare at the same time. A coevolutionary approach has been successfully applied for the first time to derive the pure strategy Nash Equilibrium (NE) of a non-cooperative game under the market framework of ADSM. The application of coevolutionary approach in this context has two unique advantages: firstly, the approach contains straightforward translation of various bid types, market settlement rules and participant configurations. The construction of the algorithm is intuitive and does not require additional assumptions which could be unrealistic in practice (e.g. KKT method often assumes the supplier offers exactly the amount of required demand). Secondly, the coevolutionary approach relies on repeated search and evaluation to improve the solution quality. Considering that the solution does not have to be a global optimum but rather a strategy NE to guide the operation, the proposed coevolutionary approach is as effective as the conventional method while maintaining the simplicity of the model (i.e. it does not require additional reformulation techniques).

Comparative case studies have been carried out to investigate μVPPs' operation strategies under different market frameworks of the current DSM, PDSM and ADSM. The configuration of μVPPs in terms of their DER capacity and RES capacity has been proved to be a major factor that influences the strategic bidding/offering behaviours. The proposed ADSM structure guarantees that each μVPP can receive the promised profit by exercising its market power. This advantage is non-discriminatory to μVPPs with different DER configurations and it is valuable real market practice when the rivals' information is shielded from each other. Simulation results have pointed out that the behaviours of μVPPs in energy and reserve market under three different frameworks, even for those with the same DER/RES capacities, can be significantly different from one another. Compared with the current DSM, the deployment of ADSM can better exploit the DER assets and generate higher returns on investment. Compared with PDSM, the framework of ADSM provides a secured anticipation of the profit and can better guide μVPP owners to make bidding/offering decisions.

The proposed ADSM is a promising market framework that can accommodate the emerging μVPPs in the current distribution system. By introducing them as new entries to the local energy and reserve markets, the retail segments of electricity will be further liberalised and ultimately end-consumers will benefit from a diversified electricity supply. The proposed EPEC formulation and its coevolutionary solution provide valuable guidance for μVPP owners to gain strategic advantage in the competitive retail electricity markets.

CHAPTER 6 CONCLUSION AND FUTURE RESEARCH WORK

6.1 Conclusion

This thesis has demonstrated a plan that matches both short-term and long-term goals of a better integration of DERs into the energy supply: to achieve higher utilisation of the installed capacity; to generate higher revenue by participating in the retail electricity markets and to mitigate the risks associated with the supply adequacy and profit deviation caused by ill-advised bidding strategy. The concept of micro virtual power prosumer (μVPP) has been proposed to include MGs and VPPs that are connected to the restructured distribution system. μVPP is defined as an extension to the MG concept and the DERs located within the μVPP have a capacity that can either cover part of the load or generate excess electricity to be consumed by other μVPPs. Chapter 3, 4 and 5 has demonstrated multiple stages for the μVPP to evolve from a home-oriented energy management system to a market-oriented prosumer, where the incentives for the μVPP has also shifted from receiving compensation to creating profits. The μVPP design presented in this thesis has three contributions: It has addressed the link between a sustainable business and the role of the μVPP as MG, price-taking prosumer or price-making prosumer; it has identified a set of requirements to deliver technically sound and economically beneficial solutions; and it has provided guidance on the better utilisation of the current technologies and set the pace for the future development. In addition, the performances of the μVPP have been analysed on both simulation platforms and industrial test sites, which makes the economic analysis more persuasive and gives credibility for the prediction of market trends.

The evolution towards market-oriented μVPPs consists of three progressive steps: Chapter 3 has designed and implemented a home-oriented μVPP where the downstream DER assets including RES, ESS and DR are actively managed to achieve optimised local power flow and provide limited regulation services to the upstream distribution networks. Chapter 4 has upgraded the μVPP to a price-taker and incorporated it into the distribution system market, where the μVPP can actively bid and offer in the energy-reserve pool to pursue profit after considering its uncertainties. Chapter 5 has summarised the pros and cons of the business patterns proposed in the previous chapters and upgraded the μVPP again to a price-maker in the distribution system market, where the μVPP can secure a profitable margin by participating in the price settlement. There are three phases in each of the steps: a preliminary phase to define the scope and boundaries in the context of technological constraints and economic policies; a development phase to construct the hardware and software layers of the solution, especially the algorithmic workflow of the optimisation schemes; finally, a follow-up activity phase to analyse the performance of the proposed solution and identify any obstacles towards implementation.

The first step is the development of a configurable μVPP with managed energy services. In the preliminary phase, the μVPP design has recognised the diversity of the DER assets inside the estate and the consumption pattern of domestic appliances. The local DNO surcharge scheme has been noticed and exploited to develop the load shedding function. The scope of this step is to design the HEMS with generic algorithm architecture to facilitate different types of energy services and find out how much the bill savings are for the end-consumers and how fast the investors can recoup their investment. In the development stage, a ESS and a wireless-based home area network have been designed, manufactured and installed. The HEMS algorithm of the μVPP has adopted FLC-based strategy and delivered real-time control signals. In the follow-up phase, the unique function of each energy service has been demonstrated and the economic analysis has been carried out to distinguish those services in terms of electricity bill savings, asset utilisation rate and payback period. This part of the work has demonstrated that both end-consumers and investors could benefit more from the active response of μVPP to the electricity price dynamics. The proposed μVPP has a feasible business pattern than can recoup the upfront cost before ESS reaches its life span.

