# Multi Agent System Framework for Demand Response Management in Distribution Networks

**Submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy**

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## Abstract

The inexorable increase in penetration of clean energies and responsive loads in the Distribution Network (DN), introduces new technical challenges for network operators. The responsibilities of Distribution Network Operators (DNOs) are being adjusted to cope with current system challenges and they are transitioning to Distribution System Operators (DSOs), taking a more active role in dynamically managing power flows across the network. Further, the advancement in distribution automation technologies provides greater opportunities for energy consumers to take more effective participation in demand reduction schemes and DSOs can be enablers of Demand Response (DR). Hence, the functionality of DR can be considered an alternative, lower cost, carbon-saving and flexible solution to defer network reinforcement. This forms the rationale behind this thesis, which aims to provide an in-depth investigation of the potential responsiveness in residential demand and its effect on constraint management of the DN.

The main contribution of this thesis is the design, development and implementation of a Multi Agent System (MAS) framework for active DN management through residential DR. One advantage of the proposed platform is the capability of integrating both centralised and decentralised DR control mechanisms. It employs the responsiveness of demand from both loads shifting and shedding through price-based and incentive-based DR respectively. The feasibility and effectiveness of such a platform has been evaluated by developing and implementing the DR mechanism in three levels. The DR algorithm for several static and dynamic electricity tariffs, (Time of Use (ToU), Day-Ahead (DA) and Real Time Pricing (RTP)), is designed and developed in Low Voltage (LV) feeders. This is then expanded and implemented in a Medium Voltage (MV) feeder under an RTP environment. Finally, two incentive-based DR schemes: emergency and local community DR, are merged in the MV/LV network to improve its reliability and security.

The implementation of the MAS framework demonstrated its configurability and scalability through three case studies under different scenarios. One novel aspect of this research is the consideration of customers' characteristics in the design of the DR algorithms. In addition, at MV level, the tariffs and the required DR are allocated to each LV feeder specifically taking into account their DR potential and participation effects on the overall network performance. The simulation results at LV level show that maximum peak demand reduction and the most flattened load profile are achieved with RTP. At MV/LV network, MAS provides a community environment where the consumers can collaborate to decrease their overall demand. Moreover, the local community can reduce their dependency on the grid during daytime with PV generation. It is concluded that DR trading can benefit all players economically and also lessen DN violations from stipulated limits.

## Author’s Declaration

The work described in this thesis has not been previously submitted for a degree in this or any other university and unless otherwise referenced it is the author’s own work.

# Acknowledgement

I would like to express my deepest gratitude to my principal supervisor, Dr Ioana Pisica, for her valuable guidance, support, and encouragement. My thanks also go to my second supervisor, Professor Gareth A. Taylor, for his valuable comments and recommendations. Finally, I would like to thank my family to whom this thesis is dedicated.

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# List of Abbreviations

| | |
|---|---|
| ACOPF | Alternative Current Optimal Power Flow |
| ADNM | Active Distribution Network Management |
| DCC | Data Communication Company |
| DCL | Demand Curtailment Level |
| DECC | Department of Energy and Climate Change |
| DG | Distributed Generation |
| DLC | Direct Load Control |
| DMS | Distribution Management System |
| DN | Distribution Network |
| DNO | Distribution Network Operator |
| CPS | Curtailment Potential Scheme |
| DR | Demand Response |
| DRPA | Demand Response Provider Agent |
| DSM | Demand-Side Management |
| DSO | Distribution System Operator |
| DW | Dish Washer |
| EDR | Emergency Demand Response |
| FES | Flexibility Energy Scheme |
| HA | Home Agent |
| HEMS | Home Energy Management Systems |
| IBT | Inclining Block Tariff |
| LCDR | Local Community Demand Response |
| LPM | Linear Prediction Model |
| LR | Load Reduction |
| LTA | Local Transformer Agent |
| LV | Low-Voltage |
| MAS | Multi-Agent System |
| MV | Medium Voltage |

| | |
|---|---|
| NB | Number of Branches |
| NG | National Grid |
| PAPR | Peak-to-Average Power Ratio |
| PED | Price Elasticity to Demand |
| PR | Participation Rate |
| RDRA | Residential Demand Response Aggregator |
| RE | Renewable Energy |
| RPLI | Real Power Loss Index |
| SA | Supplier Agent |
| SCADA | Supervisory Control and Data Acquisition |
| SI | Sensitivity Index |
| SO | System Operator |
| TD | Tumble Dryer |
| ToU | Time-of-Use |
| VDI | Voltage Deviation Index |
| WDR | Without Demand Response |
| WM | Washing Machine |
| TC | Transformer Capacity |
| TSO | Transmission System Operators |

# List of Symbols

***Variables for Households:***

| | |
|---|---|
| h / H | Index and set of Households |
| A | Attitudes |
| D | Demand |
| $l$ | Load |
| d | Ancillary binary variable represents users constraints |
| $\mu$ | Binary variable reflect the attractiveness of tariff |
| $p$ | Price of electricity |
| $\delta$ | Satisfaction factor |

***Variables for Appliances:***

| | |
|---|---|
| j | Number of controllable appliances |
| f | Non-controllable appliance |
| x | Operating status of appliance |
| z | Start-up of appliance |
| k | Availability of appliance |
| $\Delta t$ | Length of appliances' operating |
| ph | Phase of operating of appliance |
| D | Binary decision-making variable for starting the appliance |
| $\lambda$ | Binary variable reflect the appliances operating constraint |

***Variables for Power Networks:***

| | |
|---|---|
| c / C | Index and set of clusters |
| t/T | Timeslot and time period |
| $w$ | Weighting factor |
| n | Node |
| $E$ | Energy |
| G | Generation |
| L | Power loss |
| R | Resistance |

| | |
|---|---|
| Q | Reactive power |
| S | Apparent Power |
| V | Voltage |
| $\Delta P$ | Required DR |

***General Symbols and Notations:***

| | |
|---|---|
| $\Delta$ | Difference |
| $'$ | Prediction |

# Chapter 1 Introduction

## 1.1 Motivation

The electrical power network of Great Britain (GB) is being pushed to its capacity limit due to a significant increase in distributed renewable energy sources and increasing demand. Since the control and management of conventional power systems mostly rely on increasing generation and network capacity in line with demand, expansion of network infrastructures is vital to maintaining security of supply in the future. This expansion is a time-consuming process and would require costly investments. Demand Response (DR) is an alternative solution for reducing overall costs, improving network capability and flexibility, as well as delaying future network investments. In the GB transmission network, DR is an established tool in controlling and supporting the network under stress condition. However, its implementation in the Distribution Networks (DNs) of GB has been very limited so far. The future role of DR in electricity DN is getting more significant due to the ever increasing importance of consumer engagement in peak reduction, flexible demand sources and advanced distribution automation technologies. Moreover, the emerging capabilities of recent sophisticated programmes provide the achievability of more intelligent, efficient and flexible DR. This is reflected in the transformation of DR's role from typically shaving peak demands to becoming an increasingly valuable tool to manage the modern electricity network. Hence, the motivation behind this research is the knowledge gap in DR effectiveness at distribution level and the current limited understanding of how residential flexible loads can be employed to improve distribution systems' reliability and efficiency.

### 1.1.1 Environmental Concerns

According to the World Energy Council, the definition of sustainability of energy is based on three core dimensions: energy security, energy equity and environmental sustainability [1]. The effect of environmental issues such as climate change can have a direct influence on these aspects of energy sustainability. Consequently, the need to decarbonise electricity generation is a key player in environmental sustainability. Through the Climate Change Act 2008 [2], GB took the lead in the environmental policies and in setting legally binding 'carbon budgets' in the world. Under the proposed legislation, the emission of carbon dioxide should be cut by 80% of the 1990 baseline by 2050, with an interim target of at least 27% by

2020 [3]. Accordingly, the Committee on Climate Change recommended that the carbon intensity of power generation should be reduced by 90% by 2030 [4]. The total electricity generation in 2016 was 337.7 TWh with 42% from fossil fuels, 4% from nuclear and 19% from Renewable Energy (RE) sources [5]. Based on this decarbonisation action plan, by 2020 the renewable sources should provide 15% of energy demand [6]. Besides, increasing the penetration of REs, improves the security and reliability of GB's future energy supply by decreasing the dependency level of energy from fossil fuel.

Along with deploying clean energy technologies, there is a great requirement for improving the energy usage efficiency. This refers to the goal to use less energy to provide the same service. Thus, the energy bills can be reduced and the carbon reduction objectives can be met. In April 2013, the Department of Energy and Climate Change (DECC) set GB's ambitious Energy Efficiency policy target to 18% reduction in final energy consumption relative to the 2007 business-as-usual projection [7]. In this respect, the energy demand reduction by 2020 for residential sectors is estimated to be approximately 6%. On the other hand, the need for electricity is increasing due to the introduction of new loads into the network, e.g., plug-in Electrical Vehicles (EVs) [8], increased use of electronic devices, etc. A 28% growth in the total annual residential electricity demand is anticipated in 2050 compare to 2017 [9].

### 1.1.2 Challenges in the Distribution Network

In GB, fourteen Distribution Network Operators (DNOs) are in charge of distributing electricity from the transmission network owned by National Grid (NG) to their licenced areas [10]. Their main responsibility is to develop and maintain the distribution network efficiently and economically. This is done by monitoring and determining the network operational status of the distribution of electricity on a real time basis and upgrading the infrastructure based on planning. The safety and reliability of the electricity that is provided to customers is assessed by the government regulator for Electricity and Natural Gas Markets, Ofgem [11]. DNOs do not generate or sell energy; this is addressed by energy suppliers who purchase the electricity from the electricity producers, e.g., power stations [12].

The classical control techniques of DN focus more on average load and demand management [13, 14]. In the contemporary GB power network, monitoring the network operational status is performed centrally using Supervisory Control and Data Acquisition (SCADA) system. However the control of the network is undertaken at transmission level. The resilience of DN is satisfied by redundancy of infrastructure equipped with a level of over-capacity. When performing routine maintenance, upgrading network infrastructure or repairing failed components, this allows various parts of the network to be shut down without compromising supply to consumers [15]. This type of network management is due to the conventional unidirectional power flow and predominantly passive characteristic of the power network. However, since the increase in RE and Distributed Generation (DG) can reverse the power flow, this becomes a bi-directional flow. Moreover, due to the uncertainty and intermittency of these sources, technical issues within the DN, e.g., increasing voltage profile levels, transient voltage variations and harmonic distortions [16] are probable. Therefore, this creates a need to upgrade traditional DNs towards more intelligent platforms for controlling and coordinating these clean energy sources.

DR can be an alternative solution which also provides a great source of power flexibility in the network. The alignment between generation from RE and the demand can be notably increased [17]. For instance, DR enables the shifting of demand to times of relatively high REs generation and low load. At household level, increasing the number of installed DGs enables DR to evolve further and maintain the demand-supply balance in a real-time environment [18]. In this way, DG and flexible load resources can be directly controlled by their owners [19] to improve the reliability and security of DNs. Consumers can maximise the local usage of DGs and thus increase their independency from power grid. This can result in accommodating increased RE and DGs in constrained areas with limited grid connection. Feed-in-tariffs can also provide the opportunity for residential consumers to sell their local generation to the grid. In addition, DR can contribute in the network management through other valuable sources such as provision of firm capacity and operational flexibility. The former can eliminate the need for conventional peaking capacity especially in high REs penetration [20]. In the latter, DR can provide operating reserves to the system to avoid the need for loading the thermal generators partially [21].

Another challenge in the future of DN is the changes in the load shapes due to the introduction and growth of new loads in the network. According to the UK energy consumption 2016 report, the total domestic electricity consumption has significantly changed due to a 46% increase in the number of households, as well as a 17% population increase since 1970 [22]. Therefore, in spite of improvement in the efficiency of home appliances, their frequency of use, cyclic length as well as energy consumption are rising

[23]. National Grid creates and develops energy scenarios each year to visualise and plan the UK future energy evolution landscape. In 2017, four scenarios have been determined which consider various potential pathways that can affect the future of energy. These are consumer power, two degrees, steady state and slow progression as shown in Figure 1-1 [9].


**Figure 1-1:** UK future energy scenarios 2017 [9]

The impact of these scenarios by 2050 on the residential annual electricity demand is shown in Figure 1-2. As can be seen, consumer power has the deepest increase in electricity demand among all scenarios where it has been anticipated that the demand reaches to 152TWh excluding EVs. This increment is 132TWh for both slow progression and steady state and 116TWh for two degrees scenarios.

Theses show a great need for coordinating various loads in order to minimise peak loads. DR can notably mitigate the negative impacts of integration these new loads by optimising the operation time [24]. For instance, the appliances scheduling can be managed to shift the charging of EVs to off-peak times without creating inconvenience to the end user. This can ultimately reshape the consumers' loads towards more flattened demand profiles over time. Therefore, DR can not only effectively contribute in relieving power flow constraints in the DN but can also provide integration of more additional loads.

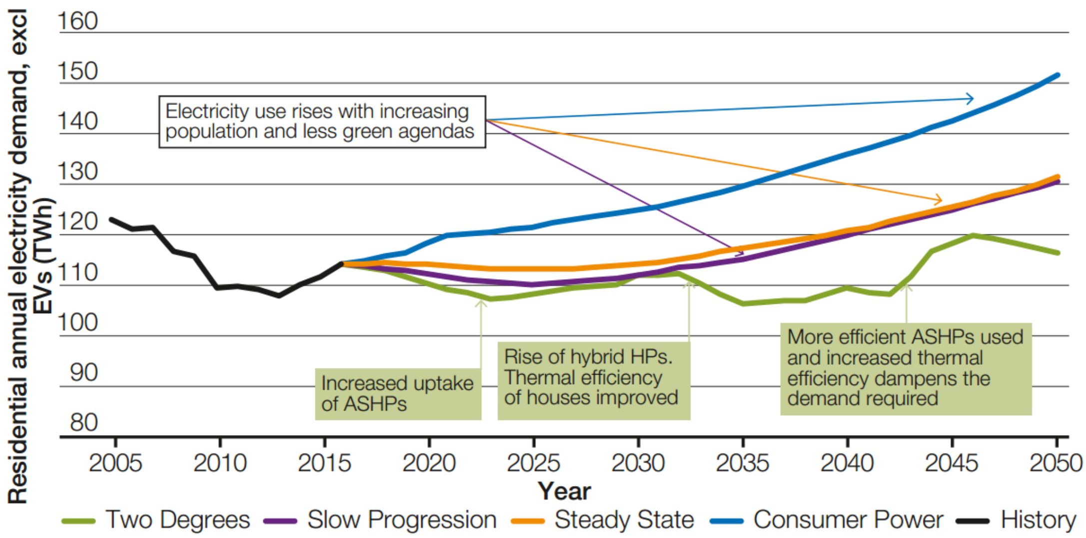


**Figure 1-2:** The predication of annual residential electricity demand by 2050, as estimated future energy scenarios [6]

In spite of the discussed challenges in the DN, the advancement of automated infrastructure technologies in the DN provides new opportunities for electricity customers to engage in demand curtailment plans. This consequently creates new roles for the DNOs [25]. For instance, the majority of UK households will be equipped with smart meters by 2020 [26]. This two-way communication infrastructure between customers, DNOs and suppliers, enables the development in the electricity markets to introduce and apply various electricity tariffs and feed-in tariffs. Employing domestic DR in a number of trials has proven that providing DR to DN can be considered as an alternative, lower cost, carbon-saving and flexible solution to defer network reinforcement compared to the existing methods. These trials are explored in depth in the next chapter. The financial saving could be passed onto all consumers in the form of lower bills.

Based on the above discussion, by accommodating the penetrations of the new loads and generation as well as new technologies, GB is poised for a significant transformation in how electricity is generated and consumed. DNOs will be required to adapt and invest more smartly to manage this new energy demand-supply paradigm [27]. Accordingly, the management of the DN should be developed towards more decentralised energy networks which need System Operators (SOs) at the local distribution level of the network. Moreover, the operation of DN should be undertaken in a real-time environment with actual flows on the network. In the attempt to provide a smart and active DN in GB, the traditional passive managing role of DNOs is now changing to Distribution System Operators (DSOs). This change is defined by the Energy Networks Association (ENA) board as the TSO-DSO project

[28]. The project, divided into four main work streams including T-D definition, impact assessment, regulatory enactment and design, building and testing, has been anticipated to be completed by 2030 [29].

In general, three main tasks should be considered in the transformation of traditional DNOs: active control management of DN, more local control of supply-demand balance and increasing and improving the customer engagement [30]. Accordingly, two complementary strategies are used: planning out ahead the functions of a DSO and innovation. The latter refers to trials of new approaches in supervising and controlling the network and accordingly using the data to provide a smart flexible network. Among market innovations and opportunities, Demand Side Management (DSM) and DR are well-known tools in providing direct benefits to the DN in relation to energy demand reduction [31]. The characteristics and challenges in the future of managing demand-supply and considering the role of DR in shifting from DNO to DSO are shown in Figure 1-3.

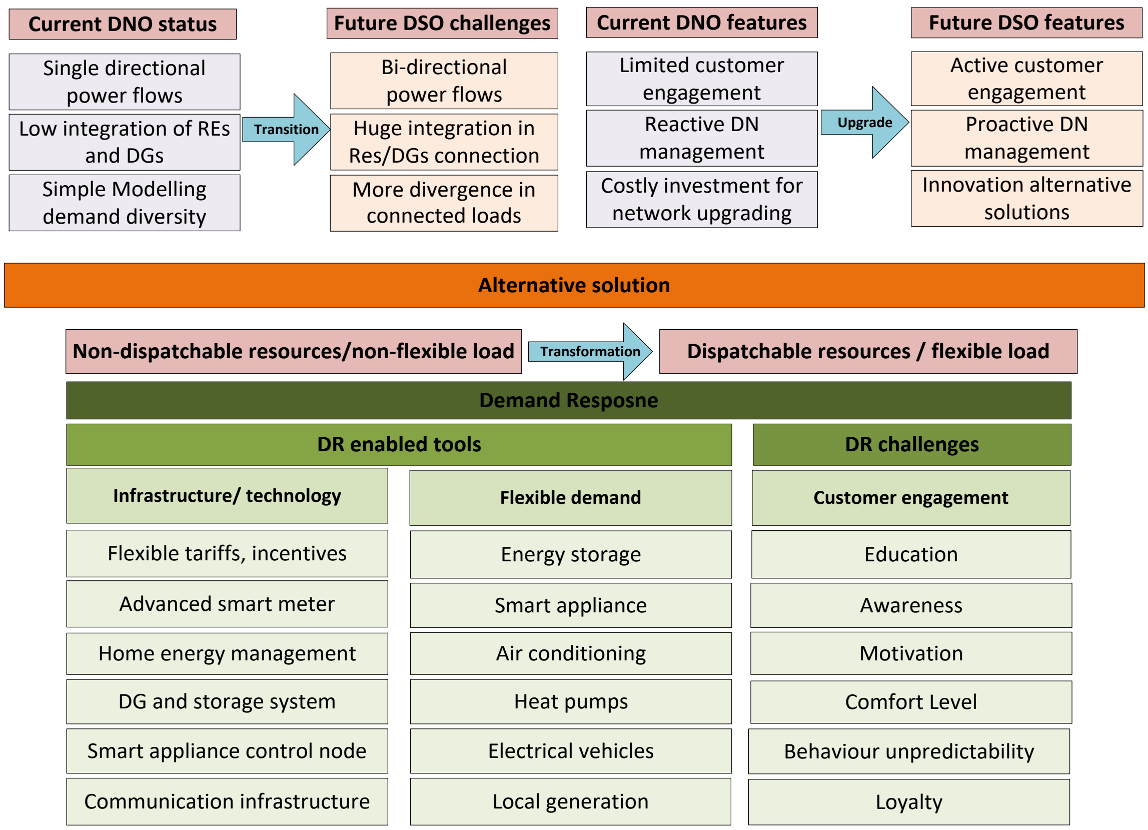


**Figure 1-3:** Features and challenges in the transition from DNO to DSO and DR as an alternative

## 1.2 Distribution Network Management

This section discusses in depth the concept of DSM and DR along with their respective role in current and future power networks. In this thesis, the DR controller refers to a load management system that implements DR services at either household or network level. The procedures and methodologies that enable DR are known as the DR activation strategies.

### 1.2.1 Demand Side Management and Demand Response

DSM refers to a series of programmes designed with the intention of changing the consumer energy usage pattern to help in balancing the generation and supply [32]. According to [33]: "Demand-side management encompasses the entire range of management functions associated with directing demand-side activities, including programme planning, evaluation, implementation, and monitoring". This concept was first introduced in the late 1970s where the DSM was categorised into two different schemes: energy efficiency and DR [34, 35] as illustrated in Figure 1-4. In general, the focus of energy efficiency is on long-term benefits with reduction in overall energy consumption and peak demand. On the other hand, DR emphasises on reducing peak demands for short periods of time when there is a need for load reduction, e.g., during peak demands periods. Since this thesis is focussed on DR, an in-depth discussion on this topic is presented in this chapter and the next.

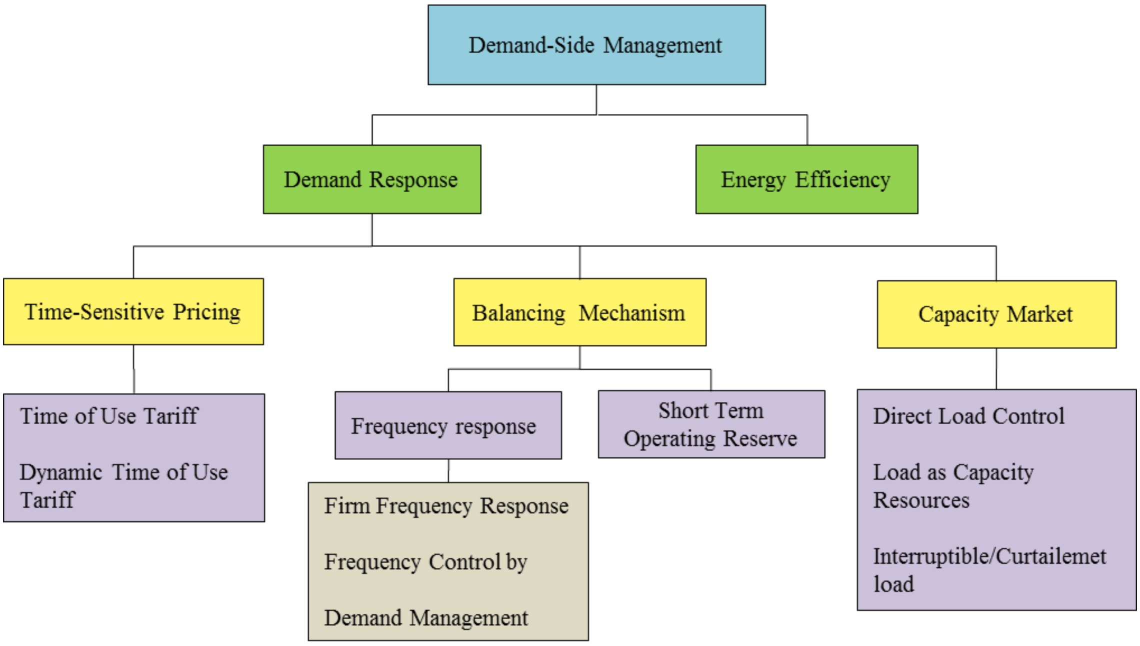


**Figure 1-4:** Components and categorisation of DSM and DR in UK [36, 37]

DR is a class of DSM programmes in which the customers receive some incentives from energy suppliers for reducing electricity consumption during peak periods or under network stress conditions [38]. Management of energy usage patterns can also lead to an overall peak demand reduction, demand curve reshaping and increased sustainability of the grid, thus reducing the overall cost and carbon emission levels [39]. DR can dramatically diminish power generation costs for DSOs and lower bills for consumers [40, 39]. In general, DR has been considered as one of the noticeable technologies to improve the operation, economy, security and reliability of the electricity network [41, 42].

Customers can participate in DR through three different responses: on-site standby energy generation, load shedding and load shifting. In the first one, customers can respond to demand reduction instructions by meeting some of their electricity needs through onsite or backup emergency generator [43]. Therefore, their demand will be reduced with only minor loss of their comfort level. In load shedding, customers reduce their usage during high price periods or DR program events, e.g., by turning off lights or turning down the air conditioner thermostat, which may result in temporary loss of their comfort level. The last one involves updating the schedules of appliances based on the price over specific time periods. In this case, using shiftable appliances such as washing machines or dishwashers can be delayed from higher peak-time prices to lower non-peak time.

### 1.2.2 MV/LV Network Management with Demand Response

The topology of Medium Voltage (MV) and Low-Voltage (LV) networks is typically radial. In GB, primary substations voltages are 33 kV to 11 kV and the secondary level is 11 kV to 415 V. In order to determine the DN capacity under all loading conditions and network configurations, AC load-flow analysis is crucial. The load flow through each node of the network is affected by the disposition and loading of each prior node point and by the system losses [44]. As a consequence, the load flow is limited by some constraints. The recent DNO projects and trials are mainly focussed on the active management of the power flow with concerns regarding voltage and/or thermal constraints [45]. This is because these are the main constraints in the integration of new loads and generation in the DN. Accordingly, the attention towards loss mitigation has lessened compared to the traditional power networks. In this regard, these two key constraints are considered in this thesis and are discussed together with the role of DR in relieving them.