The second step is the development of a price-taking μVPP in a passive distribution system market (PDSM), where the μVPP contributes its energy and reserve flexibilities to the local pool and makes profit. In the preliminary stage, the μVPP design has recognised the uncertainties in the RES generation, load forecasting and price forecasting and the associated risks that could lead to undesirable load loss. Therefore, a two-stage settlement market has been adopted to combine the realisation of uncertain RT situations and the deterministic DA scheduling problem. Uncertain μVPP portfolio has been delivered by a combination of the Monte Carlo simulation and scenario reduction technique: firstly, repeated sampling has been conducted to generate a large number of scenarios based on a realistic (i.e. adopted in practice by California ISO) truncated normal distribution of the uncertain parameters. Then the scenario reduction algorithm has selected a small number of the original scenarios to hasten the computation speed while maintaining the probabilistic distribution of the selected sample. To mitigate the real-world risk of involuntary loss of load in the RT operation, chance-constrained method has been utilised to incorporate the precautions into the DA scheduling where adequate ramping capacity of the dispatchable generation is reserved to supply the load should the risk arise in RT. In the follow-up phase, various case studies have been carried out to analyse the impact of the uncertainties, the impact of network congestion, the impact of carbon tax policy and to address the advantages of the proposed chance-constrained method. This part of the work has provided strategic propositions for price-taking μVPP to seek increased revenue while enhancing the ability to meet peak demand. Conclusion has also been drawn that the increment of profit by narrowing down the forecast errors is not guaranteed to be gradual therefore rash expansion of the RES may not deliver the expected rise in revenue. In addition, the findings have pointed out a passive distribution system market is still manipulated by the current compensation policies and market power should be given to the μVPPs to encourage the diversification of the DERs.

Following the argument in the second step, the third step is the development of price-making μVPPs in an active distribution market (ADSM), where the μVPPs submit price-quantity bids/offers sourced from their DERs and compete with the traditional electricity suppliers. In the preliminary phase, the ADSM has been distinguished from the current DSM and PDSM based on its non-cooperative nature and the “price-maker” role of μVPPs. The scope of this step is to solve the market equilibrium of the proposed ADSM which consists of the bidding strategies of all market participants and the market clearing results. In the development phase, bilevel equilibrium problems with equilibrium constraints (EPEC) have been utilised to form the ADSM model with upper-level problems that maximise each μVPP’s profit and a lower-level problem that maximises the social welfare of the market clearing. A novel application of the coevolutionary approach has been successfully implemented to find the market equilibrium. In the follow-up phase, the behaviours of the μVPP in different market structures have been compared, addressing the advantages of the ADSM setup. This part of the work is the unique contribution towards the body of new knowledge and it has demonstrated the benefits of the proposed ADSM: μVPPs with their different configurations of DERs can receive the projected profit as promised by pricing their bids strategically. The strengths of the coevolutionary approach has also been demonstrated: it preserves the realistic interpretation of the non-cooperative market where the rivals’ information is kept from each other; it could be applied to market with various bid types and complex clearing rules; the approach is based on intuitive, repeated search and evaluation to improve the solution quality and it can effectively produce strategy NE without bringing in reformulation complexity.

6.2 Future Research Work

Based on the progress presented in this thesis, the future research efforts could be dedicated to the following aspects.

Firstly, in the development of a configurable μVPP with managed energy services, there are three improvements could be made in the future:

- Firstly, more detailed modelling could be applied to the controllable loads with consideration for the thermo-dynamics of the building and the driving patterns of the EV owners. Currently the physical constraints of both EVs and eHeat Pumps take the form of minimum up and down times, but more specified physical boundaries such as the required temperatures should be applied. Once the metering system has added devices such as smart thermostats, this improvement could be easily implemented.

- Secondly, the EVs in the μVPP could be utilised as both controllable appliances and energy storages through a bi-directional charging/discharging scheme. Currently the EVs are utilised as pure load blocks but the bi-directional scheme could improve the total ESS capacity significantly within the μVPP and yield more savings.

- Thirdly, in the development of price-taking μVPPs in the passive distribution system market, the case studies could include the results from robust optimisation or CVaR optimisation to address their pros and cons in determining the bidding strategies.

Additionally, in the development of ADSM and the price-making μVPPs, the quality of the market equilibrium solution could be further improved by considering the uncertainties in the real-time market scenarios.

LIST OF PUBLICATIONS & OUTCOMES

Journal Papers

[1] **Hao Fu**, Zhi Wu, Xiao-Ping Zhang and Joachim Brandt, "Contributing to DSO's Energy-Reserve Pool: A Chance-Constrained Two-Stage μVPP Bidding Strategy," *IEEE Journal,* Submitted

[2] **Hao Fu**, Xiao-Ping Zhang, "Market Equilibrium in Active Distribution System with μVPPs: A Coevolutionary Approach," *IEEE Access*, Accepted in March 2017

[3] **Hao Fu**, Zhi Wu, Jianing Li, Xiao-Ping Zhang and Joachim Brandt, "A Configurable μVPP with Managed Energy Services: A Malmo Western Harbour Case," *IEEE Power and Energy Technology Systems Journal*, vol. 3, no. 4, pp. 166-178, 2016. (Open Access, DOI: 10.1109/JPETS.2016.2596779)

[4] Xiao-Ping Zhang, **Hao Fu**, Jianing Li, "The UK Retail Electricity Market Reform and Challenges," *Automation of Electric Power Systems*, vol. 40, no. 11, pp. 10-16, 2016. (Available Online, DOI: 10.7500/AEPS20150508001)

[5] Xiao-Ping Zhang, **Hao Fu**, Jianing Li, "Distribution Power & Energy Internet: From Virtual Power Plants to Virtual Power Systems," *Proceedings of the CSEE*, vol. 35, no.14, pp. 3532-3540, 2015 (Available Online, DOI: 10.13334/j.0258-8013.pcsee.2015.14.007)