***Thermal Constraints:*** The temperature of the electrical components in the network can significantly rise through heat dissipation. As current flowing through components such as line conductors and transformers increases, their temperature rises. Therefore, exceeding their thermal limit may cause undesirable situations, e.g., thermal expansion, increase in electrical resistance, and the thermal breakdown of components. The temperature limit and accordingly thermal capacity of a component/line depend on its physical characteristics. Therefore, the thermal rates of components in a network are considered as a constraint. Thermal rating of each MV/LV line or the maximum capacity of a transformer are both defined as the maximum current or MVA that can be transferred over the line/transformer without exceeding their specified maximum operating temperature [46].

***Voltage Constraint:*** Voltage limits are among the most prominent constraints in a DN. These are essentially determined based on the quality of feeding the Low Voltage (LV) consumers. This is because most LV end-users' appliances do not have voltage-adjustable capabilities. The limit for LV connection points in the UK is determined within the statutory limits of +10% and -6% of the nominal 230V [47]. The voltage of each node point varies according to its location in the DN as it is dependent on the node's injected or consumed power. In a DN without DG, the voltage profile gradually decreases along the feeder. Therefore, characterising the DN in terms of strong and weak parts can be achieved by analysing voltage profiles at different locations in the DN.

The constraints in the DN can be managed by controlling the power flow. DR can effectively contribute in relieving those constraints by reducing peak demands and thus controlling overloading on the network. This can also help in flattening the total load profiles of consumers. In the current GB network, the DR mainly focusses on the temporary reduction of the power flow in the DN by offering incentives to willing participants. However, with the increasing importance and attention being paid to DR schemes, the role of the DR can go further and incorporate new features. For instance system operators can be enabled to participate in supply security schemes.

### 1.2.3 Active Distribution Network Management

Under the DSO model, network entities can take more active role in order to manage the demand and generation locally. As a result, Active Distribution Network Management (ADNM) can be securely operated and developed. ADNM integrates different components in the power network through intelligent metering and advanced communications in order to monitor and control the network. In this way, new technologies, e.g., DGs, flexible loads, storage devices and etc., can be implemented in an efficient way to run and manage the network safely while improving network operation. ADNM can reduce the expensive investment of network reinforcement and connection costs. The core of the ADNM is the

Distribution Management System (DMS) which supervises the network operation. This is done through real-time/near-real-time measurements or forecasting methods in order to determine the required control signals for either consumers or generators. DMS communicates with the Intelligent Electronic Devices (IEDs) that are distributed across the DN with protection and operation purposes.

Since conventional networks are mostly centralised, the current implementation of ADNM control schemes in many systems can face several limitations. In such systems, a comprehensive knowledge of the total system is needed as the decision-making is taken via a single centralised point. Thus, any failure in central management could cause problematic operational issues. Another drawback is that the computational formulation of the centralised controller is complex and this complexity increases with the network extension. Moreover, the data communications is complicated due to the huge data interaction among active components in ADNM. Therefore, a decentralised mechanism needs to be integrated with the centralised control to allow local decision-making during failures or system stress conditions. For instance, constraint management at the MV feeder can be done by the local measurement at LV feeder. This can be extended to a more distributed ADNM in which each LV feeder can have a control level access in order to take some local actions.

One of the methods for improving the ADNM system is using the Multi-Agent System (MAS). Each agent can act independently which improves the total system resilience and robustness as they are not affected by any local failure at component or communication pathway [48]. One advantage of such a framework compare to centralised control scheme is the greater scalability due to provision of intelligent and computing power at each agent. The complex calculation burden of a centralised controller is lessened using a decentralised approach. The communication timing as well as the complication of the communication interactions in the network is reduced. This enables the optimisation of the network with the same computational burden of the conventional centralised ADNM and also save the costly central processor. Since the framework implemented in this thesis is based on MAS structure and a thorough description is provided in chapter 3.

## 1.3 Research Aim and Objectives

The aim of this research is to develop and implement a decentralised MAS ADNM platform in order to activate DR services from residential load responsiveness in MV/LV feeders.

Under MAS framework, different DR participants can be integrated in the network to enable optimal and widespread functionalities of DR at distribution level. Therefore, DR trading can maximise social welfare for all DR participants, e.g., end users, DSOs and energy suppliers. In order to achieve this aim, the following research objectives have been defined:

**Objective 1.** Design and develop a decentralised ADNM in a MAS framework for managing the LV feeders through available residential flexible loads in real time.

**Objective 2.** Implement and evaluate the proposed price-based DR in a unified centralised and decentralised ADNM with the view to manage the MV network constraints though LV feeders.

**Objective 3.** Investigate the effectiveness of combining the proposed DR mechanism with incentive-based DR schemes, aiming to improve the security and reliability of MV/LV network.

The summary of the proposed DR control strategies, scenarios and advantages in order to meet the objectives of this thesis is provided in Table 1-1.

**Table 1-1:** Main DR strategies and advantages of proposed DR-based MAS ADNM framework

| Control level | Objectives | DR type | Price signal | Advantages |
|---|---|---|---|---|
| **LV feeders** | Mitigate the distribution transformer overloading | Price-based, voluntary, load shifting | ToU / Day-ahead / RTP | Fully decentralised DR control mechanism and independent decision-making at each LV feeder from a central controller at MV feeder |
| **MV feeders** | Constraint management (voltage and thermal limits) and power loss reduction | Price-based, voluntary, load shifting | RTP | Simplify the computational processing and communications, complexity doesn't increase by the size of the network, easy to tune |
| **MV/LV feeders** | Congestion management, Maximise local usage of renewable generation | Incentive-based, contractual obligation, voluntary, load shedding | Complimentary incentives: feed-in-tariffs and a novel reward for local utilisation of generation | Merging the advantages of both price-based and incentive based DR and thus improving the reliability and security of demand-supply balance |

## 1.4 Research Methodology

Based on the aforementioned objectives, the overall design structure and implementation of the DR-MAS-based ADNM platform are focused on two levels: MV and LV feeders. For both cases, the same methodology is employed and is as follows:

- Designing the DR management architecture consisting of a physical and a cyber-layer:

  - *Cyber layer:* A MAS framework is constructed. The architecture of agents, their behaviour, attributes and interactions, in the proposed system are defined.

  - *Physical layer:* A typical DN, consisting of several MV feeders connected to residential consumers through lateral LV feeders, is modelled. The required data for each consumer, including daily load profile, willingness to DR participation and price elasticity to demand is determined from a pilot's dataset.

- Developing DR mechanisms at the LV feeder, for distribution transformer and the home level, and MV/LV feeder for distribution substation and LV feeders. Real time pricing will be considered for the first two objectives and a novel reward scheme for the last one.

- Implementing the proposed DR-MAS-based ADNM in the typical DN in order to tackle overloading issues by controlling the power flows in MV/LV feeders.

- Evaluating the feasibility and efficiency of the proposed framework. The performance of the proposed control algorithms and the dynamic behaviour of the system, including the proposed agents, under normal and network stress conditions are investigated through simulations for one typical day period.

## 1.5 Principal Research Contributions to Knowledge

The work in this thesis contributes to the activation and implementation of ADNM through residential demand responsiveness. The main output of this research provides an understanding of how residential flexible loads can be used as an alternative low-carbon and low-cost solution for tackling future challenges in the GB distribution network. The principal research contributions to knowledge can be summarised as follows:

- Development of a novel DR-MAS-based ADNM framework for local management of distribution transformer overloading under day–ahead and real time environment with the following original features:
  - ✓ Optimal load scheduling for shiftable appliances based on consumption behaviours and dissatisfaction factor of different clusters of consumers taking into account their social and technical attributes.
  - ✓ Price prediction model for the above home energy management system to improve its accuracy in real time environment.
  - ✓ Two probabilistic methods in order to determine the quantity of both potential and available DR in each LV feeder. The former has been designed for day-ahead analysis whereas the latter is applicable in real time. This has been done based on aggregation of responsiveness load from different clusters of households within that LV feeder.
  - ✓ A new four-level piece-wise linear cost function design for energy suppliers to implement real time tariffs based on required and available DR or for day-ahead tariffs on required and potential of DR.

- Design and implementation of a new DR-MAS-based ADNM framework for voltage and current constraint management of MV feeders through available DR at LV feeders under real time environment with the following novel achievements:
  - ✓ A less computationally demanding decision-making for households on the starting point of any available shiftable appliance compared to optimisation methods.
  - ✓ An optimal DR control mechanism for DSOs to determine the amount and most effective locations of the required load curtailment over specific time horizon. This has been determined based on the available DR from LV feeders, voltage sensitivity of each bus, voltage deviation and power loss indexes considering thermal, voltage and power loss constraints.
  - ✓ A new real time tariff based on a two-level piece-wise linear cost function for each LV feeder according to their DR availability as well as the total required DR at the network.
  - ✓ An original wide-area DR framework that demonstrates the advantages of the DR-MAS based ADNM by applying the proposed methodologies for smart distribution system.

- An original unified price-based and incentive-based DR scheme to mitigate possible network congestions and ensure the performance of the DR-MAS-based ADNM including the following contributions:
  - ✓ Optimisation of the households' electricity usage in the community level based on reduction of their demand dependency on the power grid by utilising local RE sources.
  - ✓ A probabilistic method in to determine the quantity of demand that can be shed during emergency conditions for each cluster of customers.
  - ✓ A DR management scheme for local aggregators at LV feeders to maximise their local usage of available renewable generation.
  - ✓ An emergency DR scheme at LV feeders with a merit order based on the DR potential of different clusters of contractual customers.

## 1.6 List of Publications from the PhD

### 1.6.1 Journal Publications

S. Davarzani, I. Pisica, G. A. Taylor, and J. Munisami , "A review of residential demand response strategies and applications in the active distribution network management, "IEEE Access, Under review; Submitted 12/06/2018.

S. Davarzani, I. Pisica, G. Taylor, R. Granell, "Implementation of a Novel Multi-Agent System for Demand Response Management in Low-Voltage Distribution Networks, "Applied Energy, Under review; Submitted 31/05/2018.

S. Davarzani, I. Pisica, L. Lipan, "Novel model for defining electricity tariffs using residential load profile characterisation," International Journal of Renewable Energy Technology, Paper ID IJRET-206777, Accepted 13 February 2018.

K. Blazakis, S. Davarzani, G. Stavrakakis, I. Pisica, "Lessons Learnt from Mining Meter Data of Residential Consumers," Periodica Polytechnica Electrical Engineering and Computer Science, Vol. 60, no. 4, pp. 266-272, September 2016.

### 1.6.2 Conference Publications

S. Davarzani, I. Pisica, G. Taylor, “Consumer-led power management in local distribution networks”, in Proc. UPEC, 4-7 September 2018, Glasgow, Scotland. Under review; Submitted May 2018.

S. Davarzani, I. Pisica and G. Taylor, “Development of a Novel Multi-Agent System for Residential Voltage Control Using Demand Response based on Customer Behaviour," in Proc. IEEE ISGT Europe, 26-29 September 2017, Torino, Italy.

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## 1.7 Organisation of the thesis

The work in this thesis is structured as follows.

***Chapter 2 – Demand Response as Enabler for Active Distribution Network Management:*** A critical analysis of relevant literature is presented in this chapter. The review looks into past attempts at activating and applying DR with the focus on residential areas. Various DR mechanisms are classified and a comparative analysis is performed. Implementation of DR services to manage the DN is investigated at both consumer and network level. Moreover, a summary of more prominent DR pilots and projects in the GB is provided. Finally the potential of residential load responsiveness as well as challenges in implementing DR are discussed.

***Chapter 3 - Proposed MAS Framework***: This chapter introduces the proposed MAS framework and focusses on its cyber layer. The general model including the MAS architecture and platform is described. The overall methodology for each of the three objectives of the thesis as well as the role of each stakeholder in the network is explained in detail. The MAS structure and DR mechanism in each case study is elaborated along with mathematical formulation.

***Chapter 4 – Parameters for Multi Agent System Modelling:*** The simulation environment and modelling is described. A comprehensive description of the dataset and extracted information to create the load profiles of households is explained in detail. A characterisation-based clustering technique considering customers personal attributes such as social, technical, educational and financial, is applied. External factors including time, day and seasonal effects, are also taken into account. The set up parameters for each objective are determined. In addition, a general description of the network features before implementing DR is provided.

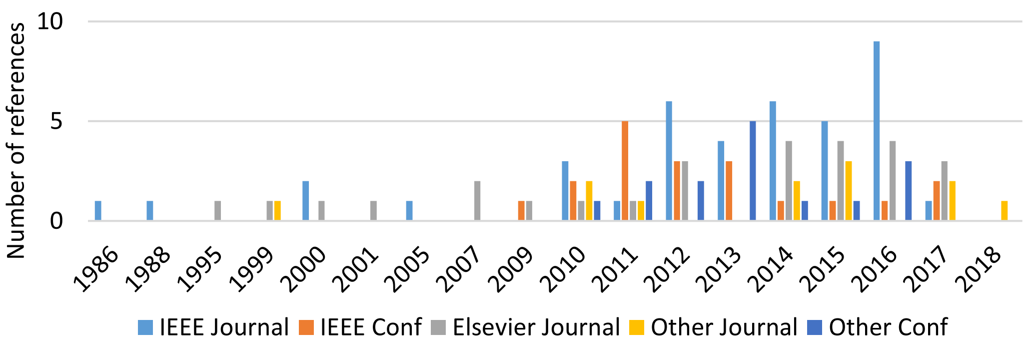
***Chapter 5 – Simulation Results and Discussion:*** The main contributions of this thesis are presented in this chapter. For each objective, the proposed methodologies explained in chapter 3 are implemented to investigate the feasibility, as well as the effectiveness, of the proposed DR-MAS-based framework for ADNM. For this purpose, various scenarios are considered and the simulation results are compared. Comprehensive analytical investigation on the results obtained and the advantages of the proposed model are provided. The effect of satisfaction level of households on the quantity of available DR, and hence the performance of the DR mechanism, is studied.

***Chapter 6 - Conclusion and Future Work:*** The conclusion of this thesis is presented in this final chapter along with an overview of the work that have been undertaken to fulfil the aim and objectives of this research. The key findings and achieved results are presented and discussed. Finally, further possible investigations and recommendations for this work are provided.

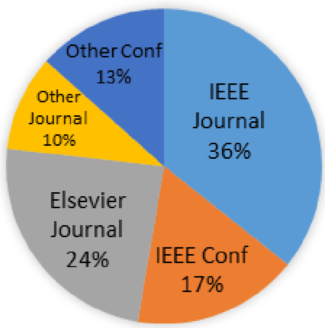
# Chapter 2 Demand Response as Enabler for Active Distribution Network Management

## 2.1 Introduction

The objective of this chapter is to investigate and review the resources, development and performance of the DR for the residential sector with the focus on the activation strategies. Different DR frameworks and schemes, with the focus on GB networks, are explained in detail. The research papers studied for this literature review have been classified in terms of the year, Figure 2.1(a), and the type of the publication, Figure 2.1 (b). A hierarchical breakdown of the DR mechanism based on categories adopted in this thesis is depicted in Figure 2-2 (a). The DR activation strategies are categorised and studied in two levels: consumers and network. An illustration of the division of these categories is depicted in Figure 2.2 (b). The application of DR in managing different constraints in the DN is investigated and categorised in Figure 2.2 (c). A detailed discussion of these categories is provided in sections 2.4 and 2.5. Several pilot studies along with the requirements, capabilities and challenges for the effective implementation and operation of DR approaches are also part of this comprehensive literature review.

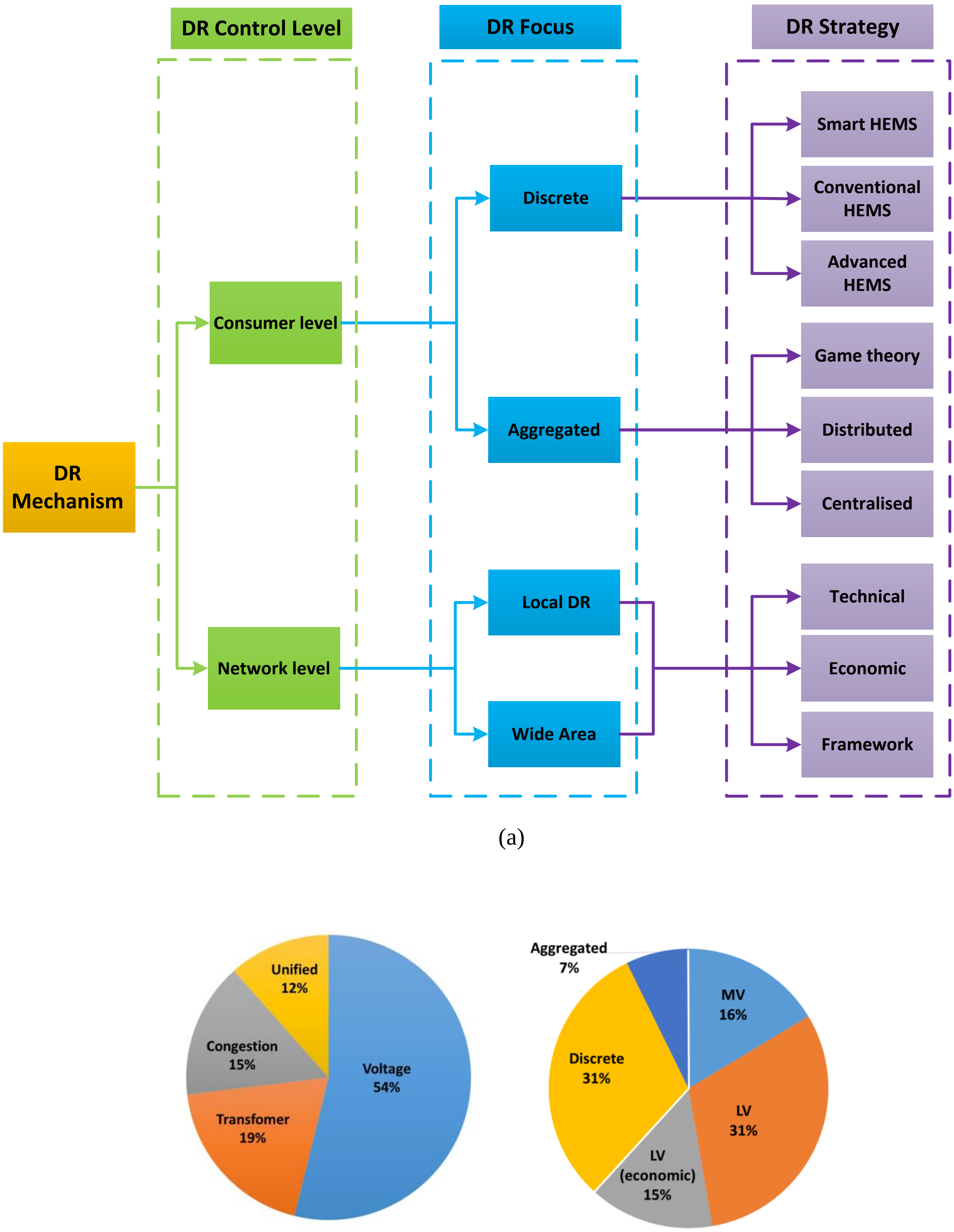



(a)




(b)

**Figure 2-1:** Comparative analysis of literature search based on year (a) and type of publication (b)




(a)

(b) (c)

**Figure 2-2:** Classification of DR mechanism based on DR control level (a), focus (b) and strategy (c)

## 2.2 Classification of DR Programmes

Different criteria have been used in the literature to classify DR programmes. The two main classifications are incentive-based DR and price-based rate programmes, as depicted in Figure 2-3.

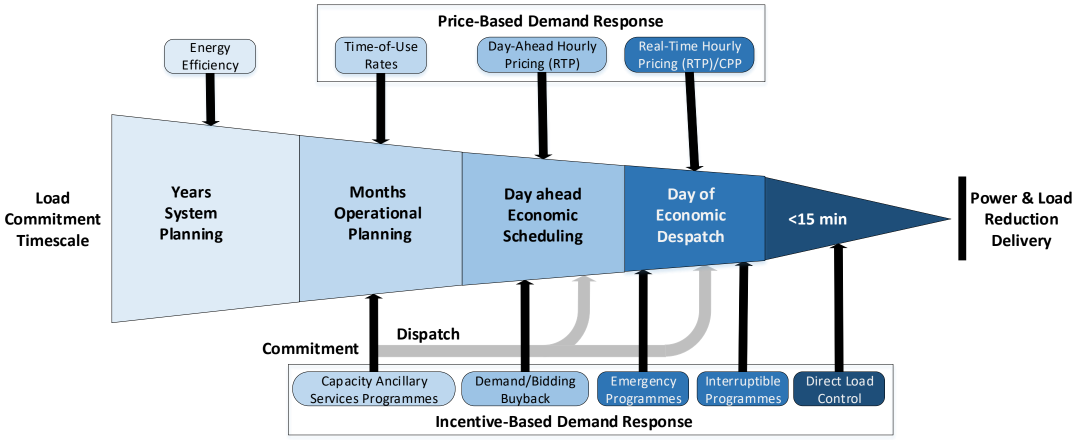



**Figure 2-3:** Time-based classification of DR programmes [227]

The former refers to programmes where the participants receive predefined contractual incentives for providing DR services mainly during system stress conditions, e.g., grid congestions. In the latter, consumers are offered time varying tariffs in different timeslot during the day. The price-based rate DR, the focus of this thesis, is usually more appropriate for residential customers while the incentive-based ones are better suited for larger customers, e.g., commercial ones [49].

### 2.2.1 Incentive-Based Demand Response Programmes

***Direct Load Control (DLC):*** DR participants, in a pre-agreed contract, give remote access to the network operators for controlling their appliances such as air conditioner, or dishwasher. This can directly address contingencies of the power system and enhance its reliability. In the GB, a DLC programme, the "NINES" trial, has been implemented with a view to control electric storage heating during grid emergencies or peak demand periods [50].

***Interruptible/Curtailed (I/C) Load Programmes:*** Participants agree with pre-defined load reduction/curtailment to receive set incentives. Non-responders may get penalties by higher cost of electricity depending on the terms and conditions. Residential loads are typically considered as aggregated loads by a third party entity and this eases the network operators' management and communications.

***Demand Bidding/Buyback (DB) Programmes:*** Unlike DLC and I/C programmes, DB provide the potential for consumers to take part in wholesale electricity market by offering bids for specific load curtailment. Bids less than the market price are accepted and customers are obliged to curtail the committed demand to avoid sanctions. These programmes are considered as low-risk for customers and operate in short periods, typically a day or hour ahead.

***Capacity Markets (CM) Programmes:*** These act as reserve generator capacity in which DR participants pledge to provide specific load curtailment. The participants should be able to demonstrate the ability to provide a minimum load curtailment as they receive compensation even if they are not called to curtail. Customers receive the price notification on a day-ahead basis and can be penalised if they do not comply. Unlike DB, these programmes operate over medium and long timeframes. Such a programme was recently introduced in GB where bids are made from both Demand Side Response (DSR), embedded generation and electricity storage, as well as new and existing generation capacity, Combined Heat and Power (CHP), [51].

***Ancillary Service Markets (ASM) Programmes***: These act as operating reserve services which enable interested customers to bid their load reduction in the spot-market [52]. Large and regular energy consumers are the main participants in this programme and the type of reserve that is supplied is based on the extent and promptness of the customer's response.

***Emergency Demand Response (EDR) Programmes:*** DR participants receive pre-defined incentives for demand curtailment during reliability events such as voltage instability, network congestions, and operating reserve shortfalls. The duration of DR event is usually regulated by the system operator and partakers are notified in advance to respond to EDR. Participation in this scheme is voluntary and therefore non-responders are not subjected to any penalty.

### 2.2.2 Price-Based Rate Programmes

***Fixed pricing:*** This is the traditional pricing scheme where the price is constant over specific period of time, e.g., season or year. Therefore, reducing energy bill is only possible by simply using less electricity.

***Time-of-Use (ToU) Rates:*** The price rate is defined for pre-determined periods of time during the day or week. The customers are informed of these prices days to months ahead. ToU rates reflect the average price of wholesale market, typically with higher rates during peak time. ToU is another form of fixed rates with more pricing bands during a typical day. [53] showed that peak demand reduction through ToU is the weakest approach among DR schemes. This could be due to two main reasons. Firstly, customers do not receive any practical incentive for power reduction. Secondly, prices are attractive only for off-peak periods while they remain relatively high for peak-demand hours. Currently, the ToU tariff in GB, also known as the Economy 7 tariff, has two pricing bands: one for day and one for night [54].

***Dynamic (dToU) Time-of-Use Rates:*** This is a derived form of ToU in which the notification of changes in price is shorter, e.g. one hour ahead. Though the price can be set nearer to the actual electricity price, this comes with the trade-off of customers losing foresight and hence the promptness in their response. An example of such a tariff is Low Carbon London (LCL) that was trialled in London, aiming to investigate the potential of dToU in residential responsiveness to DR [55]. This trial is discussed in more detail in section 2.6.

***Critical Peak Pricing (CPP):*** This price scheme is another type of ToU tariff comprising higher than average ToU rates during critical peaks. The new energy price is usually announced to participants a day ahead. CPP increases the reliability of the system during critical conditions by engaging more participants and consequently providing greater demand curtailment. However, the probability of negative net benefits for energy suppliers is high [56].

***Real-Time Pricing (RTP):*** This programme provides dynamically varying prices in a uniform time step, thus reflecting the real price of wholesale market. Therefore, consumers can adopt their usage to their advantage based on the actual energy price. The need for continuous real-time communication for risk-averse domestic users, the complexity of big data exchange as well as the lack of communications infrastructures between the energy supplier and the customers are the main challenges for implementing RTP scheme. An alternative RTP-based solution is the Day-Ahead RTP (DA-RTP) [57] wherein the predicted prices over time for the next day are announced to the customers beforehand.

***Vickrey-Clarke-Groves (VCG):*** The price for each time period is calculated by a centralised mechanism based on load profile information provided from voluntary customers [58]. In the aim of encouraging customers to provide truthful information, some incentives are paid to participants. The VCG pricing scheme can be used for lowering power consumption or load shifting purposes.

## 2.3 Players, Prerequisites and Interactions in GB Demand Response

DR services are an efficient alternative for new generation sources and can be treated under a market-based layout. As a result, the modern power system can be modelled as a networked environment where DR participants can interact with each other.

This is suitable for assessment of both technical and economic aspects of the DN. Regulated market participants, e.g., Transmission System Operators (TSOs), DSOs and deregulated players such as aggregators and producers are connected and interchange information among each other [59]. Moreover, developments in the modern electricity network have introduced new roles and relationships for all those who interact with the electricity system. A general block diagram of the data flow between different market players in the GB energy network is presented in Figure 2.4. The relevant players, include consumers, energy suppliers, DSOs, aggregators, with Ofgem as the regulatory body. Besides, in GB power network, the interaction between consumers and other authorised entities is undertaken by the Data Communication Company (DCC). The role and functionality of this interface is given in chapter 4. They are described below with emphasis on communications and interactions.

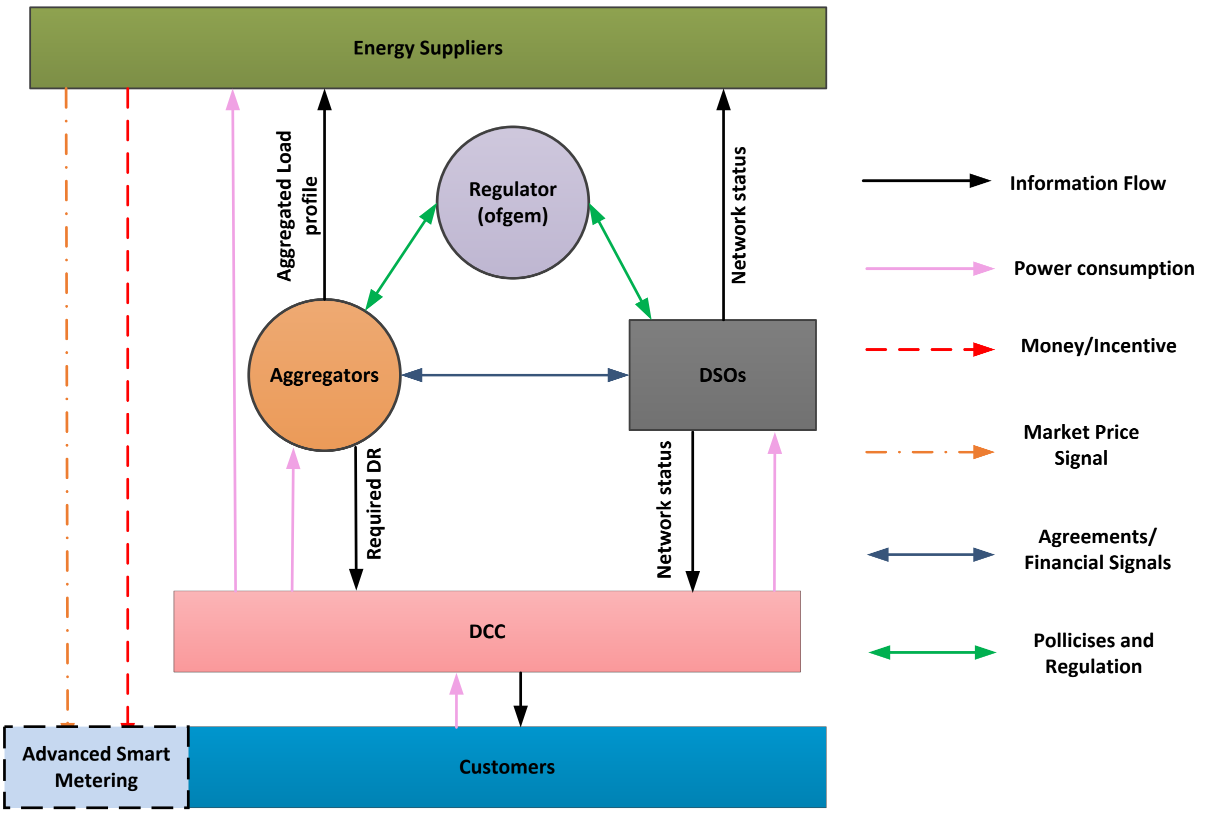



**Figure 2-4:** Block diagram of entities in the DR framework

***Consumers***: The rollout of smart meters has enabled consumers to take an active role in the market and created new sources of flexibility. Consumers are able to not only provide information regarding their demand over time, but also monitor and control their consumptions near real time. The impact assessment published by Ofgem in 2010, shows that the total consumer savings was £6.43 billion which consisted of energy savings of £4.23 billion and load shifting/ToU tariffs of £1.06 billion [60]. However, in order to enable an automatic and intelligent DR control scheme, consumers also need to be equipped with Home Energy Management Systems (HEMS).

***Energy Suppliers:*** They trade energy by purchasing electricity from either wholesale markets or directly from generators and selling it to their individual customers. Currently there are six main suppliers in GB (British Gas, EDF Energy, RWE npower, E.ON UK, Scottish Power and SSE) as well as several other medium/small-size ones, each offering different tariffs [61]. The main aim of these suppliers is to provide competitive tariffs and incentives to customers in order to increase their market share. This is the rationale behind the move towards a more dynamic tariff, which would be possible with the implementation of smart meters.

***Distribution System Operators:*** As discussed in chapter 1, in the current GB power network, DNOs are responsible for controlling and maintaining the power equipment in the DNs, e.g. power lines, underground cables and substations. On the other hand, DSOs are also designed to deliver a secure network by providing system services, such as voltage control, network restoration, etc., and by controlling power flow in the active DN. There are 14 licensed DNOs, owned by six different groups, each responsible for a specific geographical area [62]. The cost of DNO/DSO services is added to the consumers' bill, but the total revenue that can be collected from customers are set and controlled by Ofgem. The DNOs/DSOs are also incentivised by Ofgem to investigate novel innovations for improving the efficiency and power quality of the system.

***Aggregators:*** In today's competitive electricity market, a DR aggregator acts as an interface between a group of energy consumers and other stockholders [59]. The reason behind the use of this third-party entity is to enable the individual small responsiveness demand to actively participate in DR programmes. Aggregators are mainly responsible for satisfying all connecting participants' interests.

## 2.4 Demand Response Activation Strategies for Residential Consumers

Residential DR controllers can be classified into two levels; discrete level [63, 64, 65, 66, 67, 68, 69, 70, 71, 72] and aggregated level [73, 74, 75, 76]. Discrete level activates the DR control mechanism for a single user while aggregated level adopts a centralised DR control strategy for multiple users in a neighbourhood area. A review of these levels, with respect to price-based rate DR, is explored next.

### 2.4.1 Discrete Level

HEMS are utilised to optimise home energy usage by managing controllable appliances. The principal method of achieving DR via Home Energy Management System (HEMS) is to reduce power usage of particular flexible loads. Thus, customers can save money by reducing the overall demand, even in fixed tariffs or by consuming less power during system stress in CPP tariffs. With the introduction of more variable rate energy tariffs, e.g., ToU or RTP, HEMS helps customers to further increase their economic benefits and consequently provides greater DR. HEMS can schedule appliances that consume power in adjustable timeslots where their operations can be stopped, adjusted, or shifted to other timeslots. Based on such an energy management mechanism, HEMS can therefore be classified into three areas: conventional, advanced and smart HEMS. The focus of the first category is solely on load management, assuming a time-based price signal [63, 64, 65, 66] while the second one also considers the energy price prediction [67, 68, 69, 70]. The smart HEMS on the other hand, applies an intelligent learning-based DR strategy [71, 72]. The fundamental DR methodology in the two last groups are essentially the same as conventional HEMS, with the difference of embedding more advanced capabilities to improve the performance and accuracy of the system. For the sake of relevance only the first two categories will be dealt with in this thesis.

#### 2.4.1.1 Conventional HEMS

When designing DR algorithms for HEMS, several considerations have to be taken into account.

***Appliances models and constraints:*** The major appliances studied, modelled and which have the highest potential of contribution in DR schemes are:

- Shiftable appliances: wet appliances [77], EV [78]
- Non-shiftable appliances: heat pumps [79], air conditioner [80]
- On-site generation: PV [81], storage system [82]

The appliances constraints can generally be classified as either technical or user constraints. The former refers to individual characteristics of each specific appliance such as:

- Task constraints: Starting and ending time, continuity and consecutiveness for each task of shiftable appliances;
- Energy constraints: For shiftable appliances, total cycle operation to be completed within a day and the minimum and maximum required energy consumption for non-shiftable appliances;
- Storage system constraints: Storage level, charge and discharge limits of battery charges;
- Comfort constraints: Minimum and maximum temperature of water heater, fridge/freezer, air conditioner and electric heater.

User constraints on the other hand, relate to the satisfaction and comfort level of customers and include:

- *Time* constraints: Maximum waiting time, limits for starting and ending times of shiftable appliances;
- Thermal constraints: Thermal comfort level of non-shiftable weather-based appliances.

***Objective function and solver:*** The objective of DR controllers at consumer level is primarily to reduce electricity cost by either minimising the total electricity consumption [65] or maximising overall net utility [64]. This aim can be also achieved by minimisation of peak hourly load [63] which ultimately results in bill saving. This goal of the DR can be modelled as a single objective function. On the other hand, some HEMS incorporate more targets such as minimisation of the total electricity price and peak load [63] or minimisation of the total electricity price and dissatisfaction [67, 66]which can be expressed by a multi-objective function.

Defining the objective function of HEMS is dependent on the nature of the objective function, the variables and constraints, which can be linear, non-linear, convex or non-convex. If all or some of the variables of the objective function are integers, then the problem is considered as an integer or a mixed-integer problem respectively. Considering shiftable appliances, as dealt with in this thesis, binary decision variables are needed to determine their start-up as well as their operation status (on/off). Therefore, the optimisation problem can be formulated as a mixed integer combinatorial problem [83] and solved by Mixed-Integer Programming (MIP). This methodology can be further extrapolated to either

Mixed Integer Linear Programming (MILP) or Mixed Integer Non Linear Programming (MINLP).

A load scheduling objective function is usually formulated using MILP due to the complex nature of the MINLP methodology for solving such problem. MILP is applied by simplification and using a limited number of appliance models [84] or by considering the relaxed version of the optimisation problem [66]. Another approach [64] utilised the Generalized Benders Decomposition (GBD) to develop an algorithm for solving MINLP problems for optimal load scheduling without relaxation. The proposed algorithm provides a higher flexibility for integrating a wider variety of appliances with different characteristics.

***DR type*:** Apart from DR decision variables, the control strategy of the DR procedure is also dependent on the incentives introduced to customers to reduce/shift their demands. In conventional HEMS, the price of electricity during energy scheduling period can be set as either a static tariff, e.g., ToU [63, 64], or a dynamic tariff, e.g., RTP [85, 65, 66]. Although the overall optimisation strategies in both tariffs are similar, RTP provides a more dynamic environment. It is worth noting that for time-variant conditions, a dynamic optimisation framework should be implemented. Consequently, the price and problem constraints should be updated after receiving new price. In RTP-based tariff, the HEMS decides on load scheduling based on a day-ahead pricing information. The uncertainty in RTP can be modelled through probabilistic methods such as Monte Carlo iterative method [65].

#### 2.4.1.2 Advanced HEMS

In a RTP, the price changes dynamically at regular time interval. Therefore, the capability for predicting the upcoming price needs to be integrated with conventional HEMS. Embedding a price predictor in a HEMS enables planning ahead and results in more accurate and optimal management of the household energy consumption [86].

A general model for combining HEMS with price predictor under a dynamic pricing framework is illustrated in Figure 2-5. Using real-time prices fed to smart meters by the electricity supplier, the price predictor unit determines the price. Then an optimal scheduling of residential consumers is achieved through HEMS.

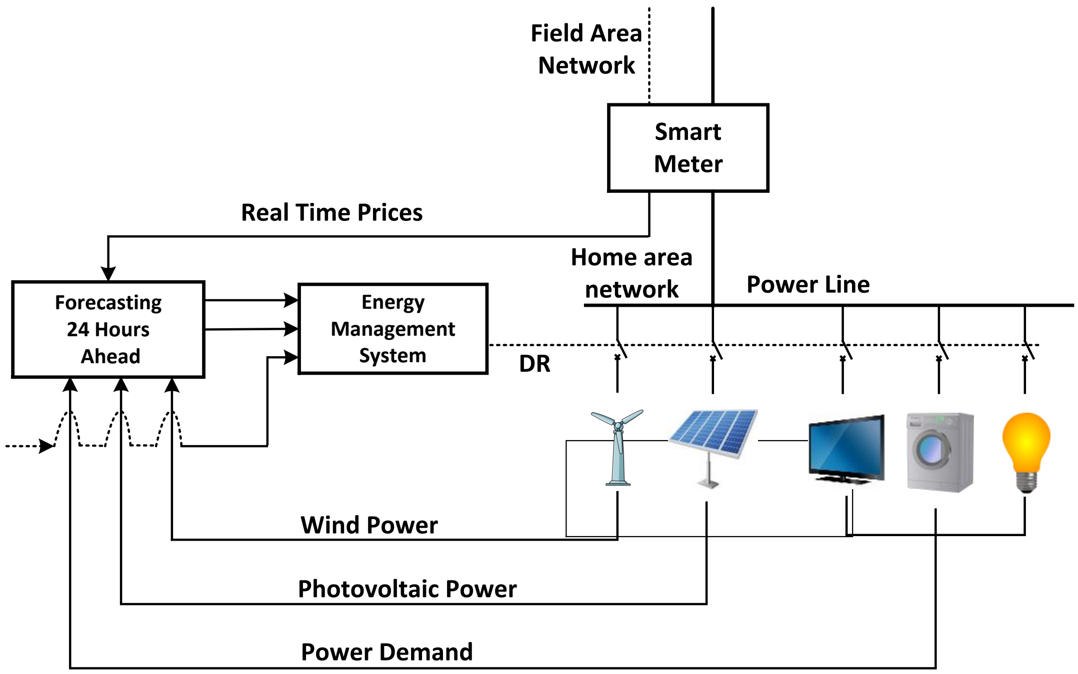



**Figure 2-5:** HEMS with price prediction capability [87]

The price of electricity for each time interval can be affected by several factors particularly the wholesale market prices. Apart from the inherent complexity in predicting these prices, there are other factors that influence the pricing. The time of day, e.g., afternoons or nights, and the type of day, for instance a week day or weekend, a hot summer day or a cold winter day, are a few of these factors [68]. Although using such information can potentially be useful in predicting the price values, yet it will not be enough for a high degree of accuracy. This can be explained by the fact that electricity price does not directly depend on the absolute demand as long as the network constraint is satisfied [67].

Several models have been developed to forecast the upcoming prices using different parameters. These models were initially based on the conservation rates model with Inclining Block Tariff (IBT) [88] where the price is a linear function of total demand. Some utility companies have since the 1980s adopted a two-level IBT model for their pricing tariff [89, 90, 91]. This model is used to determine the DA-RTP and RTP for the proposed framework in this thesis as explained in detail in chapter 3.

A basic approach to estimate load and price is using historical data and prior knowledge [68]. Mathematically, this can be modelled as:

$$C_h = \hat{p}_h(l_h) = \begin{cases} \hat{a}_h\,, & \forall\ \ 0 \le l_h \le \hat{c}_h \\ \hat{b}_h\,, & \forall\ \ l_h > \hat{c}_h \end{cases} \tag{2.1}$$

where, $h$ denotes the hour of the day, $\hat{p}_h$ is the predicted price, $l_h$ is the total load and $\hat{c}_h$ represents the threshold.

The payment linearly increases with the amount of energy consumption in a default price $\hat{a}_h$ and once the energy exceeds the pre-determined threshold $\hat{c}_h$, the price changes to a higher value $\hat{b}_h$. This model can reveal the generation cost in RTP environments. The threshold parameter is usually constant on a daily basis but may vary over seasonal changes.

Generally, the estimation of parameters $\hat{a}_h$ and $\hat{b}_h$ from equation (2.1) is done using statistical analysis such as Linear Prediction Model (LPM). An example [67] where equation (2.1) is considered as a piecewise linear function is shown in equation (2.2)

$$C_{i,t+1} = \begin{cases} \propto_1 l_h + \beta_1 , & \forall \quad 0 \leq l_h \leq \hat{c}_h \\ \propto_2 l_h + \beta_2 , & \forall \quad l_h > \hat{c}_h \end{cases} \tag{2.2}$$

A norm approximation by Newton's method [67] is applied to estimate the slopes $\propto_1$and $\propto_2$ of price function. $\beta_1$ and $\beta_2$ are constants which reflect the fixed prices, e.g. fixed cost of generation. Using historical data, the load is normalised and scaled in order to fit the simulation.

Another approach [68] applied a weighted average price prediction filter to the RTP to obtain the optimal values of the coefficients $\hat{a}_h$ and $\hat{b}_h$ of equation (2.1). Based on the statistical analysis of demand and price, in yearly, monthly, weekly and daily basis, they showed that the prediction of prices for each day is likely to be related to the price of the previous day, the day before the previous day, and the same day of the previous week. Therefore, as an example, the $\hat{a}^h$ can be obtained by:

$$\hat{a}_h[t] = \ k_1 a_h[t-1] + k_2 a_h[t-2] + k_7 a_h[t-7] \tag{2.3}$$

Where, $a_h[t-1]$, $a_h[t-2]$and $a_h[t-7]$ represents the previous day, day before that and the same day from the previous week of parameter $\hat{a}^h$ respectively. Simulation results verify the effectiveness of integrating HEMS with a price predictor. They were successful in not only reducing users' payments but also in decreasing of Peak-to-Average Ratio (PAR) in load demand. The proposed model has an average prediction error of 13% and result in 1.3% reductions in user's energy cost when the RTP is known only for the next two hours.

A two-step adjustment process is proposed in [69], day-ahead scheduling and RTP adjustment. First, a deterministic problem for optimal load scheduling for the next day is solved by the day-ahead prediction of spot prices. Then, based on updated information of RTP, the scheduling is adjusted to deal with uncertainties introduced by errors in prices prediction.

A two-level IBT model for defining electricity pricing tariff is depicted in Figure 2-6 where $C_{min}$ and $C_{max}$ are the minimum and maximum electricity price.

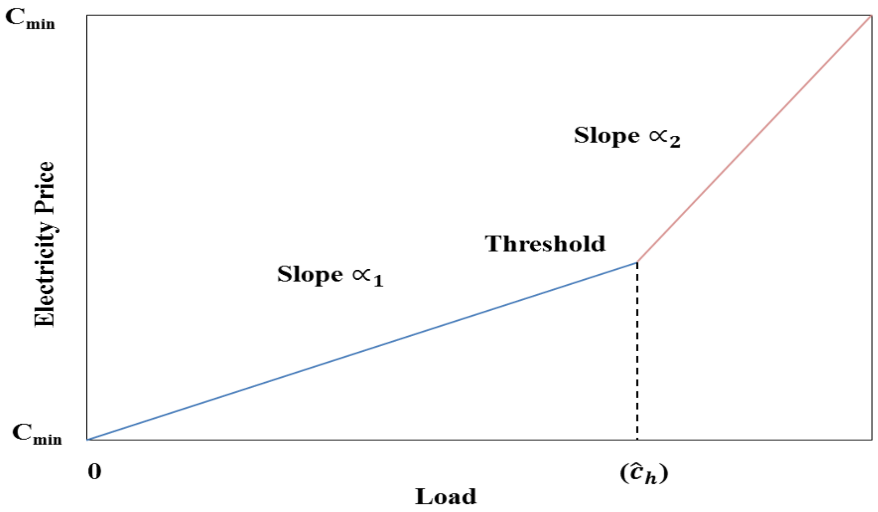



**Figure 2-6:** Two-level piecewise linear pricing function

Artificial intelligence techniques have also been considered for price prediction. A day ahead price prediction model proposed in [70] was applied in [68] and then further developed by using Artificial Neural Network (ANN). The results show that although both LPM and ANN methods are efficient in reducing bill cost comparing to RTP without prediction model, with better results achieved by LPM.

It should be noted that in terms of residential household, price predictors should have low computational complexity to be implemented easily for energy scheduling purposes. Based on the above discussions, it is clear that the deployment of the optimal energy consumption scheduling schemes with a price predictor, specifically in a RTP environment, is beneficial for both the end users and the utility companies. However, in order to achieve the most efficient DR, residential loads need to be considered as an aggregated model. This adds another level of complexity which triggers the need for a third party entity to manage the communication as well as the interactions between different components in the network. This is discussed in detail in the next section.

### 2.4.2 Aggregated Level

Time-varying prices DR integrated with HEMS can improve the efficiency of power networks. However, a non-coordinated response of DR participants may lead to drastic peak rebounds at non-peak periods with lower prices. Accordingly, a distributed and aggregated DR management model is required to coordinate DR schemes in order to alleviate the effects of peak rebounds. The objective of DR load scheduling at aggregated levels is to flatten the total load profile [73] of aggregated demands while minimising end users energy cost. In most literature, however, load scheduling has been based on a day-ahead pricing. Several DR control methodologies have been developed to meet these objectives.

***Game Theory:*** This model is based on a theory where the end users' roles are that of players and the daily schedules of demands are their strategies [92]. One study adopted this theory to model an incentive-based energy consumption algorithm [74]. The optimal solution of the proposed energy usage scheduling game was achieved at the Nash equilibrium. Each participant has to submit its strategy in response to the current total load and tariffs in the network. The privacy concerns of users are maintained since users do not need to reveal their information regarding energy consumption schedules to others. The results for a single aggregator connected to 10 customers with up to 20 shiftable and 20 non-shiftable appliances, showed a reduction of 17% in Peak-to-Average Power Ratio (PAPR) and 18% in energy cost. It is to be noted that in order to solve the non-linear PAPR minimisation objective, a new auxiliary variable is introduced to convert the problem to a linear programme. The optimisation problem was then solved using the Interior Point Method (IPM) programming technique.

***Distributed DR***: In this model, each autonomous HEMS makes individual and independent decision for load scheduling. This is done based on the information received from the energy supplier. This information comprises the electricity sale prices and total load profile of the network. Subsequently, HEMS sends back the updated daily schedule of their loads to the energy supplier. A methodology is presented in [75] in which the aggregator's objective was solved in two steps. After receiving the optimal daily load schedule from all HEMS, the aggregator firstly calculates the total load profile in the form of load flattening objective. An evenly distributed total load profile is then achieved in the second stage when the HEMS asynchronously update their schedules, taking into account their least energy expenses. The scheduling problem is solved by a format for a day-ahead load scheduling with 15-minute resolution. Applying the proposed methodology to 50 customers in a Finnish DN, it was observed that the peak load decreased by 22.40% and the load factor improved by 19.63%.

***Centralised DR:*** The difference between this model and the previous one is that a centralised DR controller is applied to gather the information regarding load patterns as well as user preferences from customers. Then the load schedule is updated and sent to each user as in the proposed mechanism in [76]. The HEMS agents are charged based on not only their day-ahead allocation but also on accuracy of their actual energy usage. The purpose behind introducing this new scheme was that in practice, the customers might not always be exactly compatible to the day-ahead energy allocation. This methodology is based on a two-stage mechanism. In the first stage, the DR controller allocates hourly load schedules to each household based on information received from them a day-ahead. Then, the marginal allocation for each household is computed, aiming to share the cost of energy among them. The customer faithfulness aspect of the proposed strategy is achieved by a penalty/reward scheme inspired by the Prisoner's Dilemma standard. The objective function becomes a Mixed Integer Quadratic Problem due to quadratic nature of the price function which is computationally intractable especially in large-scale. Therefore, the problem is reformulated as a MILP by approximating the quadratic objective function with a piecewise linear function. One drawback of this mechanism is the potential privacy breach and security issue arising from households having to reveal and report their private information.

In above models, the prices are modelled by a typical time-varying electricity sale price or using the IBT model. In the latter, the actual energy cost can be considered as an ascending and convex function which can be modelled as a class of quadratic function [93] as shown in equation 2.4.

$$C_h = \hat{C}_h\ (l_h)\ = \hat{a}_h {l_h}^2 + \hat{b}_h l_h + \hat{c}_h \qquad ,\forall\ \hat{a}^h > 0, \hat{b}^h, \hat{c}^h \geq 0 \tag{2.4}$$

It is worth noting that equations 2.1 and 2.2 are in fact adopted forms of equation (2.4) with different coefficients in order to make the cost function smoother. However, for simplicity $\hat{b}_h$ and $\hat{c}_h$ are assumed to be zero.