[6] Xiao-Ping Zhang, Jianing Li, **Hao Fu**, "Global Energy Interconnection Dialogue Industry 4.0," *Power System Technology*, vol. 40, no. 6, pp. 1607-1611, 2016 (Available Online, DOI: 10.13335/J.1000-3673.PST.2016.06.001)

[7] Jianing Li, Zhi Wu, Suyang Zhou, **Hao Fu**, Aggregator Service for PV and Battery Energy Storage Systems of Residential Building. *CSEE Journal of Power and Energy Systems*, vol. 1, no. 4, pp. 3-11, 2015 (Available Online,

DOI: 10.17775/CSEEJPES.2015.00042)

Conference Papers

[1] Zhi Wu, Pingliang Zeng, Xiao-Ping Zhang, **Hao Fu**, "A fast and automatic candidate lines selection approach for transmission expansion planning", *IET Resilience of Transmission and Distribution Networks*, Sept. 2015.

[2] Zhi Wu, Pingliang Zeng, Xiao-Ping Zhang, **Hao Fu**, "Two-stage stochastic dual dynamic programming for transmission expansion planning with significant renewable generation", *IET Resilience of Transmission and Distribution Networks*, Sept. 2015.

REFERENCES

[1] European Commission. "2020 climate & energy package" [Online]. Available: http://ec.europa.eu/clima/policies/strategies/2020/index_en.htm. Accessed on: Feb. 18, 2016

[2] Department of Energy and Climate Change. "National Renewable Energy Action Plan for the United Kingdom" [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/47871/25-nat-ren-energy-action-plan.pdf. Accessed on: Jun. 3, 2017

[3] European Environment Agency. "Trends and projections in Europe 2015" [Online]. Available: http://www.eea.europa.eu/publications/trends-and-projections-in-europe-2015. Accessed on: Dec. 12, 2016

[4] Parliament. "The 2020 renewable targets progress" [Online]. Available: https://www.publications.parliament.uk/pa/cm201617/cmselect/cmenergy/173/17305.htm#_idTextAnchor009. Accessed on: Jun. 3, 2017

[5] European Commission. "Consumption of Energy" [Online]. Available: http://ec.europa.eu/eurostat/statistics-explained/index.php/Consumption_of_energy. Accessed on: Feb. 18, 2016

[6] European Commission. "Electricity production, consumption and market overview" [Online]. Available: http://ec.europa.eu/eurostat/statistics-explained/index.php/Electricity_production,_consumption_and_market_overview. Accessed on: Feb. 18, 2016

[7] Renewable Energy Policy Network. "Renewables 2016 Global Status Report" [Online]. Available: http://www.ren21.net/status-of-renewables/global-status-report/. Accessed on: Dec. 12, 2016

[8] Department for Business, Energy & Industrial Strategy. "Renewable electricity in Scotland, Wales, Northern Ireland and the regions of England in 2015" [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/556271/Renewable_electricity.pdf. Accessed on: Jun. 3, 2017

[9] Global Smart Grid Federation. "A new energy paradigm - a great need for interoperability" [Online]. Available: http://www.globalsmartgridfederation.org/2013/11/04/global-interoperability-update/.

Accessed on: Jan, 20, 2017

[10] European Commission. "Study on the effective integration of distributed energy resources for providing flexibility to the electricity system" [Online]. Available: https://ec.europa.eu/energy/sites/ener/files/documents/5469759000%20Effective%20integration%20of%20DER%20Final%20ver%202_6%20April%202015.pdf. Accessed on: Jan. 20, 2017

[11] EuPD research. "German PV storage market development" [Online]. Available: http://www.ees-magazine.com/enormous-potential-of-solar-energy-storage/. Accessed on: Jan. 22, 2017

[12] Imperial College London. "Understanding the Balancing Challenge" [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48553/5767-understanding-the-balancing-challenge.pdf. Accessed on: Jul. 1, 2016

[13] UKERC. "The Costs and Impacts of Intermittency: An assessment of the evidence on the costs and impacts of intermittent generation on the British electricity network" [Online]. Available: http://www.ukerc.ac.uk/publications/the-costs-and-impacts-of-intermittency.html. Accessed on: Jul. 3, 2016

[14] Department of Energy and Climate Change. "Demand Side Response in the domestic sector - a literature review of major trials" [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48552/5756-demand-side-response-in-the-domestic-sector-a-lit.pdf. Accessed on: Apr. 27, 2016

[15] European Commission. "Delivering the internal electricity market and making the most of public intervention" [Online]. Available: https://ec.europa.eu/energy/sites/ener/files/documents/com_2013_public_intervention_en_0.pdf. Accessed on: Jan. 20, 2017

[16] CIGRE. "Microgrid evolution roadmap" [Online]. Available: http://c6.cigre.org/WG-Area/WG-C6.22-Microgrids. Accessed on: Jan. 22, 2017

[17] FENIX. "Virtual Power Plant as a vehicle for delivering efficient integration of DER" [Online]. Available: http://fenix.iwes.fraunhofer.de/docs/documents/Project_Fenix_2009-06-08_Tutorial_Virtual_Power_Plant_as_a_vehicle_for_delivering_efficient_integration_of_DER_Goran_Strbac_v1.pdf. Accessed on: Jan. 22, 2017

[18] European Commission. "Restoring microgrids to operation following blackouts" [Online]. Available: http://cordis.europa.eu/result/rcn/85267_en.html. Accessed on:

Jan. 23, 2017

[19] European Commission. "More Microgrids - advanced architectures and control concepts for more microgrids" [Online]. Available: http://cordis.europa.eu/result/rcn/46879_en.html. Accessed on: Jan. 23, 2017