## 2.5 Demand Response Application for Distribution Network Management

From a power network's point of view, the contribution of residential flexible load in managing the DN can be studied at two levels: local DR and wide-area DR management. The first one refers to managing the LV networks where the customers connected to a MV/LV transformer. The aim is to manage the transformer overloading and voltage constraints through individual consumer's demand responsiveness. The latter analyses the role of DR at MV/LV network level where the aim is to manage the constraint, e.g., voltage or current, at through DR provided from aggregation of households in each LV feeder. Recent studies have demonstrated the advantages of applying residential DR from both technical and economic/commercial perspectives in DN [94, 95, 96, 97, 98, 99, 100, 101, 102].

The operational problems at DN such as voltage drops and overloading of network components occur mainly during periods of large aggregation of loads. This necessitates immediate actions to mitigate the constraints in the DN. Hence, from a technical perspective, studies are mainly focused on incentive-based DR programmes [103, 104, 105, 97], although market-based have been utilised [106, 107, 108] for wide-area DR management as well. This is due to the fact that the involvement of additional market entities such as aggregators, retailers and/or energy providers is needed at wide-area level. The role of these entities is to procure flexibility DR through their stockholders. However, similar to incentive-based DR approaches, DR is provided by consumers having contractual agreements. Moreover, in practice, if critical issues occur when the available flexibility can no longer be procured by the market-based control, direct approaches for load curtailment are then required [107]. Hence, a combination of both DR mechanisms guarantees the successfulness of utilising DR in generation-demand balancing of the DN [109].

The focus of this section is on the DR algorithms and methodologies that implement DR services at DN. The objective function of DR controller is examined from both the economic and technical point of view. The economic targets of DR mechanism refer to the consideration of electricity cost and incentive in the objective function of Residential Demand Response Aggregator (RDRA). The latter is a local aggregator that exchanges information with its relevant households. Therefore, the economic target is categorised at local DR level. The focus of DR aggregator, as discussed in section 2.4.2, is on the household profit maximisation while RDRA here considers its own benefit as well.

### 2.5.1 Local DR

In local DR the system model comprises one system operator that serves a secondary substation, which plays the role of an aggregator, connected to several domestic loads.

However, details about the DR request and control strategies from the system operator are not a requisite and are assumed to be known.

#### 2.5.1.1 Economic Targets

As previously discussed, integrating individual households in a wide DR management system is the key to successfully managing demand-supply equilibrium in the DN. When designing an aggregated DR framework, the three key features that need to be addressed are end users' combinatorial preferences, private information and scalability [58]. A diverse range of studies have been undertaken on the role, effect and behaviour of RDRA [110, 111]. Several attempts have been made with the aim of providing a dynamic energy management framework through simulating RDRA [74, 112, 113]. Based on the objective/s of RDRA, the literature in this section is divided into the following three main categories:

- RDRA profit maximisation [75, 114, 115]
- Social welfare maximisation [116, 117, 118]
- RDRA in electricity market [119, 120]

The first two categories focus on single RDRA which serves multiple customers. The last one considers several RDRAs within the competitive electricity market.

***RDRA profit maximisation:*** RDRAs compete to sell DR services to the system operator by providing compensation to consumers in order to modify their consumption patterns. The profit maximisation of RDRA has been modelled by many [116, 117], where the general problem has been expressed as:

$$\max \{\mathrm{R} - \sum_{\mathrm{h}\in \mathrm{H}} \mathrm{C_h}\ (\mathrm{P_h})\} \tag{2.5}$$

The term R refers to the revenue of the RDRA and the second term ($\sum_{h\in H} C_h\ (P_h)$) is the incentive paid back to customers. An optimisation model to solve this problem was proposed [116] and was based on Genetic algorithm (GA) technique [116], with customer behaviour learning. Two different learning algorithms were proposed for shiftable and curtailed loads separately. In terms of shiftable load, the aim was to procure the probability distribution patterns of various responsiveness demands to dynamic day-ahead prices. For curtailed load, the algorithm attempted to forecast the hourly quantity of responsiveness demands based on changes in price. Implementing the proposed algorithm resulted in an 11.08% increase in profit of RDRA for an aggregation of 100 households, with 5 shiftable appliances per household.

Pricing design for RDRA have been introduced in order to help RDRA in market decision-making and pricing model design. An example of such an approach can be found in [118] where the objective function of the RDRA was to maximise consumer surplus, the difference between the total amount that households agrees to pay and actual payment. The optimisation problem was formulated as a function of the dynamic price signals from the RDRA, the benefit function, and the loss of consumer comfort factors. The price signals were determined day-ahead pricing through a post-forecast treatment technique [121].The results showed savings in consumer bills of about 20% along with flatter load curves as was expected. Although the operation of RDRA can be extended to schedule in RTP, the data privacy and security of customers has not been considered in the proposed framework.

***Social Welfare Maximisation:*** In the methodology adopted in 2.4.2, it was assumed that the goal of customers is always in line with RDRA. However, in this category, both RDRA and HEMS seek to achieve their own interests. The framework proposed in [75] was extended in [114] to provide a unified approach to combine the RDRA objective in reshaping the load profiles and customers' interests in reducing energy expenses. Moreover, since the whole procedure in the proposed model is in a parallel architecture instead of a sequential process as in [75], long processing time as well as communication problems are solved.

A combination of RTP and ToU with incentives were proposed in [115] with the aim of alleviating the overloading issues in the DN**.** One of the main features of this methodology is that the network loss as well as power flow equations and limits are also included in the energy balance constraint of the optimisation problem. The non-linear parts in the constraints is linearised using Special-Ordered-Sets-of-type 2 (SOS2) technique [122, 123]. The results show the effectiveness of DR management system in managing network overloading in the presence of high penetration of Plug-in EVs. Furthermore, better results can be achieved with RTP as compared to ToU tariffs.

***RDRA in Electricity Market:*** The main focus of studies in this category is the modelling of the electricity market with several competing RDRAs connected to end users. The aim of the system operator is to minimise the network operational cost by offering rewards to RDRAs. Therefore, each RDRA attempts to maximise its profit by providing and selling the maximum DR services to the SO. However, there is a minimum threshold in amount of demand reduction provision for participants. The minimum DR is 10MW for frequency response service in UK [124]. All entities in the market are essentially self-interested and non-cooperative. This emphasises the importance of modelling a comprehensive framework that facilitates the SO's access to a full understanding of all DR-related parameters and examining the interaction of all participants in the DR market.

Towards this scope, a multi layer-based model was presented in [119], as illustrated in Figure 2-7, to investigate the behaviour of participants in the market. The first layer includes the DRAs, suppliers and renewable energy producers while the end users are modelled in the second layer. Additionally, an incomplete information game theory algorithm was used to represents the interaction between participants in the market for day-ahead as well as real-time markets.

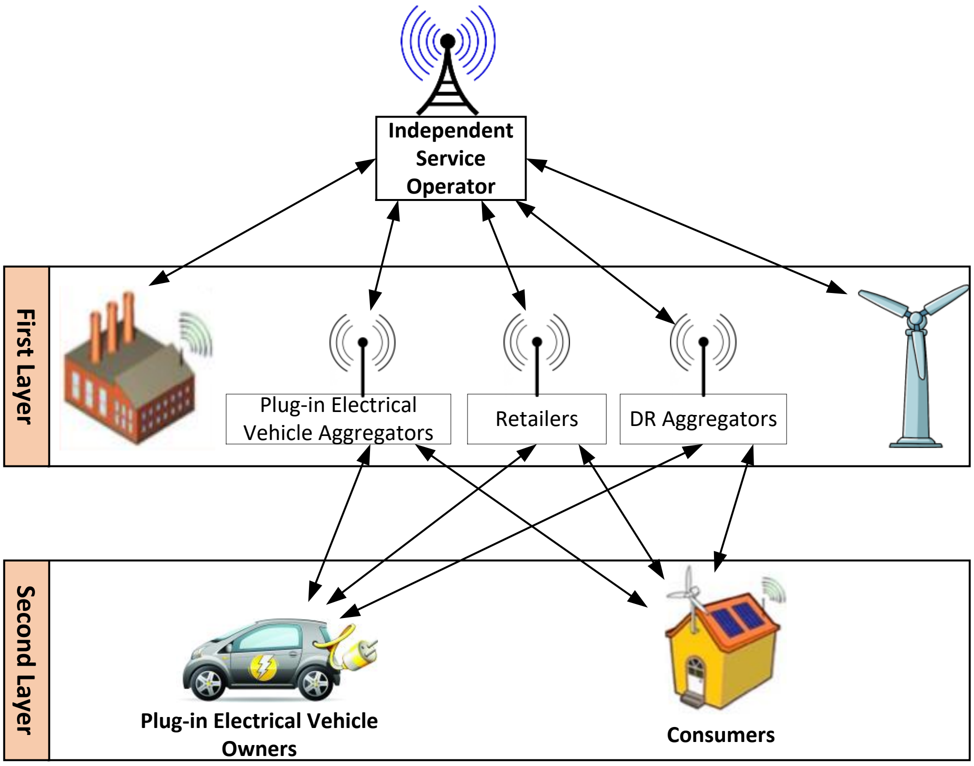



**Figure 2-7:** Multi-layer framework introduced in [119]

A hierarchical market system was introduced in [120], as presented in Figure 2-8, consisting of three levels in an RDRA framework for a day-ahead market. In the first level, the reward per unit of cost reduction is announced by the system operator with the aim of minimising cost. The next level involves competition between the RDRAs where each of them sends its offers to the SO, following negotiations with their relevant households. Finally, the system operator rewards the accepted offers. The results showed that all participants can benefit from this proposed branch-model as a result of negotiation between aggregated households. This study assumed that the response received from end users by each related RDRA is reliable.

However, the effectiveness of this assumption cannot be guaranteed due to additional incentives resulting from deliberate customer misreporting.

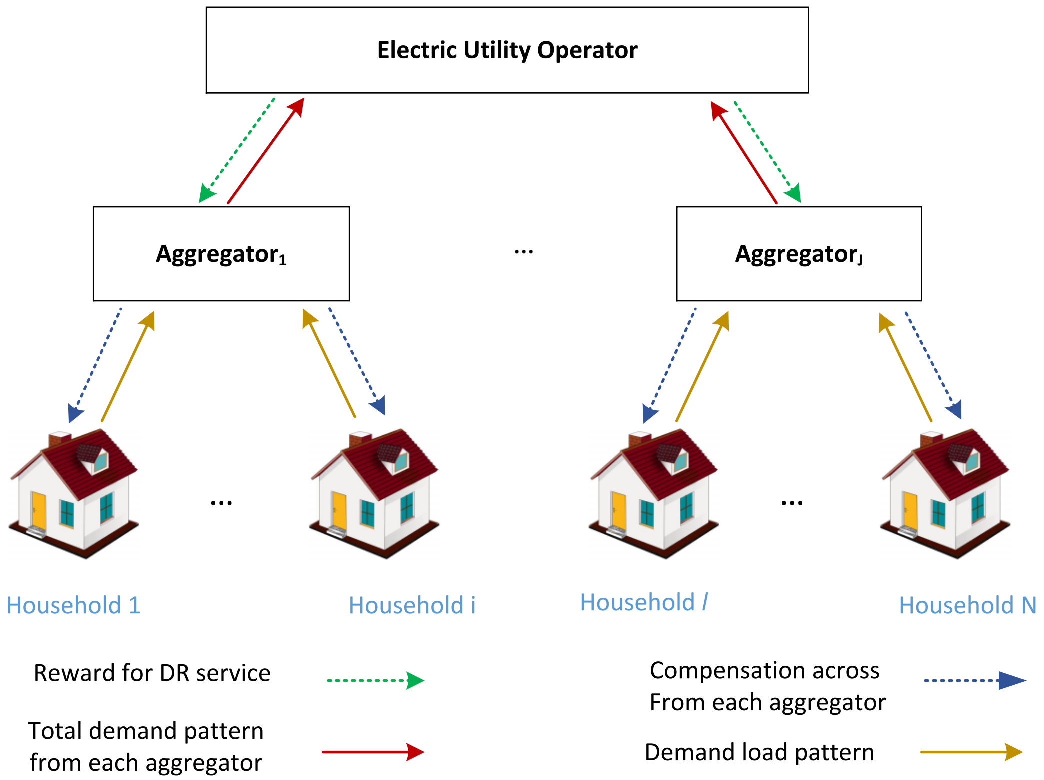



**Figure 2-8:** Hierarchical framework proposed in [120]

### 2.5.1.2 Technical targets

Generally, DR improves the lifetime of network components and the reliability of the electric distribution systems. In [94] the aging of the 80 kVA distribution transformer loaded close to the rated load was reduced up to 75% through DR provided by wet appliances of 20 households. Similarly, the analysis in [125] specified significant increment of lifetime of MV/LV transformer by integrating PV and DR in the distribution feeder. [95] employed an on-load tap changer at the secondary transformer to adjust the LV network demand. This resulted in the reduction of thermal constraints, annual network losses and of the paper insulation temperature of the cables, as well as improvement of voltage.

On the other hand, DR can help to manage the operational issues of the network by informing consumers through DR event signals. When a DR event occurs, the transformer or LV feeder aggregator/agent allocates the demand reduction boundary to each consumer or directly cut required load curtailment. The first action refers to EDR programmes where consumers can voluntary control their consumption whereas the latter is mostly for DLC programmes.

Therefore, the proposed load control strategies do not depend solely on the cost of electricity usage but also on the users' characteristics, preferences, flexibility and satisfactions.

The LV feeder controller deals with two challenges: the strategies to determine the allowable demand boundary for each household and the techniques to exchange the information with consumers. In the first one, three methods are used for load curtailment: Curtailment Potential Scheme (CPS), Flexibility Energy Scheme (FES) and a combination of them [126]. In the CPS, the total amount of required curtailment is calculated and distributed correspondingly among each household at the network by considering individual available DR. In the FES, the household's characteristics are also considered in the objective function of LV controller. Therefore, the DR mechanism seeks to maximise the comfort level of the consumers while maintaining the constraints of the network. However, this may result in more complex computational process since more advanced optimisation techniques are required. Table 2-1 shows a summary of the research work for this category.

**Table 2-1:** Classification of methodologies in determining the allowable demand boundary for each household

| Methodology | CPS | FES | CPS/FES |
|---|---|---|---|
| **Ref.** | [103] [127] [128] [129] [130] [131] | [104] [105] [132] [133] [134] [135] [136] [137] | [126] |

In an attempt towards overcoming operational issues in LV feeders through DR, two main issues have to be considered; controlling transformer overloading and voltage support.

***Overloading Management:*** Overloading issues at LV feeders occur due to exceeding the maximum capacity of either the primary or secondary transformers. In such conditions, DR events usually incorporate two features, the duration of DR event and the required amount of load shedding. The overall methodology aims to keep the instantaneous power demand at MV/LV transformer/LV feeder under specific limit during DR events.

Several strategies have been introduced and analysed in order to tackle the overloading challenges in LV networks with direct switching actions. A proposed advanced DR control mechanism [103] was based on hosting capacity and maximum allowable local generation, to relieve congestions with directly control of the output of renewable sources. A merit-order based direct control mechanism for HPs and EVs, was presented [104] and verified the feasibility of achieving 100% PV penetration in the studied LV network.

An analytic hierarchy process-based EDR strategy was proposed in [105] to reduce the power demand at the transformer level during system stress conditions. The total demand reduction was determined by demand deduction from the sorted consumption queue. In this regard, the controller at transformer level sorted all reported demands (kW) ascendingly. Then, the boundary demand for each consumer was determined at the point that the aggregated demand of households is equal or less than the total demand reduction. However, regardless of consumers' particular characteristics, the demand limit that was assigned to them during a DR event was the same. Therefore, following a DR event, the system is faced the probability of getting affected because of excessively power demand rise (e.g., demand restrike). This problem is addressed in a MAS-based framework [132, 131] by simultaneously minimising the potential rebound power demand at transformer level. Thus, the impact of undesirable new peak demand at the transformer after ending a DR event can be alleviated. Moreover, the interests of consumers regarding supplying critical loads, preserving comfort level, and minimising shiftable appliance's waiting time during a DR event, are taken into account in parallel.

***Voltage control:*** The focus of a large volume of literature on mitigating both under-voltage and overvoltage problems at the LV network is in active power curtailment of PV inverters. Different types of droop control methods, namely P-V [127, 128], Q-V [128, 129] and P-f [130] have implemented as effective tools to alleviate network constraints. For instance, [138] devised a sensitivity-based droop characteristic to allow a uniform curtailment for connected PV inverters in a radial distribution feeder. [127] presented a MAS based hierarchical approach that combined droop-based local control with a centralised overlaying control to curtail the PV injection among the consumers based on CPS. The P-V droop control mechanism in [126] is presented and is based on a linear function of voltage deviation magnitude. During normal operation, the output active power of the PV inverter is set at the maximum point and is reduced following voltage issues. These methods are not detailed here as they are out of the scope of this thesis.

On the other hand, decentralised approaches have been also proposed at the distribution transformer level to control power intensive appliances in the household. Such an approach was introduced in [133] where the demand curtailment allocated to each household depended on houses electrical panel size. However, at LV feeders, voltage issues are mainly considered in unified-based approaches along with congestion management considering flexible loads.

***Unified Approach:*** In the two previous categories, the proposed techniques aimed to manage the LV network constraints separately. However, in practice, these issues are subject to time-variable constraints and can change in hourly, daily, monthly or seasonal basis. Furthermore, there is a correlative nature between these network constraints and several researches have addressed this issue through a unified-based approach.

A unified approach focussed on agent-based hierarchical architecture is presented in [126] to deal with both network congestions and voltage limit violations over time. The DR curtailment scheme was based on predefined bilateral agreements. A CPS-DLC scheme was adopted to control the amount of injected power from the residential PV inverters. LV aggregator sent the curtailment requests to appropriate connection points using FES for controlling HPs. MIP technique was used to determine curtailment locations. This is a good example of integrating CPS-DLC scheme and FES.

Another approach proposed a novel Customer Rewards (CR) scheme based on a two-level hierarchical control scheme [134]. The aim of the primary controller is to improve the feeder voltage profile while maintaining it within a permissible band. This was done by load shifting response where the customers were dynamically rewarded on a day-basis. Customer flexibility as well as satisfaction are also considered in the decision-making process of the controller for load adjustment. The secondary controller is responsible for regulating the transformer overloading through peak load shaving. The result showed the effectiveness of the proposed CR schemes to shave the peak loads. However, appliance characteristics were not taken into account in this process.

[97] proposed a new approach that can be provided to all EVs over a charging period while ensuring that network will not exceed the statuary limits. Instead of minimising power losses and/or voltage deviations, the objective of the optimisation technique was to maximise the total amount of energy to mitigate the constraints. The voltage and thermal loading were considered for the network transformer and the mains cable connecting the transformer to the network. Results show that by controlling the charging rate of individual vehicles, high penetrations can be accommodated on existing residential networks with little or no need for upgrading network infrastructure.

### 2.5.2 System Wide DR Management

Constraint management for two principal operational issues, contingency and voltage violation, at DN is discussed in this section. The focus of DR control mechanism is on the MV network where the system operator interacts with RDRAs in LV feeders to improve the reliability and security of the DN. In addition, a summary of the proposed DR management framework for ADNM in the literature is provided.

#### 2.5.2.1 Congestion Management

Congestions in distribution networks can result when demand or generation at a certain point exceeds its maximum capacity. Generally, contingency occurs in MV network which requires the load reduction across the network. Managing the load flexibility at feeder level is advantageous and results in more local, competitive and accurate DR control. Therefore, due to the radial topology of LV networks, the households within each feeder can be treated individually and be connected to one aggregator. The typical market-based DR methodology to control the congestion at DN comprises 3 stages; firstly each aggregator optimises its individual profile of contracted consumers in order to provide local DR services. Then they send an initial demand bids based on the available DR (responsiveness demand) from their relative households to the DSO in a day-ahead/real time market. On receiving the bids, the DSO assesses the congestion status of the network by running Alternative Current Optimal Power Flow (ACOPF). If any congestion is detected, distribution congestion price is calculated. Then, aggregators reschedule their bids based on new predicted spot price and distribution congestion price. In most literature, flexible demand from aggregated residential appliances, was considered instead of multiple generation units since they are adaptable with the changes in the price.

In terms of market based DR approaches, the congestion price has been calculated through various methods such as the Locational Marginal Pricing (LMP) [106] or dynamic thermal model of the transformer [107]. In [106] the simulation result for 30 nodes verified the feasibility of the proposed method with less than 1.0% night overloading and 2% morning peak overloading. The proposed model in [107] for half-yearly and annual performances showed a significant cost saving and demand reduction during congestion times through price adjustment. However, in case of non-adequate DR flexibility during congestion periods, more direct approaches of curtailment are required. In this regards, An MIP-based selection mechanism is presented in [108] to procure a synergy between direct and indirect control approaches for congestion management. The flexible demands are calculated through two capacity market programmes which were based on the amount of power that can be maintained at all times and that can be curtailed during network emergency situations.

A different real-time market price is introduced in [96] aiming to deplete the overloading issues through price-responsive HPs to local price discrimination in each consumer zone. In this respect, a price controller was deployed in each zone that can receive the centrally dispatched RTP in the market. If overloading occurs, a supplementary zone-price is added to the market price by the local controller. Therefore, consumers in the related zone are motivated to decrease their consumption, and thereby eliminate overload. Although the feasibility of combining such auxiliary services by small flexible units with a centralised control scheme was verified, several technical challenges and social questions were raised. For instance, customers having to pay for any local problem on the network could reduce their willingness to participate in the proposed pricing scheme.

#### 2.5.2.2 Voltage Violation Control

Intermittent and unpredictable DGs or load demands as well as contingencies in the DN, may usually cause voltage violation at some buses. Voltage instability in DN could lead to voltage collapse and consequently power blackouts. Thus, identifying the strengths and weakness of buses in the network is essential to improve the stability of the system. The effectiveness of DR in reducing voltage drops across the distribution feeders and boosting the voltage at the far end of the feeders have been demonstrated by many [139, 140, 135, 137]. Similar to local DR management, studies in the voltage instability issues at MV/LV level rely mainly on load shedding with incentive-based DR including DLC or EDR. Therefore, responsive loads have a pre-signed contracts for participating in load curtailment schemes when is required.

In order to design and implement an efficient DR control mechanism, it is essential to find out the optimal load shedding of the feeder. This gives rise to two challenges: the amount of load shedding and the effective location/s where DR should be applied. The common way to determine the optimum buses for load shedding is using voltage sensitivity analysis. This is a matrix of voltage sensitivity of all buses related to changes in the generation and load parameters (P and Q) on the other buses in the network. Several methods are used to derive the voltage sensitivity in MV/LV networks. These include:

- Voltage Deviation Index (VDI) [141, 142, 143, 144]
- Updated version of Jacobian matrix [145, 146]
- Direct approach dependent on the topology of the network [147, 148]
- Adjoint network model [149]
- Y-matrix model [150]
- Constant current model [151]
- Bus power flow model [136, 152]

Using information about the voltage sensitivity of buses in the network, two methodologies to shed the required amount of demand for mitigating voltage issues have been developed:

- A loop procedure was applied in which the load reduction starts from the weakest buses that have the largest voltage deviation magnitude from required voltage change. The procedure continues and stops when the value of required voltage change becomes lower or equal to zero [139, 140]. This method has been used where the total amount of required load shedding is not known.
- A Distributed Curtailment methodology which consisted of sharing the total quantity of load shedding among buses according to the magnitude of their voltage sensitivity [135, 137]. This method has been used where the total amount of required load shedding was already calculated [137]. On the other hand, optimisation techniques have been used in instances where the amount of load curtailment is unknown [135]. The problem was modelled as single or multiple objective functions, considering voltage as a constraint. The main aim was to find the minimum required load curtailment, e.g., [135], or maximum load capacity of each bus, e.g., [136].

#### 2.5.2.3 Active Distribution Network Management Framework

This section reviews the literature on modelling of ADNM framework when implementing DR services. The overall system model comprises a set of households interacting with a Load Service Entity (LSE), e.g., DSO. The aim is to present a distributed DR scheme that computes an optimal demand schedule. The difference between these proposed models with the ones presented in section 2.51.1 is that the level of DR control is at distribution level rather than local level. Moreover, the associated power flow and system operational constraints of the DN are considered in the DR model.

Participating households in DR schemes receive the control signal from LSE through HEMS. Then, they coordinate their appliances' operations in order to meet the required objective during a DR event. The objectives of the DR model are to manage the operating of household loads in order to:

- Maximise the social welfare
- Keep the overall network demand below a certain limit during peak hours
- Satisfy the appliance operational constraints, the power flow constraints, and the system operational constraints

A residential DR was formulated in [153, 154] as an ACOPF problem. A multi objective function for the DR scheme was proposed, to maximise the aggregated consumers demand and minimise power losses in the DN. The results demonstrated two effects of DR that can be applied when designing a DR programme; first, the location effect where the feeder is more sensitive to changes in demand at the buses located at the end of the feeder. The Second one is the rebound effect where a new peak can occur after the DR event ends if the parameters are not selected properly. A DLC scheme was applied in order to enable LSE to adjust consumption of residential customers.