[20] European Commission. "FENIX - Flexible Electricity Networks to Integrate the eXpected 'energy evolution'" [Online]. Available: http://cordis.europa.eu/result/rcn/49614_en.html. Accessed on: Jan. 23, 2017

[21] FENIX. "Flexible Electricity Networks to Integrate the expected Energy Evolution - Results" [Online]. Available: http://fenix.iwes.fraunhofer.de/docs/att2x/2009_Fenix_Book_FINAL_for_selfprinting.pdf. Accessed on: Jan. 23, 2017

[22] International Renewable Energy Agency. "Renewable energy technologies: cost analysis series - Solar Photovoltaics" [Online]. Available: https://www.irena.org/DocumentDownloads/Publications/RE_Technologies_Cost_Analysis-SOLAR_PV.pdf. Accessed on: Jan. 23, 2017

[23] V. Shah and J. Booream-Phelps. "Solar Grid Parity in a Low Oil Price Era - Deutsche Bank Markets Research" [Online]. Available: https://www.db.com/cr/en/docs/solar_report_full_length.pdf. Accessed on: Feb. 20, 2016

[24] Ofgem. "New Electricity Trading Arrangements (NETA) - One Year Review" [Online]. Available: https://www.ofgem.gov.uk/ofgem-publications/76199/1109-factsheet110224july.pdf. Accessed on: Jan. 23, 2017

[25] Ofgem. "Electricity retail markets infographic: bills, prices and profits" [Online]. Available: https://www.ofgem.gov.uk/publications-and-updates/infographic-bills-prices-and-profits. Accessed on: Jan. 17, 2017

[26] Northeast Energy Efficiency Partnerships. "Opportunities for Home Energy Management Systems (HEMS) in Advancing Residential Energy Efficiency Programs" [Online]. Available: http://www.neep.org/sites/default/files/resources/2015%20HEMS%20Research%20Report.pdf. Accessed on: Jan. 25, 2017

[27] J. Ryan, "Home automation," *Electronics & Communication Engineering Journal,* vol. 1, no. 4, pp. 185-192, 1989.

[28] D. Minoli, K. Sohraby, and B. Occhiogrosso, "IoT Considerations, Requirements,

and Architectures for Smart Buildings–Energy Optimization and Next Generation Building Management Systems," *IEEE Internet of Things Journal,* vol. PP, no. 99, pp. 1-1, 2017.

[29] Frost & Sullivan. "European Home Energy Management Systems (HEMS) and Building Energy Management Systems (BEMS) market" [Online]. Available: http://now.frost.com/forms/EEHB-IG?Source=GCN_November_Issue2&gcn141102=EPSMP4. Accessed on: Jan. 25, 2017

[30] V. Namboodiri, V. Aravinthan, S. N. Mohapatra*, et al.*, "Toward a secure wireless-based home area network for metering in smart grids," *IEEE Systems Journal,* vol. 8, no. 2, pp. 509-520, 2014.

[31] M. Collotta and G. Pau, "A novel energy management approach for smart homes using bluetooth low energy," *IEEE Journal on Selected Areas in Communications,* vol. 33, no. 12, pp. 2988-2996, 2015.

[32] J. Han, C.-S. Choi, W.-K. Park*, et al.*, "Smart home energy management system including renewable energy based on ZigBee and PLC," *IEEE Transactions on Consumer Electronics,* vol. 60, no. 2, pp. 198-202, 2014.

[33] N. Baker, "ZigBee and Bluetooth: Strengths and weaknesses for industrial applications," *Computing and Control Engineering,* vol. 16, no. 2, pp. 20-25, 2005.

[34] M. Inoue, T. Higuma, Y. Ito*, et al.*, "Network architecture for home energy management system," *IEEE Transactions on Consumer Electronics,* vol. 49, no. 3, pp. 606-613, 2003.

[35] J. Byun, I. Hong, and S. Park, "Intelligent cloud home energy management system using household appliance priority based scheduling based on prediction of renewable energy capability," *IEEE Transactions on Consumer Electronics,* vol. 58, no. 4, 2012.

[36] Z. Zhao, W. C. Lee, Y. Shin*, et al.*, "An optimal power scheduling method for demand response in home energy management system," *IEEE Transactions on Smart Grid,* vol. 4, no. 3, pp. 1391-1400, 2013.

[37] I. S. Bayram, M. Abdallah, A. Tajer*, et al.*, "A stochastic sizing approach for sharing-based energy storage applications," *IEEE Transactions on Smart Grid,* vol. PP, no. 99, pp. 1-1, 2015.

[38] W. Tushar, B. Chai, C. Yuen*, et al.*, "Energy storage sharing in smart grid: A modified auction-based approach," *IEEE Transactions on Smart Grid,* vol. 7, no. 3, pp. 1462-1475, 2016.

[39] Q. Hu and F. Li, "Hardware design of smart home energy management system with dynamic price response," *IEEE Transactions on Smart Grid,* vol. 4, no. 4, pp. 1878-1887, 2013.

[40] M. Kuzlu, M. Pipattanasomporn, and S. Rahman, "Hardware demonstration of a home energy management system for demand response applications," *IEEE Transactions on Smart Grid,* vol. 3, no. 4, pp. 1704-1711, 2012.

[41] A. Saha, M. Kuzlu, and M. Pipattanasomporn, "Demonstration of a home energy management system with smart thermostat control," *IEEE PES Innovative Smart Grid Technologies (ISGT)*, 2013, pp. 1-6.

[42] O. Erdinc, N. G. Paterakis, T. D. Mendes*, et al.*, "Smart household operation considering bi-directional EV and ESS utilization by real-time pricing-based DR," *IEEE Transactions on Smart Grid,* vol. 6, no. 3, pp. 1281-1291, 2015.

[43] Z. Chen, L. Wu, and Y. Fu, "Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization," *IEEE Transactions on Smart Grid,* vol. 3, no. 4, pp. 1822-1831, 2012.

[44] R. Palma-Behnke, C. Benavides, F. Lanas*, et al.*, "A microgrid energy management system based on the rolling horizon strategy," *IEEE Transactions on Smart Grid,* vol. 4, no. 2, pp. 996-1006, 2013.

[45] S. Sethi and G. Sorger, "A theory of rolling horizon decision making," *Annals of Operations Research,* vol. 29, no. 1, pp. 387-415, 1991.

[46] M. G. Earl and R. D'Andrea, "Iterative MILP methods for vehicle-control problems," *IEEE Transactions on Robotics,* vol. 21, no. 6, pp. 1158-1167, 2005.

[47] M. Patricia and O. Castillo, *Soft Computing Applications in Optimization, Control, and Recognition*. Berlin, Germany: Springer, 2012.

[48] C.-C. Lee, "Fuzzy logic in control systems: fuzzy logic controller. I," *IEEE Transactions on systems, man, and cybernetics,* vol. 20, no. 2, pp. 404-418, 1990.

[49] L. A. Zadeh, "Fuzzy sets," *Information and control,* vol. 8, no. 3, pp. 338-353, 1965.

[50] Y. Bai and D. Wang, "Fundamentals of fuzzy logic control—fuzzy sets, fuzzy rules and defuzzifications," *Advanced Fuzzy Logic Technologies in Industrial Applications*. London: Springer, 2006, pp. 17-36.

[51] J. Lagorse, M. G. Simões, and A. Miraoui, "A multiagent fuzzy-logic-based energy management of hybrid systems," *IEEE Transactions on Industry Applications,* vol. 45, no. 6, pp. 2123-2129, 2009.

[52] B. Blunier, M. G. Simoes, and A. Miraoui, "Fuzzy logic controller development of a hybrid fuel cell-battery auxiliary power unit for remote applications," *IEEE Proceeding of Conference on Industry Applications,* pp. 1-6, 2010.

[53] A. Chaouachi, R. M. Kamel, R. Andoulsi*, et al.*, "Multiobjective intelligent energy management for a microgrid," *IEEE Transactions on Industrial Electronics,* vol. 60, no. 4, pp. 1688-1699, 2013.

[54] Z. Wu, X.-P. Zhang, J. Brandt*, et al.*, "Three Control Approaches for Optimized Energy Flow With Home Energy Management System," *IEEE Power and Energy Technology Systems Journal,* vol. 2, no. 1, pp. 21-31, 2015.

[55] P. R. O'Connor, "10 Steps to deregulation," *IEEE Spectrum,* vol. 23, no. 5, pp. 40-43, 1986.

[56] A. R. Kian, J. B. Cruz, and R. J. Thomas, "Bidding strategies in oligopolistic dynamic electricity double-sided auctions," *IEEE Transactions on Power Systems,* vol. 20, no. 1, pp. 50-58, 2005.

[57] Y. a. Liu and X. Guan, "Purchase allocation and demand bidding in electric power markets," *IEEE Transactions on Power Systems,* vol. 18, no. 1, pp. 106-112, 2003.

[58] J. M. Arroyo and A. J. Conejo, "Multiperiod auction for a pool-based electricity market," *IEEE Transactions on Power Systems,* vol. 17, no. 4, pp. 1225-1231, 2002.

[59] S. Hao, "A study of basic bidding strategy in clearing pricing auctions," *IEEE Transactions on Power Systems,* vol. 15, no. 3, pp. 975-980, 2002.

[60] J. D. Weber, "Individual welfare maximization in electricity markets including consumer and full transmission system modeling," Ph.D. dissertation, University of Illinois at Urbana-Champaign, Urbana, IL, 1999.

[61] J. Bower and D. Bunn, "Experimental analysis of the efficiency of uniform-price versus discriminatory auctions in the England and Wales electricity market," *Journal of economic dynamics and control,* vol. 25, no. 3, pp. 561-592, 2001.

[62] A. J. Conejo, J. M. Morales, and J. A. Martinez, "Tools for the analysis and design of distributed resources—Part III: Market studies," *IEEE transactions on power delivery,* vol. 26, no. 3, pp. 1663-1670, 2011.

[63] G. Liu, Y. Xu, and K. Tomsovic, "Bidding strategy for microgrid in day-ahead market based on hybrid stochastic/robust optimization," *IEEE Transactions on Smart Grid,* vol. 7, no. 1, pp. 227-237, 2016.

[64] W. Pei, Y. Du, W. Deng*, et al.*, "Optimal bidding strategy and intramarket

mechanism of microgrid aggregator in real-time balancing market," *IEEE Transactions on Industrial Informatics,* vol. 12, no. 2, pp. 587-596, 2016.

[65] F. Farzan, S. Lahiri, M. Kleinberg*, et al.*, "Microgrids for fun and profit: The economics of installation investments and operations," *IEEE Power and Energy Magazine,* vol. 11, no. 4, pp. 52-58, 2013.

[66] M. P. Moghaddam, S. Bahramara, M. Damavandi*, et al.*, "Distribution company and microgrids behaviour in energy and reserve equilibirum," *IEEE PES Asia-Pacific Power and Energy Engineering Conference*, 2015, pp. 1-5.

[67] I. G. Sardou, M. E. Khodayar, K. Khaledian*, et al.*, "Energy and reserve market clearing with microgrid aggregators," *IEEE Transactions on Smart Grid,* vol. 7, no. 6, pp. 2703-2712, 2016.