In general, implementing DR in a wide-area network needs a control framework and structure that integrates different entities with distinctive attitudes and objectives, as illustrated previously. In this way, flexible demand from residential customers can ensure the network security and reliability while satisfying all DR players' goals. In this regards, three models have been presented by studies; multi-layer framework (Figure 2-9), hierarchical framework (Figure 2-8), and MAS framework (Figure 2-7). The first one consists of different layers where each entity in each layer has similar roles or attributes. For instance, in the proposed multi-layer framework in [119], the players participating directly in electricity markets are modelled in the first layer. In the second-layer, agents connect to one of the first-layer agents in order to take part in the markets. The hierarchical structure consists of different levels where the entities in each level communicate with their upper level [120]. The top level is the main DR controller, and in the lowest level, end users are allocated. This structure is also known as supervisor-employee model. In the MAS, each network entity is modelled as an agent with specific behaviour, attitudes and objectives [127]. Agents can communicate with each other in order to achieve their goals.

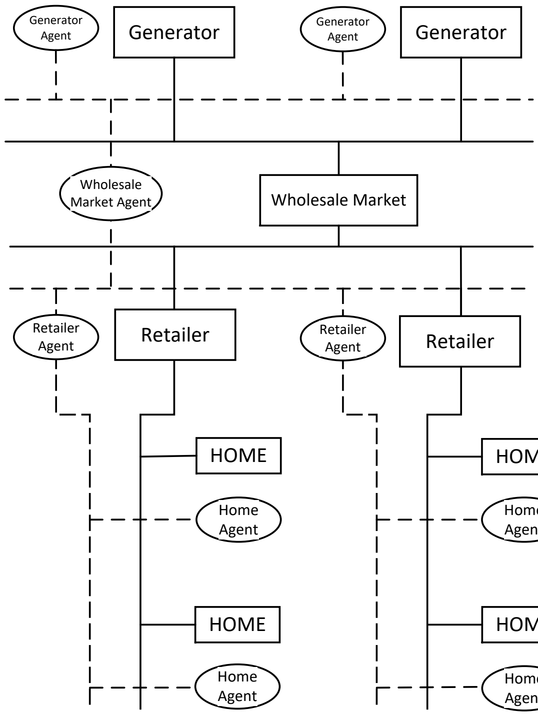



**Figure 2-9:** MAS framework proposed in [67]

## 2.6 Overview of GB Demand Response Innovation Pilots

Innovation projects refer to novel solutions as alternatives for costly upgrading of the current DN to economically benefit customers and the DNO [155]. This section provides a review of related innovation trials and a summary of the state of knowledge as applicable to residential DR in GB. The most recent projects relevant to this thesis are categorised and detailed in this section and a summary is provided in Table 2-2.

**Table 2-2:** Summary of major innovation pilots in GB network with the focus on DR

| Trial | Organisation | Location | Time Period | Category | Innovation | Scale | Solutions and Technologies | Communication Strategies | Investment | Key Lessons Learned |
|---|---|---|---|---|---|---|---|---|---|---|
| **Solent Achieving Value from Efficiency** | Scottish and Southern Electricity Networks (SSEN) | Solent | Ongoing | Education | Testing cost effectiveness of energy efficiency measurements and engagement | 4,600 homes | Financial incentive, Community energy coaches<br><br>Deploying LED lighting | Personalized data-driven messaging, one-by-one written contact, community engagement | £7 million | Consumers engaged better with local community than DNOs |
| **Energywise** | UK Power Networks | Tower Hamlets, East London | 2014 – 2017 | Education | Testing the effects of demand reduction techniques for fuel poor customers | 538 homes | ToU, incentives (vouchers, etc.)<br><br>Smart meters, smart energy monitor and devices, temperature monitoring equipment | Face-to-face communication, dedicated support line, community engagement, tailored engagement strategy and materials | £5.49 million | Successful engagement due to tailored approach |
| **Activating Community Engagement** | Northern Powergrid | County Durham | 2015 – 2017 | Incentives | Community engagement through online gaming to achieve demand reduction | - | Incentives based on demand reduction,<br><br>Smart plugs | Online game, Posters, flyers, educational programme, council website, community engagement | £1.1 million | • Complete understanding at a participant level is crucial<br>• Importance of providing adequate and not overwhelming information to participants |
| **Power Savers Challenge** | Electricity North West (ENWL) | Stockport | 2013 - 2015 | Incentives | Increasing capacity for renewable energy generation on the DN | 251 homes | Incentives based on the consumption of previous year<br><br>LED light bulbs, shower timers, Plug-in timers | Newsletter, online, events and advice, home display, community engagement | - | • Participants well supported and engaged<br>• Demand reduced |

| Trial | Organisation | Location | Time Period | Category | Innovation | Scale | Solutions and Technologies | Communication Strategies | Investment | Key Lessons Learned |
|---|---|---|---|---|---|---|---|---|---|---|
| **Community Energy Action** | Western Power Distribution (WPD) | 10 locations from central to south west England | 2012-2013 | Incentive | Assessing the feasibility of reducing peak demand by DSM in predictable and reliable | 834 homes | Cash incentives for each peak and overall consumption reductions targets for each community | Online, Newsletter, Leaflet, g, door knocking | - | Methodology was not successful and not recommended as a way to reduce demand |
| **Sola Bristol** | Western Power Distribution (WPD) | Bristol | 2011-2016 | Integrating low-carbon tech. | Assessing feasibility of integrating low-carbon tech. using new technologies and storage management | 61 homes | Sunshine tariff (ToU) PV, energy storage, DC circuits | Home display, community engagement, website | £2.8 million | • Understanding of customers'' use of energy to maximise and tune energy management • More than 60% customers engagement required for significant effect on DR |
| **My Electric Avenue** | Scottish and Southern Energy (SSE) | Across UK | 2013-2015 | Integrating low-carbon tech. | Directly control EVs to manage local LV network | - | Lease on EV at a reduced rate, free/minimal cost charging point installation, Esprit (innovative piece of technology for directly controlling EV charging) | Local community event and engagement, newsletter, social media | £9 million | • Need of intervention with increase in the penetration of EVs Forecast of around £2.2 billion savings by 2050 |
| **Customer Lead Network Revolution** | Northern Powergrid | North of England | 2010-2015 | ToU | Assess the impact of low carbon technologies including PVs, HPs and EVs and ToU for residential, industrial and commercial customers | 11,000 homes (2000 others) | ToU, Smart meters | Home display | £31 million | Reduce residential peak demand by 6.39% between 4pm-8pm |
| **Ireland Electricity Smart Metering Behaviour Trials** | Commission for Energy Regulation within the Republic of Ireland | Ireland | 2009-2010 | ToU | Investigate the potential of smart meters, ToU tariffs and DSM stimuli on load reduction/shifting | 5,028 homes | 5 ToU rates, bi-monthly billing with a demand reduction incentive | bi-monthly billing, monthly billing, bi-monthly billing with an electronic energy monitor | - | Households on average saved 2.5% on bills |

| Trial | Organisation | Location | Time Period | Category | • Innovation | Scale | Solutions and Technologies | Communication Strategies | Investment | Key Lessons Learned |
|---|---|---|---|---|---|---|---|---|---|---|
| **Energy Demand Research Project** | EDF, E.ON, Scottish Power and SSE | London and the southeast of England | 2007-2010 | ToU | • Trials by four energy suppliers<br>• Investigate the effect of supplying information on long term consumption | 60,000 homes | Financial incentives for consumption below target Smart meters, | Real time display, letters, website | £9.75 million | Results showed that overall there was no significant reduction in consumption |
| **Northern Ireland Powershift** | Northern Ireland Electricity. | Northern Ireland | Oct. 2003-Sept. 2004 | ToU | Evaluating the potential of shifting peak demand through ToU tariff | 200 homes | 3 ToU rates<br>Keypad meter with an IHD | | - | Annual bills decreased by 5.5% |
| **Low Carbon London** | EDF Energy, UK Power Network | London | 2010-2014 | dToU | Investigating the impact of dToU on demand-supply balancing and network constraint management | 5,533 | dToU,<br>Smart meters | Text messaging | £28 million | 8% reduction in demand |
| **Shetland Trial** | Scottish and Southern Electricity (SSE) | Shetland islands | 2013-2017 | ADNM | Evaluating the effectiveness of DSM on active network management | 234 homes | Battery and DSM enabled appliances, ADNM | Website, phone, home visit, local meeting | £21 million | • DSM with ADNM platform can be an alternative for future DN<br>• Learning and improving the relationship with customers in order to change their consumption behaviour |
| **Customer Load Active System Services** | Electricity North West | Clusters across GB | 2014-2016 | ADNM | Evaluating the application of innovative voltage management technologies to provide DR services | 60 primary substations serving approximately 485,000<br>domestic and industrial and commercial customers | Cash incentives<br>Smart voltage control, advanced active network management system | Leaflet, website | £8,098k | ADNM with DR can successfully provide voltage and frequency support without affecting power quality of network devices |
| **Accelerating Renewable Connections (ARC)** | SP Energy Network | Scottish borders and East Lothian area | 2012-2016 | ADNM | Combination of ADNM scheme and community engagement to manage the generation-supply by generators and locally-produced energy | Covers geographical area of 2700km$^2$ | PV, wind turbines, modification of network equipment<br>Incentive on connections engagements | Workshop with local community, online tools, | £8.46 million | Reduced infrastructure;<br>Lower cost over traditional solution<br>Save energy cost for local communities |

### 2.6.1 Global Demand Response

The trials based on global DR aim to introduce different DR pricing schemes to financially incentivise customers to lower/shift their peak electricity usage. So far in GB, ToU and dToU have been implemented and their effectiveness assessed through various pilots [156].

***Time-of-Use Tariffs:*** Key findings of the trials show that ToU tariffs can produce a shift of domestic demand from peak to non-peak times. However, results are highly varied among trials. The outcomes indicated a greater effect on peak demand than on overall energy consumption. Table 2-2 shows the variation in peak reductions across ToU trials from five main projects implemented in UK and Ireland. In some projects different ToU tariffs were introduced for better comparison. The *Energy Demand Research Project* [157] introduced two ToU tariffs by EdF and SSE. EdF trialled a daily ToU tariff whereas SSE's one was seasonal as well. The results show an approximate 4% and 8% peak demand reduction in weekday and weekends respectively for 1936 participants [158]. Five different ToU tariffs, based on the time of day and weekdays/weekend, in the *Ireland Electricity Smart Metering Trials* [159] showed 2.5-9% demand reduction from 5,000 households [158]. Although not geographically in GB, the data from the Irish pilot is considered relevant to this study due to the characteristically comparable climate. The dataset from this particular pilot will form the basis of the analytical investigation for in this thesis. This is explained in more detail in chapter 4. In another pilot, *Customer Lead Network Revolution* [160], a 6% peak consumption reduction was shown from 600 households [161]. The *Energy Control for Household Optimisation* [162] trial for controlling shiftable appliances showed that the peak load can be reduced by 75W per household. In Sunshine Tariff [163] a 13% daily demand reduction was achieved for customers with automated control technology. However, those without such technologies could only rely on behaviour change to shift their loads resulting in significantly less demand reduction. In addition, the outcome of these trials emphasises that price incentive alone is not sufficient and that education needs to accompany the introduction of ToU. The current focus of ToU tariffs are primarily on energy engagement and awareness.

***Dynamic Time-of-Use Tariffs:*** The UK's first dToU pricing initiative was implemented under the *Low Carbon London* (LCL) [164] project in the London area in 2013. The tariff aimed to investigate the potential of DR in different trial events set by suppliers or DNOs. Suppliers defined a Supply-Following (SF) event aiming to quantify the potential of dToU DR to aid in energy balancing. A Constraint Management (CM) event was designed by the

DNO to relieve the network constraints. 1,119 households received dToU tariffs which subjected them to CM and SF price events. The average consumption during high price periods was reduced by up to 9%, but increased during low price periods by 14%. Moreover, bill saving was possible for 85% of households on the dToU tariff with 4.9% mean reduction in the bill.

### 2.6.2 Community Engagement

The aim of these schemes is to explore how local communities can positively engage in DR programmes from both the DNO's and the consumers' point of view. DNOs collaborate with customers to reduce demand locally, maximise the local usage of available capacity and thus defer the network reinforcement investment. Various trials [165] have been implemented by DNOs in order to alter the customers' behaviour, reduce demand and avoid peaks by shifting energy usage to non-peak time. The recent innovation trials in local communities investigated in this section have been classified according to their focus and explained.

***Integrating Low-Carbon Technologies:*** The aim of this category is to assess the effectiveness of integrating new low-carbon technologies into the DN. For instance, in the *Sola Bristol project* [166] , households within the trial were equipped with PV panels, electricity storage units and internal DC circuits and operated under ToU tariffs. The result demonstrated the benefits of storage and ToU tariffs. However, higher density of DG is needed to make the project cost-effective. In the mentioned trial, PV should be installed for around 60% of customers to observe significant effect on demand side response. Moreover, beside monetary incentive, consumers' awareness of energy schemes is key to maximising engagement. Another trial, *My Electric Avenue* [167] explored the impact of charging clusters of EVs on local electricity networks during peak hours. This is the first trial that directly controls charging of domestic EVs to keep the demand within acceptable limit. The outcomes from analysing various kinds of LV networks across Britain showed that with penetration of 40%-70% of EVs, 32% of LV feeders will require intervention. That was estimated based on 3.5 kW charging of EVs taking into account that the capacity of a typical susceptible network is less than 1.5 kW per customer.

***Education:*** The education and awareness of consumers in low-reduction schemes are the main remit of the trials in this category. Consumers are updated with the progress of the trial and their benefits in order to motivate them and keep their interests. As an example, *Energywise* [168] project was designed with the focus on fuel poor customers to enable them to participate in energy efficiency and DSR opportunities. A face-to-face communication and support was applied to selected customers where 82% of sign-ups achieved. The main reasons for taking part to this project were energy cost reduction, better visibility of energy use and offer of free energy devices. Another such project, the *Solent Achieving Value from Efficiency* [169], sought to assess the cost effectiveness of energy efficiency measures and engagement in order to reduce constraints in the network. In this trial energy coaches work with local communities to increase awareness of sustainability and responsible energy usage with a view to encourage people towards more successful and sustained behaviour change. This is achieved by working with local drivers including community engagement events such as refurbishing local community facilities

***Incentives:*** Providing more attraction for consumers in order to improve their active engagement through incentives is the aim of these trails. In this attempt, the *Activating Community Engagement* [170] trial designed and implemented an online game where participants merited credits for reducing their demand during specific time periods. The winning community group and individual participants were awarded cash prize based on their earned points. In another community engagement programme, the *Power Savers Challenge* [171], incentives were offered to consumers who lessened their consumption compared to the baseload of the previous year. A total of 201MW in demand reduction, from 251 households who took part in the challenge, was achieved. 7 of the 10 participating areas met their reduction targets leading to an average reduction of 4% as compared to 2013. The *Community Energy Action* [172] pilot deployed a rewarding scheme for 10 communities to keep their demand under the transformer overloading rate. The incentives were allocated according to the deferment of reinforcement costs at the substation for reducing peak demand as well as overall consumption. The qualitative analysis indicated that financial community incentives alone, cannot guarantee a high level of response due to the variability and difficulty in predicting community demands.

### 2.6.3 Active Network Management

There are a few pilots that implemented the ADNM with DR services from residential loads. This section summarises two major trials aimed at demonstrating the effectiveness of DR in ADNM platforms to manage the network constraints and increase the DG penetration. The *Customer Load Active System Services* [173] project was successfully implemented and delivered important and valuable understanding of the voltage/demand relationship for all stakeholders. The trial demonstrated the application of innovative voltage management technologies to provide DR. This was done with smart voltage controllers in major substations linked to the central control system and ADNM. Customers were not affected by the voltage fluctuations from the application of the ADNM as these changes are a normal daily occurrence. Up to 3.3GW of DR potential to provide voltage/frequency support was achieved which is equivalent to a combined total reactive power of 2GVAr and two gas turbine power plants. In another project, *the Shetland Trial* [174], old inefficient storage and water heaters was replaced with modern smart storage heaters to provide DR services for 234 households. These appliances were selected as they can provide the greatest potential of demand shifting. The ADNM receives the daily energy requirements from all devices for the next day and determines the schedule before sending instructions to each device. The heating appliances in each household (e.g., set points of the space heaters and water tanks) follow the instructions of the ADNM schedule. The ADNM platform demonstrated the potential for providing a successful flexible framework for future changes to the network. Another trial, the *Accelerating Renewable Connections* [175] combined both ADNM scheme and local community engagement to manage the generation-supply by generators and locally-produced energy sources respectively. This project enabled connection of 49.5MW and 2.2MW from wind farm and PV panels respectively onto local homes. This could save households around £1.9 million in energy costs over the lifetime of the systems.

## 2.7 Attributes of demand responsiveness

The level of consumers' responses to incentive-based DR programmes depends on the level of maximum participation. In priced-based DR, this relates to price elasticity of demands which indicate the load responsiveness in price variations. Therefore, this section aims to discuss the required tools and considerations that enable SOs to assess and improve the outputs of DR strategies during the planning phase. Additionally, the barriers, limits and challenges in terms on implementing residential DR schemes are discussed.

### 2.7.1 Price Elasticity of Demand (PED)

Recently, price-based DR programmes have become the focus of interest due to greater flexibility and potential of delivering responsiveness demand. Customers can benefit from lower prices at non-peak time or pay the actual fluctuation market rate. However, the financials gains are dependent on customer distinctive characteristics. Directing to significant

DR participation, energy providers need to characterise and assess the elasticity of customer response to changes in the electricity prices in order to define more effective tariffs.

Many studies have investigated the effects of RTP tariffs [176, 177, 178, 179] and TOU tariffs [180, 181, 182] on residential demand curves and their profitability. The principal aim was centred on addressing the fundamental structures for designing more effective tariffs towards DR schemes implementation. Results show that among the different time-based tariffs, dynamic pricing, e.g., RTP, has the potential to provide the most benefits to all DR stakeholders. On the other hand, some researchers evaluated the effects of switching from static to dynamic tariffs [183, 184, 185, 186, 187]. For instance, the impact of ToU tariffs compared to flat rates studied in [187] for a group of 500 Swedish households showed reductions of 11.1% and 14.2% in the first two years of the trial with higher value being in winter. Moreover, shiftable demand from peak to non-peak periods was assessed to be 0.8% and 1.2% with higher level in summer months.

The introduction of a matrix of price elasticity becomes imperative for the modelling of the effects of price variations on customers' responses. This matrix analyses and reflects the consumer characteristics in term of their attitudes towards DR participation and potential of flexible loads. In fact, this can also be employed in electricity price adjustment procedure [188]. Many studies have demonstrated the applications and benefits of applying price elasticity including market power of generation company [189], electricity market structure [190] and modelling RTP [191, 192]. Using price elasticity of demand was shown to be helpful in determining the optimal sharing of the DR remuneration to the aggregated consumers [193].

The correlation between price and demand of households has been examined according to historical and survey data by several approaches [123][128-129]. Unlike businesses and light industries, energy usage followed less heterogeneous patterns in residential sectors. Hence, these analyses are implemented across different population groups due to the intermittent nature of residential demands. A meta-analysis [194] of empirical studies in the literature calculated the price elasticity of demand of energy which showed an average of 0.126, and of -0.365 in short term and long-term respectively. Similarly, [195] averaged the self-elasticities for ToU tariffs to −0.003 to −2.57 for off-peak hours and −0.002 to −1.41 for peak hours. Cross elasticities also varied from 0.003 to 1.57 across different studies. Spees and Lave

[196] reported those elasticities under a RTP regime to be higher than those under ToU or CPP regimes.

### 2.7.2 Potential Flexibility of Demand

The electricity consumption per households has been raised by 2.1% in 2016 compared to previous year [197]. Moreover, the number of total average number of appliances in each household has increased from 2 in 1970 to 13 appliances in 2016. According to a report from the DECC, 18% of UK's domestic electricity consumption was in wet appliances in 2012 [198] which is forecasted to increase by 25% by 2030 [199]. However, the granularity of flexible loads differs between load categories. Consumer-independent appliances, e.g. fridges and washing machines, can be more flexible without loss of utility to the consumer [200]. The annual electricity consumption by wet appliances was 15,073 GWh, including 4582 GWh Washing Machine (WM), 2431 GWh Washer Dryer (WD), 3338 GWh DW and 4722 GWh Tumble Dryer (TD). Moreover, an increment from 15,073 GWh in 2012 to 22,938 GW h in 2030, is estimated in wet appliances consumption as shown in Figure 2.11.

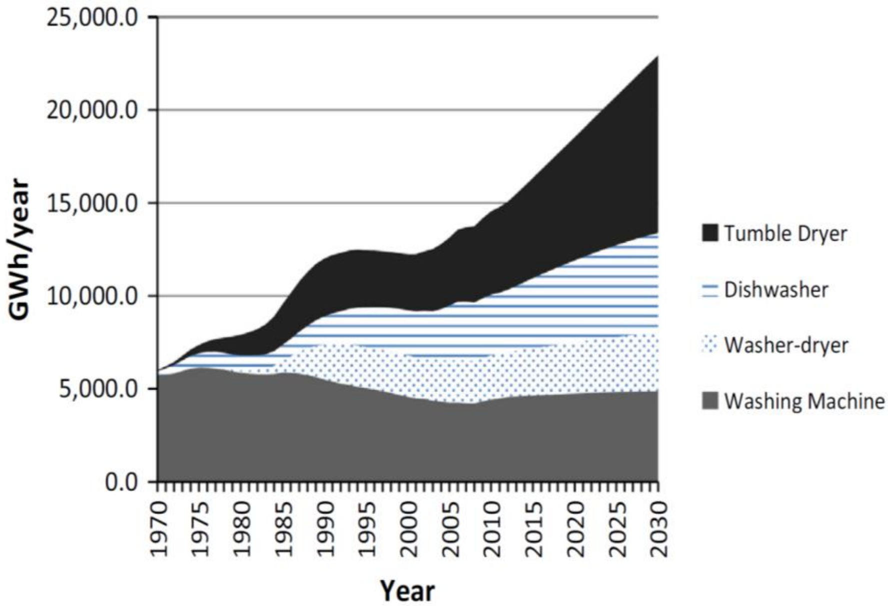
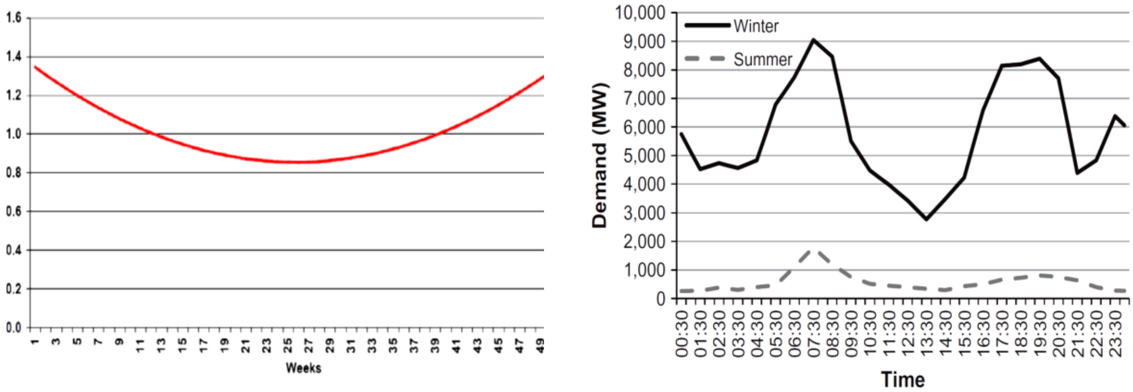



**Figure 2-10:** Annual domestic electricity demand by wet appliances 1970–2030 [199]

The demand of wet appliance electricity is subject to both weather condition and time of the day. For instance, considering seasonal variation, winter peak and summer low consumption is approximately 1.35 and 0.85 of the annual average respectively [201]. In terms of day-variation, Figure 2.11 reflects links between wet appliance load profiles in a typical day. The




(a) (b)

**Figure 2-11**: Wet appliances–seasonality effect (a) [201] and Wet appliance daily load profile in winter and summer 2030 (b) [199]

lowest usage is between 00:00 and 07:30 which is indicative of the sleep patterns and distinctive characteristics of household occupants.

The above statistics demonstrate the relatively high potential of deferrable loads that can be considered as responsive to DR programmes. Generally, the probability of residential consumption profile under DR schemes depends on the appliance usage and prosumers' attitude. Therefore, estimating the customers load profiles as well as their local engagement in DR schemes is essential for its success.

### 2.7.3 Estimating and Modelling Electricity Demand Profile

Determining the domestic DR potential from pilot data have been investigated widely in the literature. In implementing DR in macro scale, a complexity would arise due to the high level of uncertainty about consumption behaviours of distinctive households in offering the flexibility. Customer consumption patterns from the appliance level can be grouped using clustering techniques. Clusters can be considered as a representation of the whole population. In this way, each participant is attributed to one or more clusters. The time-based flexibility of customers within their cluster is then calculated and the results extrapolated to represent the region or nation. The aims of the models presented in the literature are to provide guidelines for the available DR potential [202, 203, 199] or to present a generative model of customer flexibility behaviour [204, 205]. The latter can potentially eliminate the need for time-consuming surveys as it can generate synthetic data from the available dataset, thus providing a more comprehensive and realistic analysis.