[68] I. C. Paschalidis, B. Li, and M. C. Caramanis, "Demand-side management for regulation service provisioning through internal pricing," *IEEE Transactions on Power Systems,* vol. 27, no. 3, pp. 1531-1539, 2012.

[69] M. N. Faqiry and S. Das, "Double-Sided Energy Auction in Microgrid: Equilibrium under Price Anticipation," *IEEE Access,* vol. 4, pp. 3794-3805, 2016.

[70] E. Mashhour and S. M. Moghaddas-Tafreshi, "Bidding strategy of virtual power plant for participating in energy and spinning reserve markets—Part I: Problem formulation," *IEEE Transactions on Power Systems,* vol. 26, no. 2, pp. 949-956, 2011.

[71] J.-M. Sohn, "Generation Applications Package for Combined Heat Power in On-Grid and Off-Grid Microgrid Energy Management System," *IEEE Access,* vol. 4, pp. 3444-3453, 2016.

[72] New York Independent System Operator. "Day-ahead scheduling manual" [Online]. Available: http://www.nyiso.com/public/webdocs/markets_operations/documents/Manuals_and_Guides/Manuals/Operations/dayahd_schd_mnl.pdf. Accessed on: Jul. 23, 2016

[73] B. Zhao, Y. Shi, X. Dong*, et al.*, "Short-term operation scheduling in renewable-powered microgrids: A duality-based approach," *IEEE Transactions on Sustainable Energy,* vol. 5, no. 1, pp. 209-217, 2014.

[74] W. Su, J. Wang, and J. Roh, "Stochastic energy scheduling in microgrids with intermittent renewable energy resources," *IEEE Transactions on Smart Grid,* vol. 5, no. 4, pp. 1876-1883, 2014.

[75] Z. Bao, Q. Zhou, Z. Yang*, et al.*, "A multi time-scale and multi energy-type

coordinated microgrid scheduling solution—Part I: Model and methodology," *IEEE Transactions on Power Systems,* vol. 30, no. 5, pp. 2257-2266, 2015.

[76] E. G. Kardakos, C. K. Simoglou, and A. G. Bakirtzis, "Optimal offering strategy of a virtual power plant: A stochastic bi-level approach," *IEEE Transactions on Smart Grid,* vol. 7, no. 2, pp. 794-806, 2016.

[77] J. Shen, C. Jiang, Y. Liu*, et al.*, "A Microgrid Energy Management System and Risk Management under an Electricity Market Environment," *IEEE Access,* vol. 4, pp. 2349-2356, 2016.

[78] S. Khan, W. Gawlik, and P. Palensky, "Reserve capability assessment considering correlated uncertainty in microgrid," *IEEE Transactions on Sustainable Energy,* vol. 7, no. 2, pp. 637-646, 2016.

[79] A. Fabbri, T. G. S. Roman, J. R. Abbad*, et al.*, "Assessment of the cost associated with wind generation prediction errors in a liberalized electricity market," *IEEE Transactions on Power Systems,* vol. 20, no. 3, pp. 1440-1446, 2005.

[80] R. Dahlgren, C.-C. Liu, and J. Lawarree, "Risk assessment in energy trading," *IEEE Transactions on Power Systems,* vol. 18, no. 2, pp. 503-511, 2003.

[81] R. Bjorgan, C.-C. Liu, and J. Lawarree, "Financial risk management in a competitive electricity market," *IEEE Transactions on Power Systems,* vol. 14, no. 4, pp. 1285-1291, 1999.

[82] P. Jirutitijaroen and C. Singh, "Reliability constrained multi-area adequacy planning using stochastic programming with sample-average approximations," *IEEE Transactions on Power Systems,* vol. 23, no. 2, pp. 504-513, 2008.

[83] A. Khodaei, S. Bahramirad, and M. Shahidehpour, "Microgrid planning under uncertainty," *IEEE Transactions on Power Systems,* vol. 30, no. 5, pp. 2417-2425, 2015.

[84] A. Khodaei, "Resiliency-oriented microgrid optimal scheduling," *IEEE Transactions on Smart Grid,* vol. 5, no. 4, pp. 1584-1591, 2014.

[85] F. Farzan, M. A. Jafari, R. Masiello*, et al.*, "Toward optimal day-ahead scheduling and operation control of microgrids under uncertainty," *IEEE Transactions on Smart Grid,* vol. 6, no. 2, pp. 499-507, 2015.

[86] A. Charnes and W. W. Cooper, "Chance-constrained programming," *Management science,* vol. 6, no. 1, pp. 73-79, 1959.

[87] Q. Wang, J. Wang, and Y. Guan, "Stochastic unit commitment with uncertain

demand response," *IEEE Transactions on Power Systems,* vol. 28, no. 1, pp. 562-563, 2013.

[88] H. Wu, M. Shahidehpour, Z. Li*, et al.*, "Chance-constrained day-ahead scheduling in stochastic power system operation," *IEEE Transactions on Power Systems,* vol. 29, no. 4, pp. 1583-1591, 2014.

[89] M. Lubin, Y. Dvorkin, and S. Backhaus, "A robust approach to chance constrained optimal power flow with renewable generation," *IEEE Transactions on Power Systems,* vol. 31, no. 5, pp. 3840-3849, 2016.

[90] F. Qiu and J. Wang, "Chance-constrained transmission switching with guaranteed wind power utilization," *IEEE Transactions on Power Systems,* vol. 30, no. 3, pp. 1270-1278, 2015.

[91] Z. Wu, P. Zeng, X.-P. Zhang*, et al.*, "A solution to the chance-constrained two-stage stochastic program for unit commitment with wind energy integration," *IEEE Transactions on Power Systems,* vol. 31, no. 6, pp. 4185-4196, 2016.