The potential of active demand reduction of wet appliances has been estimated in [202] through clustering 1693 Flemish households' electricity demand. Expectation maximisation clustering technique was applied to segment the customers according to their magnitude of appliances usage over time. The estimation also incorporated the willingness of customers to participate in DR programmes from a home-survey. Moreover, in order to overcome the insufficient available data, the clustering algorithm was updated to allow data upscaling. The potential for active demand reduction was estimated to be 4% of the total residential power demand, assuming that 29% of the households took part. However, because of lack of sufficient information about delay durations from the pilot, only DR in terms of load reduction rather than the rebound from shifting appliances was considered.

Using similar pilot data from and resulting clusters [202], the probability density of both smart start configuration of five deferrable appliance, including washing machine, tumble dryer, dish washer, hot water buffer and EV, and the length of the flexibility window in a typical day were calculated [204] for each cluster. In fact, this can determine the flexibility potential of shiftable appliances by estimating their maximum duration, time window of postponing/shifting while maintaining the comfort requirements of the user. The analysis shows that, using smart wet appliances, an average maximum increase of 430W and maximum decrease of 65W per household can be realised at midnight and evening respectively. Moreover, the flexibility potential of wet appliances was found to depend significantly on the time and type of the day. The highest potential occurred during evening and night-time hours, especially for weekends. The flexibility potential specifically was done on an aggregated level rather than individual household. A more realistic analysis of residential flexibility potential needs to take into account both the appliance load patterns and customers' unpredictability of habits. Two systematic methodologies were introduced [205] to model the individual customer behaviour. In the first one, the clustering inputs were the flexibility features of appliances including deadline, the latest allowed start time of the appliance. Then, probability distributions were employed to model the corresponding configuration times for each deadline cluster. In the second model, both steps from the first proposed model, were estimated in a single step. The parametric representation of customers can be utilised for synthetic data generation.

### 2.7.4 Challenges and Barriers

Implementing DR in residential areas can encounter some difficulties and restrictions. As a result, DR programs have not been implemented widely for domestic sectors. This might be due to these challenges that can be categorised as financial, social and technical.

***Initial Infrastructures:*** As discussed previously, activating DR for domestic consumers requires installing advanced technologies such as smart meters, in-home displays and HEMS. Apart from the costly investment of these devices, the important issue of whether it should be the consumer's, the retailer's, the aggregator's, or the DSO's responsibility for these initial installations, arises [206]. Authors in [207] has called this concern as an incentive-problem and concluded that costs should be split between customers and the enabling actor/s due to the common benefits from flexible demand. Also managing the big data from the increasing amount, speed and types of information produced by the network devices adds another level of complexity to this challenge.

***Engagement of Customers***: Encouraging more customers to get involved in demand reduction schemes is vital. One of the main challenges is the lack of sufficient knowledge about DR benefits and using advanced home control technologies. Even with a high willingness to participate in DR, customers still face some challenges. It is not always possible for residential prosumers to manage their electricity all day. Users can decide about changing their consumption behaviour based on the information, energy price and energy consumption, obtained from their home display systems. However, providing smart DR control via HEMS can solve this problem by rendering the DR completely automated while still considering a base level of comfort and convenience. Also, Incentives for domestic households to participate in DR programs are quite minor due to small loads existing in each household.

***Technical Issues:*** Due to the intermittent and less-predictable nature of residential demand, the exact knowledge of the DR becomes more complicated. The uncertainty in occupant behaviour is also related to factors such as social events and weather conditions [208]. Therefore a means of load-weather forecasting tools needs be developed and this could also serve as a tool for aggregators to provide a more effective planning of their actions [209]. Another obstacle relates to the DR strategy in how to coordinate the aggregated demand to mitigate peak rebounds. This can risk the reliability of the network especially in situations where more customers are willing to shift their demand in response to the higher electricity price [52].

## 2.8 Summary

This chapter provides a comprehensive literature on DR activation tools, techniques and strategies with the focus on residential level. Background concepts are described on price-based and incentive-based DR programmes together with the key players within the active distribution network. DR control schemes are classified in terms of consumer and network level. These are further split into another two categories based on the control strategy. At consumer level, discrete and aggregated options are considered where the concentration of DR design is on single or multiple households respectively. The DR control mechanism can be implemented in LV, local area, and MV feeder, wide area. A summary of classification of research papers investigating residential DR at network level is shown in Table 2-3. The considered constraints rely on the fact that voltage violation occurrence is most likely at LV feeders whereas the grid congestion is more common at MV level.

**Table 2-3:** Classification of litreature in wide area network DR contrlloers based on constrints in different level

| Constraint / Network Level | Voltage | Transformer Overloading | Congestion | Unified |
|---|---|---|---|---|
| **LV** | [127] [126] [128] [129] [130] [133] [138] | [103] [104] [105] [132] [131] | - | [97] [126] [134] |
| **MV** | [135] [136] [137] [139] [140] | - | [106] [107] [108] [96] | - |

Relevant recent DR pilots in the innovative transformation of DNOs to DSOs in GB are reviewed. A significantly increasing trend towards actively involving local communities in the demand-supply balance schemes has indicated significant energy reductions. Finally, the challenges and obstacles in DR implementation are explored from financial, social and technical perspectives. According to the results achieved by both literature and pilots, it can be concluded that DR can provide the most cost-effective and reliable alternative solution for flattening the demand curve under system stress conditions.

# Chapter 3 Proposed MAS Framework

## 3.1 Introduction

Recently, MAS has been applied in power systems in order to provide a decentralised and dynamic framework to undertake control and coordination of the network. A MAS consist of multiple autonomous and distributed intelligent nodes called agents. The system environment can be grouped into domains called regions that usually model a physical local area [210]. A dynamic set of heterogeneous agents resides in each region in the physical network and are distributed over the system. The agents, e.g., physical devices, players and decision makers, interact with each other cooperatively to achieve the overall system target. MAS usually deal with complex and conflicting objectives which cannot be solved by sole agents. To obtain the system objective, the tasks are split into several subtasks and shared among all agents. These tasks can be executed either synchronously or asynchronously. However, each agent can also work as an individual entity to meet its own goals while communicating, negotiating and collaborating with other agents in the system environment.

The overview of the structure and methodology of this thesis is shown in Figure 3-1 and Figure 3-2 respectively. The methodology is detailed in this chapter and the implantation is presented in the next two charters for all three objectives. The development of proposed MAS framework, if adopted by DNOs, can be an important tool to support the transition to the DSO model. Hence, the platform considered the future of DNOs where the term DSO is used in the proposed model as a replacement of DNOs. Furthermore, it can be used by aggregators or energy suppliers in order to investigate and model the behaviour of the system and consumers. This chapter details the proposed MAS framework implemented in this thesis with the focus on the cyber layer which is mentioned in chapter 1. This includes the creation of individual agents, communication procedures and data flows among agents. Different MAS structures for each objective and various case studies are provided. In addition, for each agent, the aim, tasks, methodologies and the overall system goal are explained in details.

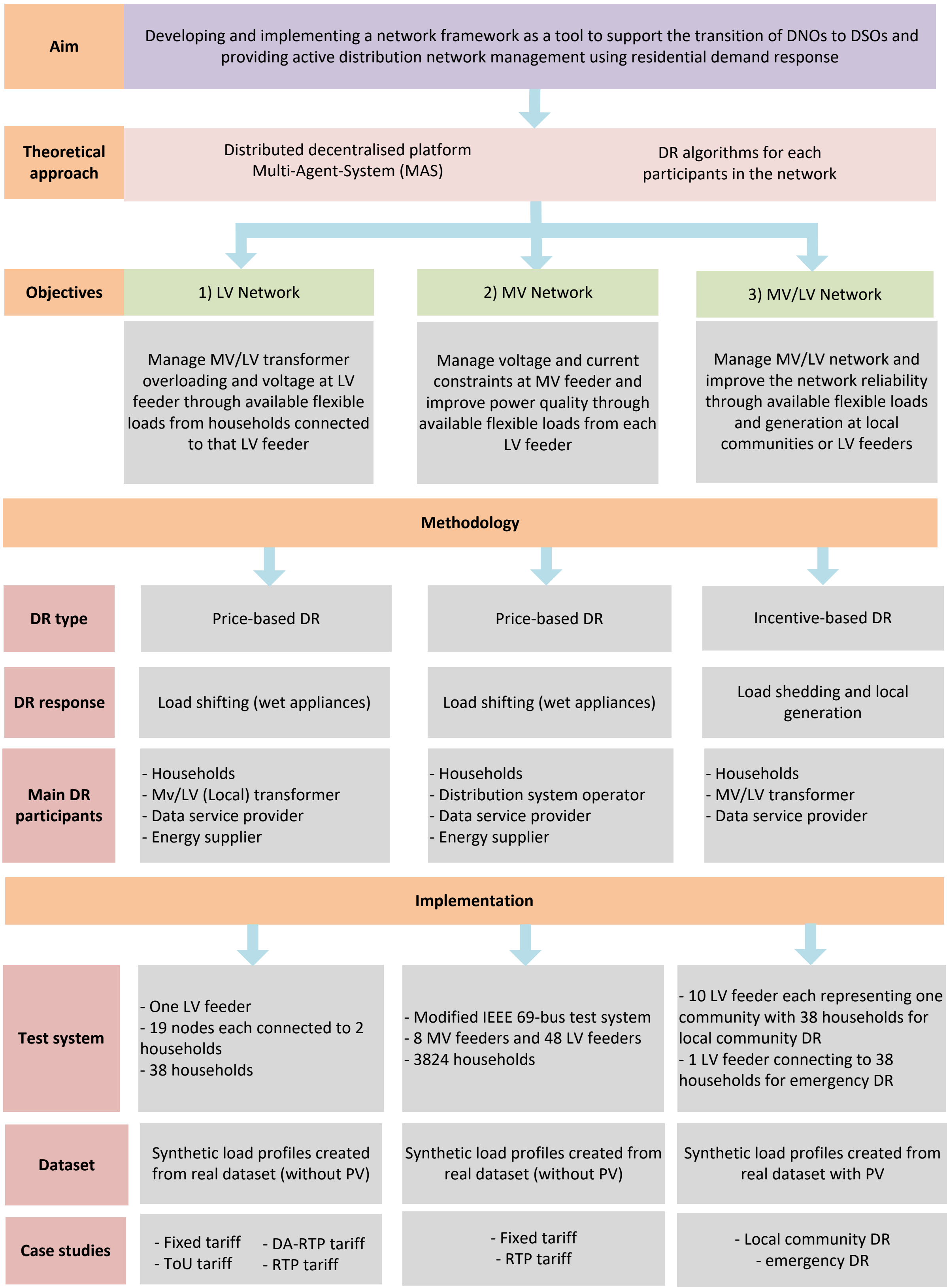



**Figure 3-1:** Overview of the research structure

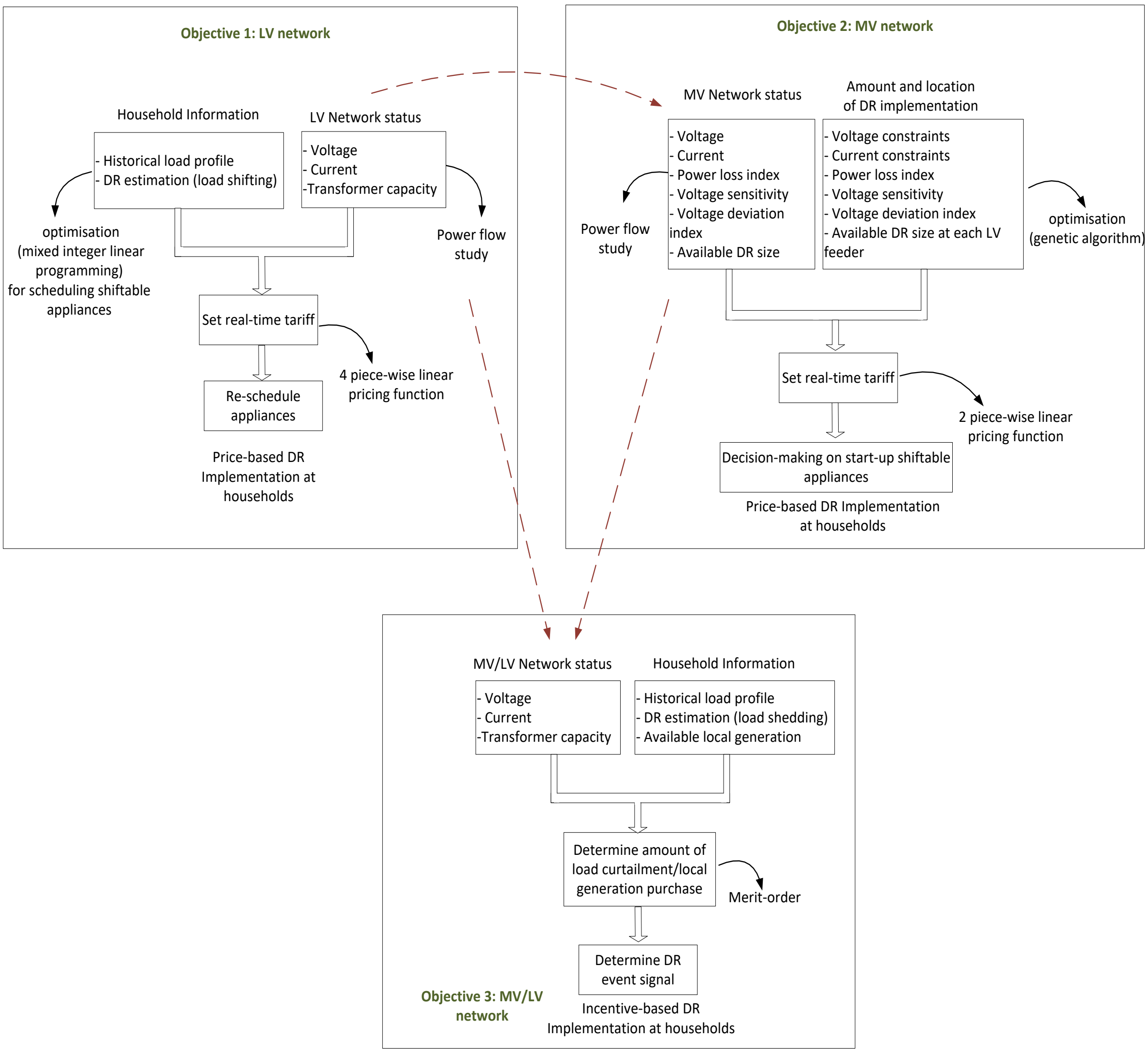



**Figure 3-2:** Overview of the research methodology

## 3.2 Model Description

### 3.2.1 Framework

The general proposed MAS Framework for implementing an ADNM through residential DR is shown in Figure 3-3. The platform comprises two different layers: physical and cyber. Physical layer is the DN in which each entity is connected to its corresponding agents in cyber layer. The conceptual communication flows and interactions among different agents are provided. Four main agents defined in the framework are DR Provider Agent (DRPA), Supplier Agent (SA), Local Transformer Agent (LTA) and Home Agent (HA).

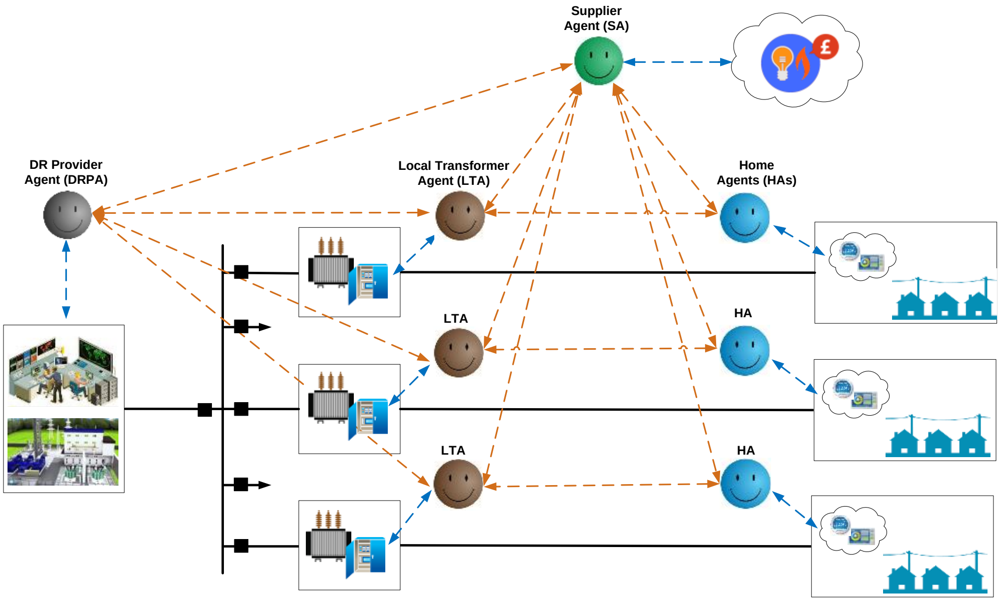



**Figure 3-3:** Proposed MAS framework and conceptual communication flows. The solid line represents physical layer/power line and the dashed line refers to cyber line/agents

***Supplier Agent (SA ):*** The electricity retailer is modelled as SA which is responsible for setting the tariffs and incentives aiming towards DR fulfilment. The pricing schemes are designed by the feedback received from LTA or DRPA regarding network status. Prices are then delivered to other agents for planning their future DR strategies in various time bases according to the DR type, e.g., day/months ahead or real-time.

***Home Agent (HA):*** This agent resides at each household which is modelled as a smart home that incorporates smart meter, HEMS and controllable appliances. HAs can take an active role to participate in DR schemes. This can be done by changing its power consumption behaviour through collaboration with its related HEMS to meet the network goal. The actions and interactions of HAs are triggered after receiving prices from the SA (price-based DR) or receiving a DR event signal from their associated LTA (incentive-based DR).

***Local Transformer Agent (LTA)*:**

Each LV feeder is controlled by a local distribution transformer which is modelled as a LTA. This agent connects to a number of HAs as:

$$HA_{lv} = \{HA_{lv,1}, HA_{lv,2}, \dots, HA_{lv,H}\}, \ \ lv \ \in \qquad (3.1)$$

where, $H$ denotes the number of corresponding HAs connected to $lv^{th}$ LTA. The main task of LTAs is to monitor and assess the operating state of distribution transformers. LTAs are connected to a DRPA and SA in order to exchange information. In price-based DR, the LTA relays their information to a SA or DRPA for activating DR services if needed. On the other hand, in incentive-based DR, in case of emergency conditions, e.g., transformer overloading or receiving DR signal from DRPA, LTAs work with their associated HAs to mitigate the network constraints.

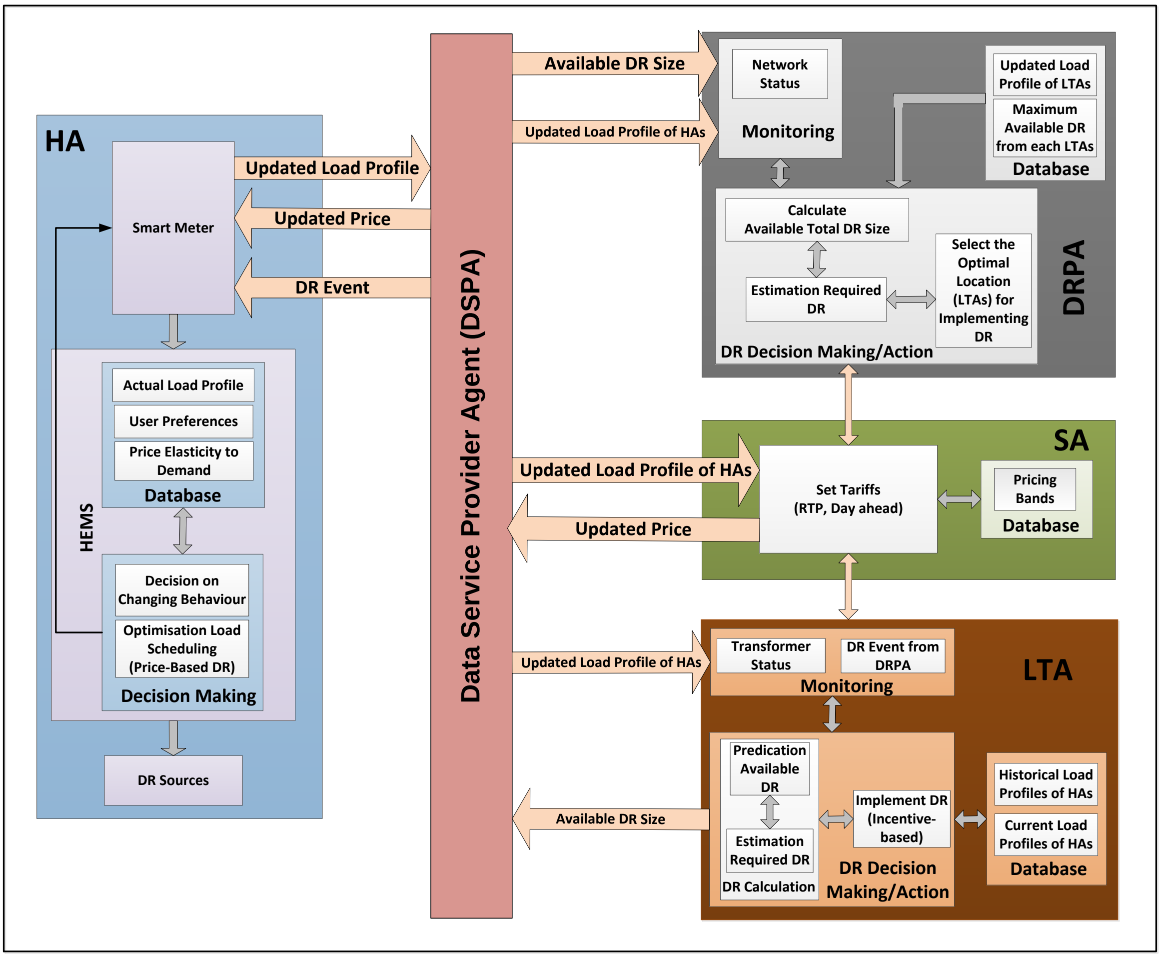
***Demand Response Provider Agent (DRPA):*** DSO which comprises of several lateral LV feeders is modelled as DRPA. Hence, DRPA is connected to several LTAs as:

$$\mathrm{LTA} = \{\mathrm{LTA}_1, \mathrm{LTA}_2, \dots, \mathrm{LTA}_{\mathrm{LV}}\} \qquad (3.2)$$

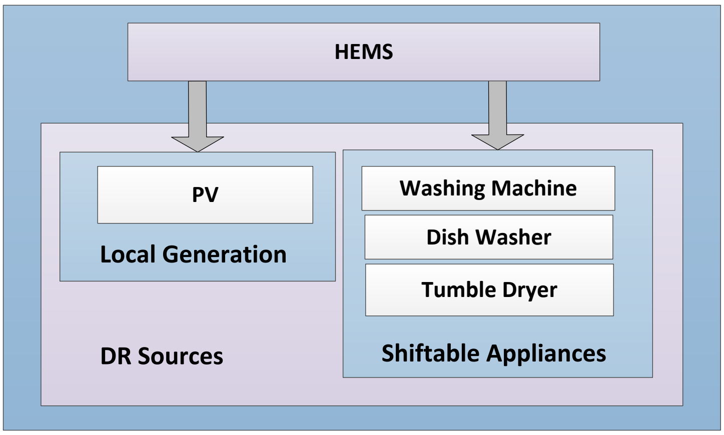
Where, $LV$ indicates the number of LV feeders within the network. The main role of DRPA is to monitor the overall network status and constraints (power balance, network operating limit) in order to provide the required information for SAs and LTAs to implement DR. In other terms, DRPA does not take any direct action in controlling the DN.

### 3.2.2 Architecture

The overall architecture of the MAS along with data exchange and flows among agents within the network is depicted in Figure 3-5. The DSPA is an additional agent in the proposed framework which gives a better representation of GB power system. In the latter, smart meters are interconnected to DSOs, suppliers and authorised service entities of the network through DCC [211]. This network interface entity is responsible for data communication establishment and management. In this respect, DCC is modelled as a DSPA in order to enable data exchange between the HAs and the LTAs, SA and DRPA. The functionality of DSPA is solely that of an interface between HAs and other agents. In this respect, DSPA is not studied in this chapter. However, it is considered in the description of data flow and overall DR algorithm.




(a)




(b)

**Figure 3-4:** MAS architecture and overall scope of data communications among agents (a) and DR sources in home agents (b)

Connecting a new agent with specific attributes to the proposed system is feasible due to the configurability feature of the proposed platform. In addition, the agent's goals, tasks and accessibility to other agent's information can be modified during system operation.

The architecture presented in this section provides a general view of the decision-making and tasks for each agent according to the received information as well as its database. This has been constructed with a view to implementing price-based DR. The assumptions that have been considered for all three case studies in the proposed model are:

- All consumers are equipped with smart meters and HEMS in order to enable them to activate and perform DR schemes.
- The model of all shiftable appliances for all households is the same.
- Consumers' participation in price-based DR is based on load shifting, through wet appliances, whereas in incentive-based DR, the consumers' responsiveness demand is considered as load shedding.
- Home agents only communicate with local transformer agents or supplier agent through data service provider agent.
- The network utilises the same DSO and electricity supplier having different tariffs. Nevertheless, as discussed previously, the proposed framework and control algorithm can be extended in order to include various DRPAs and SAs in the network.
- The time $T$ of updating data is discretised into a set of timeslots in sequence $t = \{1, \dots, T\}$, with a finite time horizon. Agents can only take actions within $t \geq 1$ which shows the time horizon of the environment for the simulation. In this thesis, T = 48 due to half-hour meter reading resolution.

As discussed in chapter one, three main objectives are defined for this thesis. The methodologies proposed for each objective are discussed separately in the next sections. The general MAS framework is the same for all objectives but the structures are modified as appropriate.

## 3.3 Distribution Transformer Management (Objective 1)

The focus of DR mechanism in this objective is on LV feeder aiming to manage the distribution transformer overloading. Four price-based DR namely fixed, ToU, DA-RTP and RTP were considered. The fixed tariff is considered as a benchmark. The nature of ToU and day-ahead RTP are similar since they both are pre-known prices. Therefore, only DA-RTP is discussed in the methodology description. The overall MAS structure is presented in Figure 3-5 where the red dash line shows the area of the network where DR is implemented. The multi-layer structure has been modelled for the MAS platform which consists of four layers: market, MV feeder, LV feeder and end-user layer. Allocated agents to these layers are SA, DRPA, LTAs and HAs respectively. In other words, each agent or set of homogeneous agents is located in one particular layer which exchanges their data with upper and/or lower layer. SA is modelled differently as it is an independent entity in the DN and communicates with all other agents. It is assumed that the MV network is run under normal condition and hence no DR event is occurs from DRPA. This scenario is studied for the other two objectives in 3.3.2 and 3.3.3. Hence, although DRPA can access the data from SA or LTAs, it is not studied in this section. DR algorithms and agents' tasks have been designed at the distribution transformer feeder and the home level.

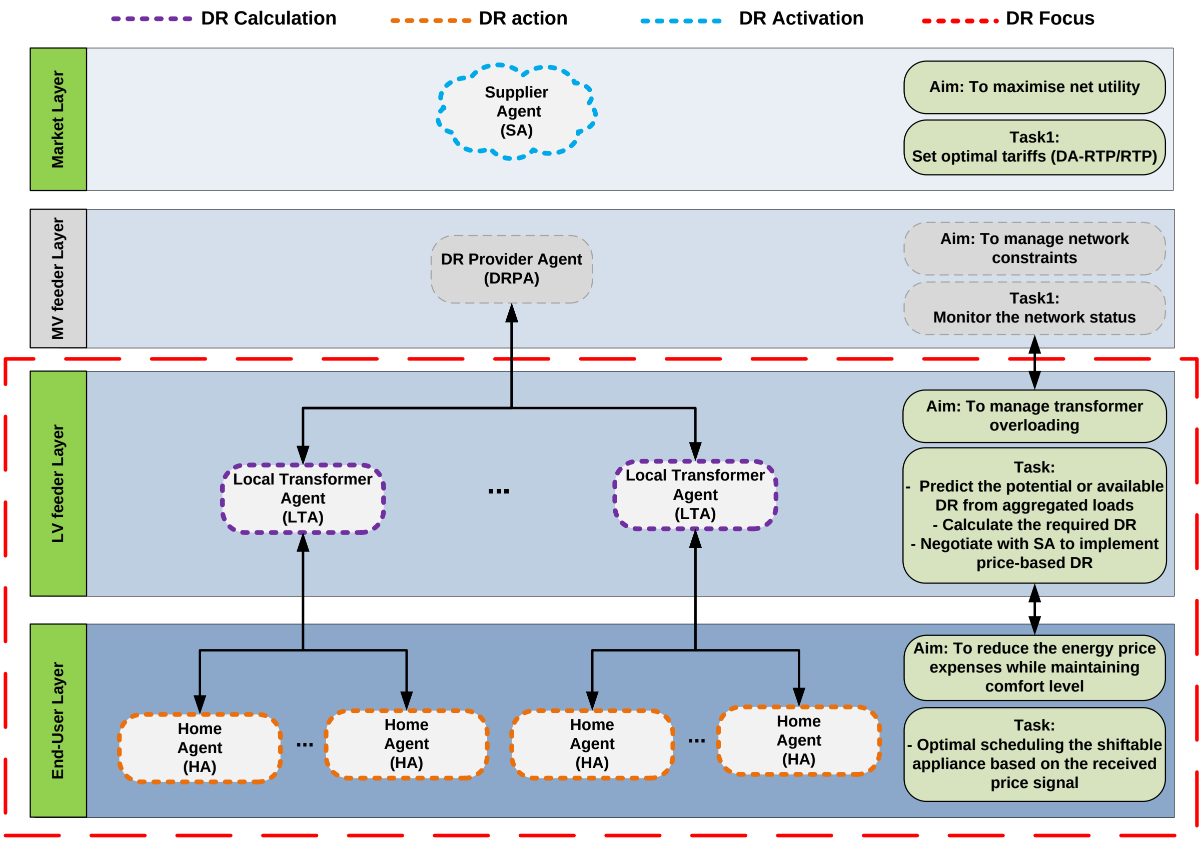



**Figure 3-5:** MAS structure for managing LV networks through price-based DR

## 3.3.1 Home Agent

HA represents a smart house where the home appliances operation are controlled and coordinated automatically. This is done by HEMS based on the price signal received via the smart meter.

- ***Home Appliances***

Each household has a set of controllable and non-controllable appliances where the flexible demands provided by the former is expressed as.

$$AP_{lv,h} = \{ap_{lv,h,1}, ap_{lv,h,2}, \dots, ap_{lv,h,j}\} \tag{3.3}$$

where $j$ is the total number of controllable appliances for $h^{th}$ HA connected to $lv^{th}$ LTA in the network. For simplicity, $lv$ is not assigned in the mathematical derivations for the rest of this thesis.

The total loads $(l_{h,t})$ in each household, defined as a set of aggregated individual loads from all appliances over specific time period, is expressed as:

$$l_{h,t} = \sum_t l_{h,t}^{ap} = \sum_t l_{h,t}^{sh} + \sum_t l_{h,t}^{f} \quad \forall \; h \in H, t \in T, \{ap, sh, f\} \in AP \tag{3.4}$$

Where $l_{h,t}^{sh}$ and $l_{h,t}^{f}$ are the load consumption from shiftable and other loads, considered as background demand of household $h$ at timeslot $t$. Three major wet appliances that can be shifted during a typical day are considered in this research and these are WM, DW and TD. Therefore, total load, $l_{h,t}$ in each household is:

$$l_{h,t}^{sh} = l_t^{WM} + l_t^{DW} + l_t^{TD} \tag{3.5}$$

$l_{h,t}^{WM}$, $l_{h,t}^{DW}$ and $l_{h,t}^{TD}$ are load consumption of WM, DW and TD respectively for $h^{th}$ household at timeslot $t$. The appliances characteristics and modelling are explained in details in the next chapter.

- ***Home Energy Management System***

The main aim of each HEMS is to provide an intelligent management system for scheduling the operation of shiftable appliances for a day period.

***Objective function:*** The objective of HEMS is to minimise the energy expenses and maintain the life satisfaction level. Accordingly, the objective function of the optimisation problem of HEMS is expressed as:

$$f = \left( \sum_{h,t} (l_{h,t}^{ap} * p_{h,t}) - \left(l_{h,t}^{sh} * \delta_{h,t}\right) \right),$$

$$\forall\ h \in H, t \in T, \{ap, sh\} \in AP \tag{3.6}$$

The objective function is divided to two-sub objectives: the electricity payment of household $h$ ($\sum_{h,t}(l_{h,t}^{ap} * p_{h,t})$) and maximising the satisfaction factor $\left(l_{h,t}^{sh} * \delta_{h,t}\right)$.

The electricity price $p_{h,t}$ is determined by SA and is described further in this section. Satisfaction factor is a linear function of load regarding satisfaction level of household $h$ to scheduling shiftable appliances. This term ensures that the scheduling levels find a suitable trade-off between the minimum electricity payment and the comfort level of the household. $\delta_h^t$ is determined as a set of individual characteristics of each household that can highly affect usage pattern and probability of shifting appliances using the following equation:

$$\delta_{h,t} = \varepsilon_{h,t} . A_{h,t}, \quad \forall\ h \in H, t \in T \tag{3.7}$$

$A_{h,t}$ is the willingness of household $h$ to participate in DR programs and $\varepsilon_{h,t}$ is the elasticity of demand to changes in the electricity price in each time interval $t$. The methodology and procedure of calculating these parameters are explained in detail in the next chapter.

***Constraints:*** The objective function is limited to a set of energy and timing constraints (3.8)-(3.13).

The start-up of appliances can be selected at any time due to voluntary-participation of DR employment in this objective. Neither LTA nor DRPA sends the band limit to HAs. However, in order to consider load safety at household and avoiding peak rebound, it is assumed that only one controllable appliance can be run at any given time. Therefore, (3.8) is defined as:

$$\sum_{\mathrm{t}} \mathrm{l}_{\mathrm{h,t}}^{\mathrm{ap}} \leq \mathrm{l}_{\mathrm{h}}^{\max}, \forall\ \mathrm{h} \in \mathrm{H}, \mathrm{t} \in \mathrm{T}, \mathrm{ap} \in \mathrm{AP} \tag{3.8}$$

$\mathrm{l}_{\mathrm{h}}^{\max}$ is determined by adding the maximum power consumption of WM, as the most power consuming appliance, to the background loads ($\mathrm{l}_{\mathrm{h,t}}^{\mathrm{f}}$), shown in Figure 3-6 and formulated as:

$$\mathrm{l}_{\mathrm{h}}^{\max} = \mathrm{l}_{\mathrm{h,t}}^{\mathrm{f}} + \left(\frac{E^{WM}}{\Delta t^{WM}}\right), \forall\ \mathrm{h} \in \mathrm{H}, , \mathrm{k} \in \mathrm{K}, \{\mathrm{f}, \mathrm{WM}\} \in \mathrm{AP} \tag{3.9}$$

where, $\Delta t^{WM}$ is the duty cycle of the WM. Constraint (3.9) guarantees that aggregated loads of each home will not exceed the maximum pre-determined band limit ($l_h^{max}$) at any given time. $E^{WM}$ is the total energy consumption for completing operating cycle of a WM.

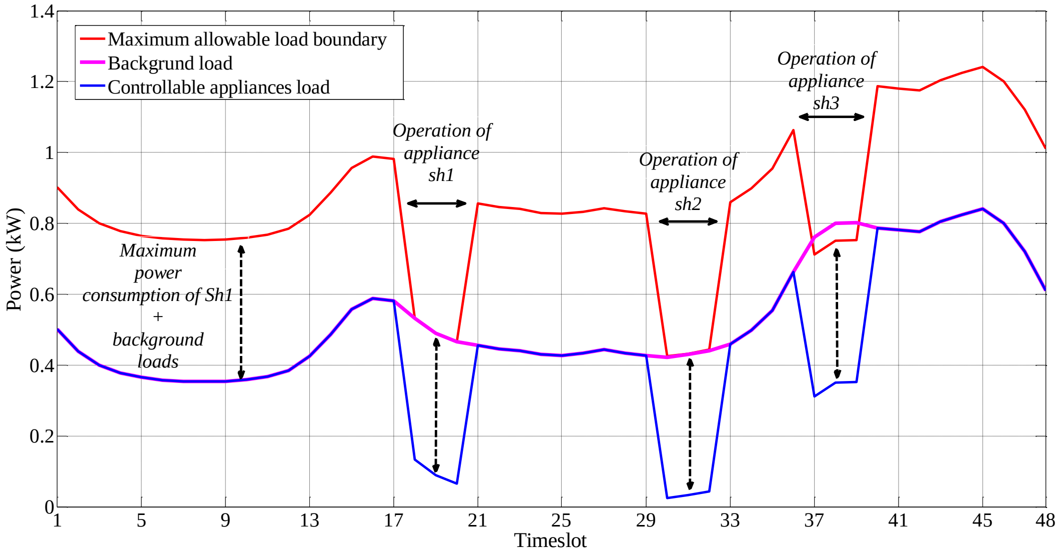



**Figure 3-6:** Calcuation of the maximum boundary limit ($\mathbf{l_h^{max}}$) for each household

Constraint (3.10) is to ensure that the required energy for completing operating cycle of all controllable appliances ($E^{sh}$) is provided.

$$\sum_t l_{h,t}^{sh} = E^{sh} \ ,\forall \ h \in H, t \in \{t_{s\,h}^{\ sh}, t_{s\,h}^{\ sh} + \Delta t^{sh}\}, \mathrm{sh} \in \mathrm{AP} \tag{3.10}$$

Where, $t_{s\,h}^{\ sh}$ is the start of operation time and $\Delta t^{sh}$ is the length of operating the corresponding appliance *sh*.

A set of constraint (3.11) is defined in order to consider the power rating of all controllable appliances. The operating status of any appliance *sh* is denoted by a binary variable $x_{h,t}^{ap}$. Therefore, its corresponding required power is equal to its nominal power rating if it is operating and is 0 otherwise.

$$\begin{cases} l_{h,t}^{sh} = l_{h,t}^{sh} \cdot x_{h,t}^{sh}\,, & \forall \ h \in H, t \in T, sh \in AP \\ x_{h,t}^{sh} = 1 \quad ,\forall \ h \in H, t \in \Delta t_{h,t}^{ap,pref}, sh \in AP & \\ x_{h,t}^{sh} = 0, \forall \ h \in H, t \in T - \Delta t_{h,t}^{ap,pref}, sh \in AP & \end{cases} \tag{3.11}$$

Where, $\Delta t_{h,t}^{ap,pref}$ specifies the user time preference that constraint the running status of appliances to be only within the allowable window. In other words, $x_{h,t}^{ap}$ is set to 1 when the *t* is within the $\Delta t_{h,t}^{sh,pref}$ and set to 0 in other times. The appliances should be run for those households that own them during the simulation day within the home user's preferable time window. This is modelled by the following constraint:

$$1 \leq \quad t_{s\,h}^{\,sh} + \Delta t^{sh} \leq 48\,, \forall \;\; h \in H, sh \in AP \qquad (3.12)$$

It is assumed that the frequency of use per appliance is once per day. Moreover, although an appliance may operate multiple but interruptible cycles, this thesis considers that all wet appliances should be operating continuously until the end of their operating time. These are modelled by constraint (3.13) as a single start-up and un-interruptible operation constraint.

$$\sum_{t} z_{h,t}^{sh} = 1, \forall \;\; h \in H, t \in T, sh \in AP \qquad (3.13)$$

$z_{h,t}^{sh}$ is a binary decision variable which indicates the start-up of appliance *sh*.

- ***Real Time Price Prediction Model:***

In the optimisation of the appliances scheduling, the electricity price of all households connected to $lv^{th}$ LTA ($p_{lv,h,t}$) needs to be considered as a vector of the scheduling time period $T'$.

$$\left[p'_{\mathrm{lv,h,t}}\right]_{1*T} = \left[\acute{p}_{\mathrm{h},t_{start}}, \dots, \acute{p}_{\mathrm{h},t_{end}}\right]_{1*T'},$$

$$\forall \; lv \in LV, h \in H, \; T' \in T, T' = (t_{end} - t_{start}) + 1 \qquad (3.14)$$

where, $t_{start}$ and $t_{end}$ are the start and end time of the optimisation period for HEMS. For instance, in a DA-RTP, the $\acute{p}_{lv,h,t}$ has 48 values ($\acute{p}_{lv,h,t_{start}} = 1\,, \acute{p}_{lv,h,t_{end}} = 48$) which indicates the prices for whole day. However, in RTP, the energy scheduler needs to predict the upcoming prices in real time which comprises two steps as illustrated in Figure 3-7.

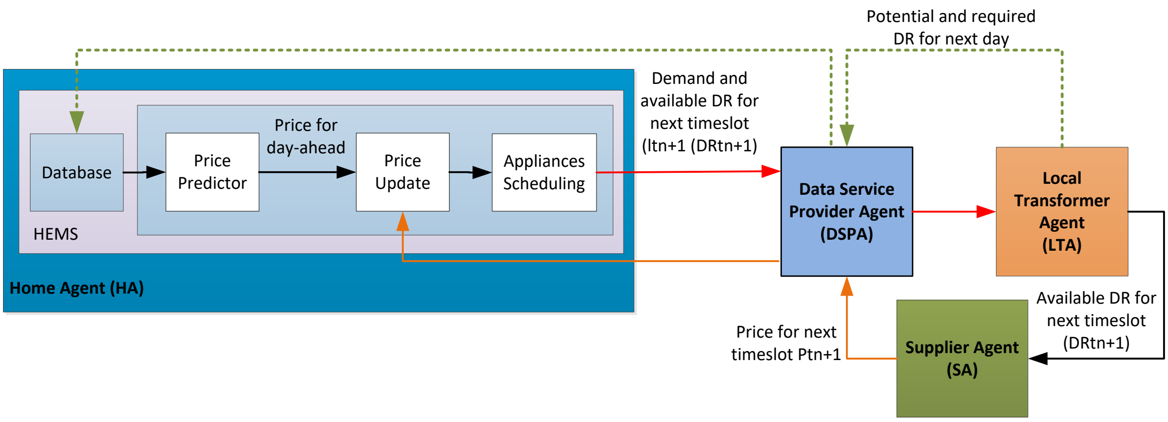



**Figure 3-7:** HEMS model with price prediction capability

Firstly, the electricity prices for the next day are predicted based on the total required DR that has been anticipated by LTA for all connected HAs. The data received from LTA, is discussed in detail in the next section. An IBT is used where the electricity payment linearly increases with the required amount of energy to be shifted. The overall price prediction methodology is based on the fact that the higher the need for DR, the more engagement of customers is required. A four-level piecewise linear price function is modelled to present the predicted price of electricity in each time interval and is expressed as:

$$\acute{p}_{h,t} = \begin{cases} \propto_1 \acute{PR}^{DR}_{lv,t} + \beta_1 , & \forall \quad 0\% < \acute{PR}^{DR}_{lv,t} \leq 40\% \\ \propto_2 \acute{PR}^{DR}_{lv,t} + \beta_2 , & \forall \quad 40\% < \acute{PR}^{DR}_{lv,t} \leq 60\% \\ \propto_3 \acute{PR}^{DR}_{lv,t} + \beta_3 , & \forall \quad 60\% < \acute{PR}^{DR}_{lv,t} \leq 80\% \\ \propto_4 \acute{PR}^{DR}_{lv,t} + \beta_4 , & \forall \quad 80\% < \acute{PR}^{DR}_{lv,t} \leq 100\% \end{cases}$$

$$\forall \propto_1 < \propto_2 < \propto_3 < \propto_4, h \in H, lv \in LV, t \in T \tag{3.15}$$

where,

$$\acute{PR}^{DR}_{lv,t} = \left( \frac{\acute{l}^{DR,req,total}_{lv,t}}{\acute{l}^{DR,pot,total}_{lv,t}} \right) * 100 \tag{3.16}$$

$\acute{PR}^{DR}_{lv,t}$ is the predicated Participation Rate (PR) which is defined as the ratio of the predicted total required DR ($\acute{l}^{DR,req,total}_{lv,t}$) to the potential of DR ($\acute{l}^{DR,pot,total}_{lv,t}$) for the next day in percentage form. These parameters are sent by LTA in each day for decision-making. $\beta_1$, $\beta_2$, $\beta_3$ and $\beta_4$ are constants reflecting the fixed prices. $\propto_1$, $\propto_2$, $\propto_3$ and $\propto_4$ are the slopes of the segmentation in each step. An illustration of the proposed 4-level linear piecewise price function is given in Figure 3-8 for ease of understanding.

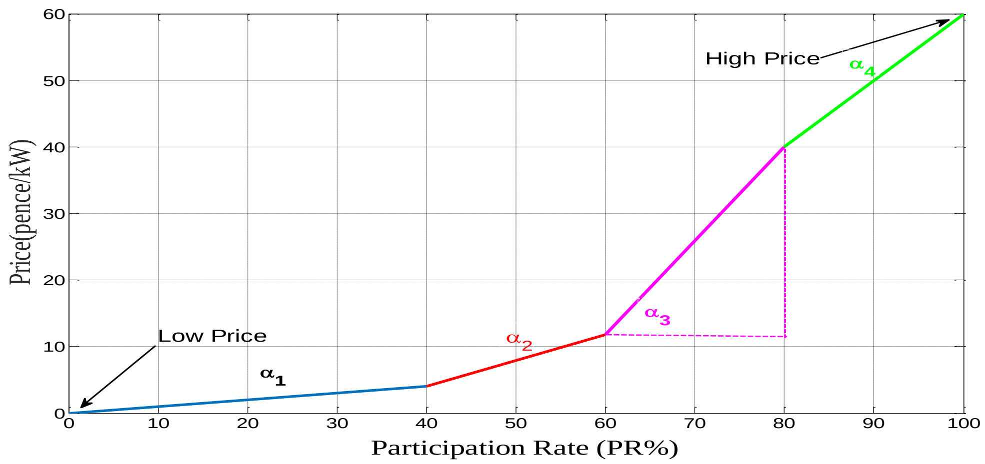



**Figure 3-8:** Four-level piecewise linear price prediction function for HEMS

In the second step, the predicted price is updated with the upcoming price in real time. It is clear than the $p_{h,t}$ takes less values over the course of the day. For instance, if the real price received at timeslot 10, the $T'$ is 39.

- ***DR Availability in Real Time:***

In real time, each HA calculates the available DR size at each time interval $t$ and sends it to LTA. For this purpose, HA specifies the available appliances that have not been run or are not running by setting a binary variable as:

$$\begin{cases} k_{h,t}^{sh} = 1\,, & \forall\ z_{h,t}^{sh} + x_{h,t}^{sh} = 0 \\ k_{h,t}^{sh} = 0\ , & \forall\ z_{h,t}^{sh} +\ x_{h,t}^{sh} \neq 0 \end{cases}$$

$$,\forall\ \ h \in H, t \in T, sh \in AP \tag{3.17}$$

where, $k_{h,t}^{sh}$ is the availability of appliance *sh* at timeslot *t* which is set to 1 if both start-up and operation status of that appliance at *t* are 0. The sum of power consumption from all available appliances is approximated as the maximum available DR ($l_h^{DR,ava}$).

$$l_{h,t}^{DR,ava} = \sum_{h,t}^{sh} k_{h,t}^{sh} \,.\, l_{h,t}^{sh}\,,$$

$$\forall\ h \in H, t \in T, sh \in AP, \tag{3.18}$$

(3.18) shows the maximum demand that can be shifted in timeslot *t*, if a rescheduling is performed by HEMS.

- ***Problem Formulation***

The nature of objective function $f$ defined in (3.6) and its constraints is linear. Hence, the problem is solved by mixed integer linear programming technique. It is worth to clarify that since the load flexibility is provided by shiftable appliances, the decision variables in the objective functions are $l_{h,t}^{WM}$, $l_{h,t}^{DW}$ and $l_{h,t}^{TD}$. Hence, $\sum_t l_{h,t}^{ap}$ are not decision variables. However, they are required to calculate the overall electricity payment of the household. Moreover, regarding the (3.11), the decision variables can be defined as a set of binary variables ($x_{h,t}^{sh}$) for all values $\{sh, t\}$, of which appliance *sh* is known and *t* is unknown. The value of $x_{h,t}^{sh}$ can be 1 at a particular timeslot *t* and 0 for all the remaining slots. This formulation provides an optimal decision-making for appliances scheduling with their respective start and end timeslot. In this regard, the optimisation problem formulation is described as:

$$\min_{sh,t} f(x_{h,t}^{sh})$$

Subject to: (3.8)-(3.13)

$$\forall\ h \in H, t \in T, sh \in AP \tag{3.19}$$

The timescale is divided into 48 timeslots in which the $x_{h,t}^{sh}$ is defined as a vector of 48 values.  Since maximum three shiftable appliances for each household is considered, the total binary variables for the optimisation problem is 196.

It should be noted that if the load scheduling cannot find a feasible solution, for instance when $\delta_{h,t}$ is too low, the households demand remains unchanged. However, it does not affect the goal of overall DR mechanism since the most evenly distributed total load profiles from all HAs are considered for controlling the transformer overloading.

### 3.3.2 Local Transformer Agent

The objective of LTA is limited to provide the SA with the required information within its feeder. This information is the required DR size as well as potential or available DR along the feeder. Determination of DR potential or availability in LTAs is a valuable source for guiding

SA and DRPA to potential opportunities. The exchanged data is through DSPA and the period depends on the type of DR, which is daily-basis for DA-RTP and half an hour-basis in RTP. Moreover this information is sent in a day-ahead to HAs for load scheduling. Since only the aggregated data regarding household's demand is sent, the data privacy of homeowners is maintained.

***DR Availability:*** In RTP, the LTA receives the available DR from its associated HAs. Then, it calculates the total DR availability by aggregating the available DR size from all its associated HAs as:

$$\mathrm{l}_{\mathrm{lv,t}}^{\mathrm{DR,ava,total}} = \sum_{h,t} l_{h,t}^{DR,ava}$$

$$\forall\, c \in C\,, h \in H, t \in T, lv \in LV \qquad (3.20)$$

***DR Potential:*** An estimation of the potential responsiveness in HAs demand is calculated for DA-RTP. This is updated in RTP to eliminate the uncertainty in prediction. In terms of DR potential (DA-RTP), the overall methodology is based on probabilistic method for shiftable appliances during a day for different clusters of customers. This includes three steps: load estimation, load shifting probability and DR potential probability. The household segmentation is done by a classification-based clustering evaluation. The clustering procedure is explained in detail in the next chapter.