[92] D. Bertsimas, D. B. Brown, and C. Caramanis, "Theory and applications of robust optimization," *SIAM review,* vol. 53, no. 3, pp. 464-501, 2011.

[93] Frontier Economics. "Competition and entry in the GB retail electricity market " [Online]. Available: https://www.frontier-economics.com/documents/2011/01/frontier-report-competition-and-entry-in-the-gb-electricity-retail-market.pdf. Accessed on: Dec. 20, 2016

[94] Elexon. "Getting the most from distributed energy resources" [Online]. Available: https://www.elexon.co.uk/wp-content/uploads/2011/10/Getting_the_most_from_distributed_energy_resources.pdf. Accessed on: Dec. 21, 2016

[95] A. Chowdhury and D. Koval, *Power distribution system reliability: practical methods and applications* vol. 48. Hoboken, NJ: John Wiley & Sons, 2011.

[96] national grid. "Distribution Network Operator (DNO) Companies" [Online]. Available: http://www2.nationalgrid.com/UK/Our-company/Electricity/Distribution-Network-Operator-Companies/. Accessed on: Jan. 27, 2017

[97] I.-K. Song, W.-W. Jung, J.-Y. Kim*, et al.*, "Operation schemes of smart distribution networks with distributed energy resources for loss reduction and service restoration," *IEEE Transactions on Smart Grid,* vol. 4, no. 1, pp. 367-374, 2013.

[98] UK Power Networks. "Flexible Distributed Generation: FDG-B Norwich Main" [Online]. Available:

https://www.ukpowernetworks.co.uk/internet/en/our-services/documents/FDG-B_Norwich_Main_(EPN)_V2.1.pdf. Accessed on: Jan. 27, 2017

[99] F. Pilo, K. El Bakari, J. Taylor, *et al.*, "Planning and optimisation of active distribution systems—an overview of CIGRE Working Group C6. 19 activities," *Integration of Renewables into the Distribution Grid, CIRED 2012 Workshop*, 2012, pp. 1-4.

[100] D. Apostolopoulou, S. Bahramirad, and A. Khodaei, "The Interface of Power: Moving Toward Distribution System Operators," *IEEE Power and Energy Magazine,* vol. 14, no. 3, pp. 46-51, 2016.

[101] A. Saint-Pierre and P. Mancarella, "Active distribution system management: a dual-horizon scheduling framework for DSO/TSO interface under uncertainty," *IEEE Transactions on Smart Grid,* vol. PP, no. 99, pp. 1-12, 2016.

[102] B. Olek and M. Wierzbowski, "Local energy balancing and ancillary services in low-voltage networks with distributed generation, energy storage, and active loads," *IEEE Transactions on Industrial Electronics,* vol. 62, no. 4, pp. 2499-2508, 2015.

[103] P. Mallet, P.-O. Granstrom, P. Hallberg, *et al.*, "Power to the people!: European perspectives on the future of electric distribution," *IEEE Power and Energy Magazine,* vol. 12, no. 2, pp. 51-64, 2014.

[104] European Commission. "Market legislation - Unbundling" [Online]. Available: https://ec.europa.eu/energy/en/topics/markets-and-consumers/market-legislation. Accessed on: Jan. 27, 2017

[105] European Parliament. "Directive 2009/72/EC of the European Parliament and of the Council of 13 July 2009 concerning common rules for the internal market in electricity and repealing Directive 2003/54/EC" [Online]. Available: http://eur-lex.europa.eu/legal-content/EN/ALL/?uri=celex%3A32009L0072. Accessed on: Jan. 30, 2017

[106] L. Hirth, "Market value of solar power: Is photovoltaics cost-competitive?," *IET Renewable Power Generation,* vol. 9, no. 1, pp. 37-45, 2014.

[107] Ofgem. "Feed-in tariff (FIT) generation & export payment rate table" [Online]. Available: https://www.ofgem.gov.uk/publications-and-updates/feed-tariff-fit-generation-export-payment-rate-table-1-january-31-march-2017. Accessed on: Dec. 21, 2016

[108] A. A. Algarni and K. Bhattacharya, "A generic operations framework for discos in retail electricity markets," *IEEE Transactions on Power Systems,* vol. 24, no. 1, pp. 356-367, 2009.

[109] K. J. Arrow and G. Debreu, "Existence of an equilibrium for a competitive economy," *Econometrica: Journal of the Econometric Society,* pp. 265-290, 1954.

[110] S. Wang, "An existence theorem of a Pareto equilibrium," *Applied Mathematics Letters,* vol. 4, no. 3, pp. 61-63, 1991.

[111] F. Facchinei and C. Kanzow, "Generalized Nash equilibrium problems," *4OR: A Quarterly Journal of Operations Research,* vol. 5, no. 3, pp. 173-210, 2007.

[112] X.-P. Zhang, *Restructured electric power systems: analysis of electricity markets with equilibrium models* vol. 71. Hoboken, NJ: John Wiley & Sons, 2010.

[113] A. Schotter, "Why take a game theoretical approach to economics? Institutions, economics and game theory," New York University, New York, NY1981.

[114] X. Hu and D. Ralph, "Using EPECs to model bilevel games in restructured electricity markets with locational prices," *Operations research,* vol. 55, no. 5, pp. 809-827, 2007.

[115] B. Colson, P. Marcotte, and G. Savard, "An overview of bilevel optimization," *Annals of Operations Research,* vol. 153, no. 1, pp. 235-256, 2007.

[116] H. Haghighat and S. W. Kennedy, "A bilevel approach to operational decision making of a distribution company in competitive environments," *IEEE Transactions on Power Systems,* vol. 27, no. 4, pp. 1797-1807, 2012.

[117] S. Bahramara, M. P. Moghaddam, and M. R. Haghifam, "Modelling hierarchical decision making framework for operation of active distribution grids," *IET Generation, Transmission & Distribution,* vol. 9, no. 16, pp. 2555-2564, 2015.

[118] E.-G. Talbi, *Metaheuristics for bi-level optimization* vol. 482. Villeneuve d' Ascq, France: Springer, 2013.

[119] S. Dempe, *Foundations of bilevel programming*. Freiberg, Germany: Springer Science & Business Media, 2002.

[120] Q. Wang, C. Zhang, J. Wang, *et al.*, "Real-Time Trading Strategies of Proactive DISCO with Heterogeneous DG Owners," *IEEE Transactions on Smart Grid,* 2016.

[121] D. Pozo and J. Contreras, "Finding multiple nash equilibria in pool-based markets: A stochastic EPEC approach," *IEEE Transactions on Power Systems,* vol. 26, no. 3, pp. 1744-1752, 2011.

[122] L. A. Barroso, R. D. Carneiro, S. Granville, *et al.*, "Nash equilibrium in strategic bidding: A binary expansion approach," *IEEE Transactions on Power Systems,* vol. 21, no. 2, pp. 629-638, 2006.

[123] H. Khazaei, B. Vahidi, S. H. Hosseinian, *et al.*, "Two-level decision-making model for a distribution company in day-ahead market," *IET Generation, Transmission & Distribution,* vol. 9, no. 12, pp. 1308-1315, 2015.

[124] S. Zhang, C. Chung, K. Wong, *et al.*, "Analyzing two-settlement electricity market equilibrium by coevolutionary computation approach," *IEEE Transactions on Power Systems,* vol. 24, no. 3, pp. 1155-1164, 2009.

[125] F. Legillon, A. Liefooghe, and E.-G. Talbi, "Cobra: A cooperative coevolutionary algorithm for bi-level optimization," *IEEE Congress on Evolutionary Computation (CEC)*, 2012, pp. 1-8.

[126] M. Mitchell, *An introduction to genetic algorithms*. Cambridge, MA: MIT press, 1998.

[127] J. Paredis, "Coevolutionary computation," *Artificial life,* vol. 2, no. 4, pp. 355-375, 1995.

[128] W. D. Hillis, "Co-evolving parasites improve simulated evolution as an optimization procedure," *Physica D: Nonlinear Phenomena,* vol. 42, no. 1-3, pp. 228-234, 1990.

[129] Y. S. Son and R. Baldick, "Hybrid coevolutionary programming for Nash equilibrium search in games with local optima," *IEEE Transactions on Evolutionary Computation,* vol. 8, no. 4, pp. 305-315, 2004.

[130] H. Chen, K. Wong, C. Chung, *et al.*, "A coevolutionary approach to analyzing supply function equilibrium model," *IEEE Transactions on Power Systems,* vol. 21, no. 3, pp. 1019-1028, 2006.

[131] H. Chen, K. Wong, D. Nguyen, *et al.*, "Analyzing oligopolistic electricity market using coevolutionary computation," *IEEE Transactions on Power Systems,* vol. 21, no. 1, pp. 143-152, 2006.

[132] M. Ljungqvist. e-harbours electric. "Showcase Malmo" [Online]. Available: http://eharbours.eu/showcases/showcase-malmo. Accessed on: May. 20, 2016

[133] P. Kevin M, Y. Stephen, and R. Michael, *Fuzzy control* vol. 2725. Reading, MA: Addison-wesley 1998.

[134] "Nord Pool market data" [Online]. Available: http://www.nordpoolspot.com/Market-data1/N2EX/Auction-prices/UK/Hourly/?view=table. Accessed on: Nov. 20, 2016

[135] N. Lu, R. Diao, R. P. Hafen, *et al.*, "A comparison of forecast error generators for modeling wind and load uncertainty," *IEEE PES General Meeting*, 2013, pp. 1-5.

[136] California Independent System Operator. "Integration of renewable resources: technical appendices for California ISO renewable integration studies" [Online]. Available: http://www.caiso.com/1ca5/1ca5a7a026270.pdf. Accessed on: Jul. 27, 2016

[137] T. Wu, Q. Yang, Z. Bao*, et al.*, "Coordinated energy dispatching in microgrid with wind power generation and plug-in electric vehicles," *IEEE Transactions on Smart Grid,* vol. 4, no. 3, pp. 1453-1463, 2013.

[138] C. Chen, W. Wu, B. Zhang*, et al.*, "An analytical adequacy evaluation method for distribution networks considering protection strategies and distributed generators," *IEEE transactions on power delivery,* vol. 30, no. 3, pp. 1392-1400, 2015.

[139] Z. Wang and J. Wang, "Self-healing resilient distribution systems based on sectionalization into microgrids," *IEEE Transactions on Power Systems,* vol. 30, no. 6, pp. 3139-3149, 2015.

[140] Department of Energy & Climate Change. "Carbon prices and sensitivities 2010-2100 for appraisal" [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/483282/Data_tables_1-20_supporting_the_toolkit_and_the_guidance.xlsx. Accessed on: Jan. 25, 2017

[141] PJM. "Regulation lost opportunity cost" [Online]. Available: http://www.pjm.com/~/media/committees-groups/task-forces/rmistf/20151210/20151210-item-02-regulation-lost-opportunity-cost.ashx. Accessed on: Nov. 20, 2016

[142] W. Wiesemann, A. Tsoukalas, P.-M. Kleniati*, et al.*, "Pessimistic bilevel optimization," *SIAM J. Optim.,* vol. 23, no. 1, pp. 353-380, 2013.

[143] L. Jacobsen and B. Kanber, *Genetic algorithms in Java basics*: Springer, 2016.