- ***Load estimation:*** For each household $h$ within cluster $c$, the minimum load ($\acute{l}_{c,h,t}^{hist,min}$) and maximum load ($\acute{l}_{c,h,t}^{hist,max}$) are obtained from historical data. A comprehensive study of the dataset used to generate the load profiles for this analysis is provided in chapter 4. The potential of loads that can be obtained from aggregation of all shiftable appliances ($\acute{l}_{c,h,t}^{hist,sh}$) are considered as:

$$\acute{l}_{c,h,t}^{hist,sh} = \acute{l}_{c,h,t}^{hist,max} - \acute{l}_{c,h,t}^{hist,min}$$

$$,\forall\, c \in C\,, h \in H, t \in T, sh \in AP \qquad (3.21)$$

$\acute{l}_{c,h,t}^{hist,min}$ is considered as background loads which must be run at all time. On the other hand, in each cluster, the mean of peak demands from all households ($l'^{hist,max}_{c,t}$) is calculated using the following equation:

$$l'^{hist,max}_{c,t} = \frac{\sum_h l'^{hist,max}_{h,t}}{H},$$

$$c \in C, h \in H, t \in T \tag{3.22}$$

- ***Load shifting probability:*** Each wet appliance operates under a set of sequential and uninterruptible load phases. Therefore, their potential of load shifting during a typical day depends on two parameters: the probability of on/off state of that appliance and the phase of the operation. The probability of the start of appliance *sh* for households within $c^{th}$ cluster in timeslot *t*, $\mathrm{P}(Z^{sh}_{c,t})$, is estimated using weighting factor. The profile for one complete operating cycle of each appliance is fitted to the potential of maximum shiftable demand, $\acute{l}^{hist,sh}_{c,h,t}$, of that household. A weight is allocated to each timeslot *t* during a typical day ($W^{sh}_{c,h,t}$) as:

$$W^{sh}_{c,h,t} = \sum_k \left( \sum_t \sum_{ph} (\acute{l}^{hist,sh}_{c,h,t} - l^{sh}_{ph}) \right),$$

$$\forall\ c \in C\ , h \in H, sh \in AP, ph = \Delta t^{sh}$$

$$, k \in \{1, (T - \Delta t^{sh})\}, t = \{k, k + (\Delta t^{sh} - 1)\} \tag{3.23}$$

where, $W^{sh}_{c,h,t}$ is the weighting factor for each appliance, $l^{sh}_{ph,t}$ is the power usage of wet appliance *sh* at load phase *ph*. $k$ is an index which reflects the total timeslots during a day. Hence, $\mathrm{P}(Z^{sh}_{c,t})$ for each appliance *sh* is calculated as:

$$\mathrm{P}(Z^{sh}_{c,t}) = \frac{W^{sh}_{c,h,t}}{\sum_t W^{sh}_{c,h,t}}$$

$$, \forall\ c \in C\ , h \in H, t \in T, sh \in AP \tag{3.24}$$

The probability of the shiftable power usage from each shiftable appliance at each timeslot *t* for household *h*, is expressed as:

$$\mathrm{P}(l'^{sh}_{c,h,t}) = \left(\mathrm{P}(Z^{sh}_{c,h,t})\ .\, Y^{sh}_{c,h,k}\right), \forall\ c \in C\ , h \in H, t \in T, sh \in AP$$

$$,\ 0 \le \mathrm{P}(l'^{sh}_{c,h,t}) \le 1\ \ , Y^{sh}_{c,h,k} \in \{0, 1\} \tag{3.25}$$

$Y^{sh}_{c,h,k}$ is introduced to indicate the ownership of different wet appliances within household *h*. Consequently, the maximum load that can be shifted by aggregating all shiftable appliances in all household within cluster $c$ ($l'^{sh,max}_{c,t}$) is determined by the following equation:

$$l'^{sh,max}_{c,t} = \sum_{h}\sum_{sh}\left(l'^{sh}_{c,h,t} \,.\, \mathrm{P}\left(l'^{sh}_{c,h,t}\right)\right)$$

$$,\forall\, c \in C, h \in H, sh \in AP, t \in T \qquad (3.26)$$

- ***DR probability:*** Based on equation (3.26), for each cluster, the total DR size from all aggregated households ($\acute{\mathrm{l}}^{\mathrm{DR,pot,total}}_{\mathrm{c,t}}$) is expressed as:

$$\acute{\mathrm{l}}^{\mathrm{DR,pot,total}}_{\mathrm{c,t}} = l'^{hist,max}_{c,t} - l'^{sh,max}_{c,t}$$

$$,\forall\, c \in C, sh \in AP, t \in T \qquad (3.27)$$

This equation can be described as the difference of shiftable demand from actual load curve over time. Accordingly, the potential of total DR size $Lv^{th}$ LTA, from all groups of customers connected to its related LV feeder, is determined the following:

$$\acute{\mathrm{l}}^{\mathrm{DR,pot,total}}_{\mathrm{lv,t}} = \sum_{c} \acute{\mathrm{l}}^{\mathrm{DR,pot,total}}_{\mathrm{c,t}} \quad ,\forall\, c \in C, t \in T \qquad (3.28)$$

- ***Required Demand Reduction***

LTA monitors and assesses the transformer operating state by running the power flow in its feeder at each timeslot during a typical day. The Backward-Forward Sweep method is used for all power flow analysis in this thesis. The required DR in each time interval is determined by the difference of total demand and the maximum transformer capacity ($TC^{\mathrm{max}}_{\mathrm{lv,t}}$) as:

$$\acute{\mathrm{l}}^{\mathrm{DR,req,total}}_{\mathrm{lv,t}} = TC^{\mathrm{max}}_{\mathrm{lv,t}} - l'^{hist,max}_{lv,t} \quad ,\forall\, lv \in LV, t \in T \qquad (3.29)$$

(3.29) also reflects the transformer operating states which can be normal or emergency. If the aggregated demands from all associated HAs are below the $TC^{\mathrm{max}}_{\mathrm{lv,t}}$, the status is normal. Otherwise, the status is emergency which needs immediate action to reduce power demands and this is discussed in the section 3.5.

### 3.3.3 Supplier Agent

The SA is responsible for designing electricity tariffs and biding for HAs. Similar to approach in predicting price for HEMS (section 2.4.1.2), SA designs a DA-RTP in each time interval individually for each LTA. However, in RTP, the price is set for each LTA in each timeslot for the next timeslot according to its provided real data. The pricing scheme considers four different operating states of LTA. This can be expressed as:

$$p_{\mathrm{lv,t}} = \begin{cases} \propto_1 \mathrm{PR}_{\mathrm{lv,t}}^{\mathrm{DR}} + \beta_1 , & \forall \quad 0\% \leq \mathrm{PR}_{\mathrm{lv,t}}^{\mathrm{DR}} \leq 40\% \\ \propto_2 \mathrm{PR}_{\mathrm{lv,t}}^{\mathrm{DR}} + \beta_2 , & \forall \;\; 40\% \leq \mathrm{PR}_{\mathrm{lv,t}}^{\mathrm{DR}} \leq 60\% \\ \propto_3 \mathrm{PR}_{\mathrm{lv,t}}^{\mathrm{DR}} + \beta_3 , & \forall \;\; 60\% \leq \mathrm{PR}_{\mathrm{lv,t}}^{\mathrm{DR}} \leq 80\% \\ \propto_4 \mathrm{PR}_{\mathrm{lv,t}}^{\mathrm{DR}} + \beta_4 , & \forall \;\; 80\% < \mathrm{PR}_{\mathrm{lv,t}}^{\mathrm{DR}} \leq 100\% \end{cases}$$

$$\forall \propto_1 < \propto_2 < \propto_3 < \propto_4, \mathrm{lv} \in \mathrm{LV}, \mathrm{t} \in \mathrm{T} \tag{3.30}$$

where,

$$PR_{lv,t}^{DR} = \left( \frac{\mathrm{l}_{\mathrm{lv}}^{\mathrm{DR,req,total}}}{\mathrm{l}_{\mathrm{lv}}^{\mathrm{DR,ava,total}}} \right) * 100 \tag{3.31}$$

$PR_{lv,t}^{DR}$ is the Participation Rate (PR) which is defined as the ratio of the total required DR($\mathrm{l}_{\mathrm{lv}}^{\mathrm{DR,req,total}}$) to the available DR ($\mathrm{l}_{\mathrm{lv}}^{\mathrm{DR,ava,total}}$) in $\mathrm{lv}^{\mathrm{th}}$ LTA for the next timeslot.

### 3.3.4 Overall DR control

The overall algorithm for controlling the LV feeder through residential responsiveness loads for RTP is presented in Figure 3-9. The processing flow is specified for each agent with a distinctive colour. The initial step starts with agents updating their related information about the system. In addition, HAs calculate the required demand for the next timeslot ($t = t + 1$) based on a day-ahead price prediction (2.30)-(2.31). In the first timeslot ($t = 1$), LTA receives the power consumption of all associated HAs for the next timeslot. It then computes its status as well as the required DR for the next timeslot and forwards this information to SA. The price signal is defined and sent to HAs for load scheduling. Therefore, in RTP, decision-making is done in each timeslot $t$ for the next timeslot ($t + 1$). The procedure terminates at timeslot t=T.

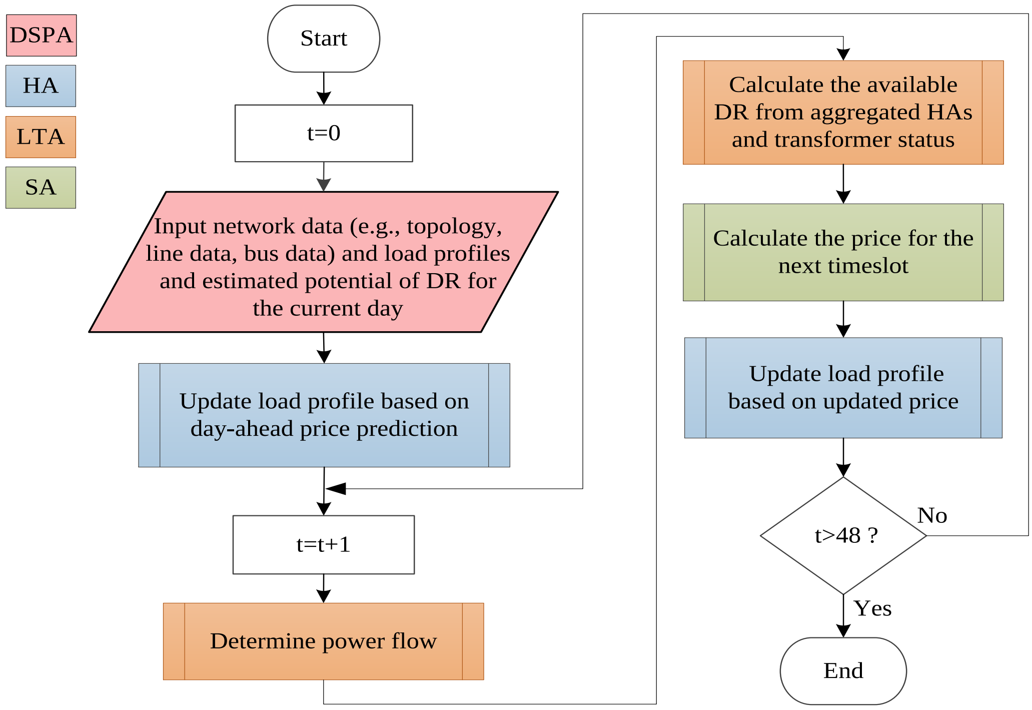



**Figure 3-9:** Overall RTP-based DR algorithm of the proposed active LV network management for one typical day

For each LV feeder, the actual DR achieved at each timeslot $t$ ($DR_{lv,t}$) can be defined as:

$$\mathrm{DR}_{\mathrm{lv,t}} = \mathrm{l}_{\mathrm{lv,t}}^{\mathrm{DR}} - \mathrm{l}_{\mathrm{lv,t}}^{\mathrm{WDR}},$$

$$\forall\ \mathrm{lv} \in \mathrm{LV}, \mathrm{t} \in \mathrm{T} \tag{3.32}$$

where, $l_{lv,t}^{DR}$ and $l_{lv,t}^{WDR}$ are the DR size obtained before and after employing DR in each LV feeder respectively. Similarly, these are determined from aggregation of all household load profiles as:

$$\mathrm{l}_{\mathrm{lv,t}}^{\mathrm{DR}} = \sum_{h} \mathrm{l}_{\mathrm{lv,h,t}}^{\mathrm{DR}} \tag{3.33}$$

$$\mathrm{l}_{\mathrm{lv,t}}^{\mathrm{WDR}} = \sum_{h} \mathrm{l}_{\mathrm{lv,h,t}}^{\mathrm{WDR}} \tag{3.34}$$

$$\forall\ \mathrm{lv} \in \mathrm{LV}, \mathrm{h} \in \mathrm{H}, \mathrm{t} \in \mathrm{T}$$

$l_{lv,h,t}^{DR}$ and $l_{lv,h,t}^{WDR}$ are the demand for $h^{th}$ household at timeslot $t$ with and without DR implementation correspondingly.

## 3.4 MV Network Constraint Management (Objective 2)

The DR control scheme in this objective aims to mitigate the constraints at MV feeder based on RTP. The overall MAS structure is presented in Figure 3-10. It is assumed that the overloading of each MV/LV transformer at LV feeder is controlled locally by the LTA, as discussed previously. Hence, each LTA only sends the total available DR size to DRPA using the same methodology as discussed in the first objective.

### 3.4.1 Home Agent

The goal of HA is to make an optimal decision on when to start any available shiftable appliance in real time. The two objectives targeted are minimising the energy expenses and maintaining the life satisfaction level. The methodology applied for this objective is computationally less demanding and therefore is an advantage compared to the ones previously discussed.

The power consumption at each timeslot $t$ for $h^{th}$ household is the aggregation of background loads and the power usage of selected shiftable appliances $sh$. This can be defined as:

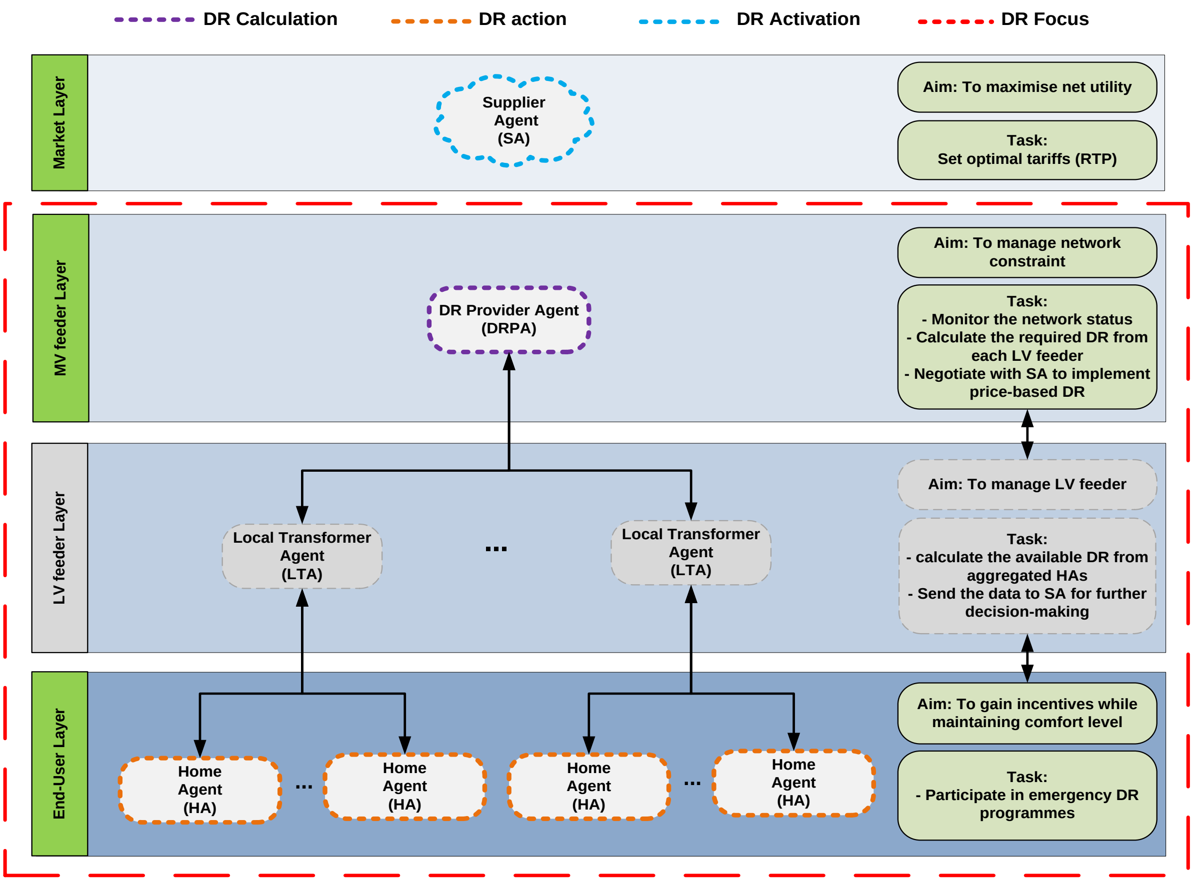



**Figure 3-10:** MAS structure for managing MV networks through RTP

$$l_{h,t} = l_{h,t}^{ap} = l_{h,t}^{f} + \sum_{sh} \left( l_{h,t}^{sh} * D_{h,t}^{sh} \right) \ ,$$

$$\forall \ h \in H, t \in T, \{ap, f, sh\} \in AP \ , D_{h,t}^{sh} \in [0, 1] \tag{3.35}$$

where, $D_{h,t}^{sh}$ is a binary decision-making variable for starting the appliance *sh* at timeslot *t*. $D_{h,t}^{sh}$ is 1 for any appliance that is selected and is 0 otherwise and is expressed as:

$$D_{h,t}^{sh} = \begin{cases} 1, & \forall \ d_{h,t}^{sh} > 1 \\ 0, & \forall \ d_{h,t}^{sh} < 1 \end{cases} \quad , \quad \forall \ h \in H, t \in T, sh \in AP$$

where,

$$d_{h,t}^{sh} = \left( \mu_{h,t}^{sh} \, . \, \delta_{h,t}^{sh} \right) + \lambda_{h,t}^{sh} \tag{3.36}$$

$d_{h,t}^{sh}$ is an ancillary binary variable which represents users constraints. $\mu_{h,t}^{sh}$ reflects the first objective of HA in which the price signal, defined by the SA, should be low enough to encourage it to start the available shiftable appliance. If the price is attractive for HA, $\mu_{h,t}$ is set to 1. $\delta_{h,t}^{sh}$ reveals the comfort level of household which is set to 1 if the appliance can be selected at that time interval. The binary variable $\lambda_{h,t}$ is introduced to reflect the appliances ownership.

- $\mu_{h,t}^{sh}$ *is expressed as:*

$$\mu_{h,t}^{sh} = A_{h,t}^{sh} . \ E_{h,t}^{sh} \tag{3.37}$$

$A_{h,t}^{sh}$ is the attitude of each HA towards participating in DR. $E_{h,t}^{sh}$ states the elasticity of HA to the price signal at timeslot *t* as:

$$E_{t,h} = \begin{cases} 1, \ \forall \ \acute{E}_{h,t}^{sh} \geq \acute{l}_{h,t} \\ 0, \ \forall \ \acute{E}_{h,t}^{sh} < \acute{l}_{h,t} \end{cases} , \forall \ t \in T \ , h \in \ H \tag{3.38}$$

where, $\acute{E}_{h,t}^{sh}$ is a linear function of elasticity $\varepsilon_h$ and is defined as:

$$\mathrm{E}'_{\mathrm{t,h}} = \Delta\mathrm{C}_{\mathrm{h,t}}\varepsilon_{\mathrm{c,h}} + \mathrm{b}_{\mathrm{c,h}} \tag{3.39}$$

$\Delta C_{h,t}$ is the changes of the price at timeslot *t* with respect to the based price. $\varepsilon_{c,h}$ and $b_{c,h}$ are demand elasticity to changes in price and constant factor respectively. $\acute{l}_{h,t}$ is the total demand at timeslot *t* if the available selected appliance is started**.** The estimation of the value of parameters in (3.39) is described in the next chapter.

- $\delta_{h,t}^{sh}$ *is stated as:*

$$\delta_{h,t}^{sh} = \begin{cases} 1, & \forall \ (w_{h,t}^{sh} \,.\, k_{h,t}^{sh}) = 1 \\ 0, & \forall \big(w_{h,t}^{sh} . \, k_{h,t}^{sh}\big) = 0 \end{cases},$$

$$\forall \ h \in \ H \,, t \in T, sh \in AP \tag{3.40}$$

$\delta_{h,t}^{sh}$ represents a set of constraints regarding the availability of appliances and user preference. $w_{h,t}^{sh}$ is the user time preference and $k_{h,t}^{sh}$ states the availability of *sh* at timeslot *t*. The first parameter $w_{h,t}^{sh}$, implies that appliances can only be run in allowable window of time $\Delta t_{h,t}^{sh,pref}$ which is set by consumers as follows:

$$w_{h,t}^{sh} = \begin{cases} 1, & \forall \ t \in \ \Delta t_{h,t}^{sh,pref} \\ 0, & \forall \ t \ \notin \ \Delta t_{h,t}^{sh,pref} \end{cases},$$

$$\forall \ h \in \ H \,, t \in T, sh \in AP \tag{3.41}$$

$\Delta t_{h,t}^{sh,pref}$for operating an *sh* which is similar to (3.11) and is discussed in details in the following chapter. The availability of appliance at timeslot *t*, $K_{t,h}^{ap}$, can be expressed as:

$$k_{h,t}^{sh} = \begin{cases} 1, & \forall \ (x_{h,t}^{sh} \,.\, z_{h,t}^{sh}) = 1 \\ 0, & \forall \big((x_{h,t}^{sh} \,.\, z_{h,t}^{sh}\big) = 0 \end{cases}$$

$$, \forall \ h \in \ H \,, t \in T, sh \in AP \tag{3.42}$$

Binary variable $x_{t,h}^{ap}$ reflects the constraint regarding the assumption of un-interruptible feature for all shiftable appliances. Binary variable $z_{t,h}^{ap}$ indicates both the unique frequency of usage as well as a maximum of one appliance operating at one time.

- $\lambda_{h,t}^{sh}$ *:* $\lambda_{t,h}$ is defined to ensure that the *sh* is selected for those households that own them.

### 3.4.2 Demand Response Provider Agent

The goal of DRPA is to determine the required demand curtailment from each LV feeder in order to manage the MV-LV network constraints. It assesses the network status to ensure the network operates within specific limits for the overall load on the system. Therefore, the objective of DRPA is to devise a multi-objective function aiming to manage the voltage and thermal constraints and improve the quality of the DN. This is achieved through available flexible demands over time.

***Objective function:***

$$f = w_1 \sum_{lv,t} \frac{\Delta P_{lv,t}^{DR}}{SI_{max,lv}} + w_2 VDI_t + w_3 RPLI_t$$

$$, \forall \; lv \in LV, t \in T \tag{3.43}$$

where $w_1$, $w_2$ and $w_3$ are weighting factors for each objective term contributing to the multi-objective function value. This is based on the following limitations:

$$\textstyle\sum_{i=1}^{3} = 1, \quad \forall \; 0 \le w_i \le 1 \tag{3.44}$$

The term $\left(w_1 \sum_{lv,t} \frac{\Delta P_{lv,t}^{DR}}{SI_{max,lv}}\right)$ aims to minimise the total curtailed load requirements ($\sum_{lv,t} \Delta P_{lv,t}^{DR}$) in each LV feeder while maximising the ratio of the required DR allocated to the most influential LV buses. In order to share and apply the required DR in the optimal locations of the network, a sensitivity analysis is applied which is detailed in the next chapter. In this regard, the buses that are most sensitive, when each *lv* bus is subject to a change in active power ($SI_{max,lv}$), are respectively chosen. The other two terms are considered to minimise two technical factors in the DN, *Voltage Deviation Index* (VDI) and *Real Power Loss Index* (RPLI).

VDI is the sum of the voltage deviation at all buses (except at the substation where voltage is specified) from the reference point. Here, VDI is computed from the squares of the deviation of the magnitude of the maximum voltage ($V_{max}$) and minimum voltage ($V_{min}$) from the nominal voltage ($V_{nom}$). This can be mathematically defined as:

$$\mathrm{VDI} = \frac{\sum_{\mathrm{n,t}}\left(\mathrm{V_{nom}} - \mathrm{V_{min,n,t}^{DR}}\right)^2 + \left(\mathrm{V_{nom}} - \mathrm{V_{max,n,t}^{DR}}\right)^2}{\sum_{\mathrm{n,t}}(\mathrm{V_{nom}} - \mathrm{V_{min}})^2 + (\mathrm{V_{nom}} - \mathrm{V_{max}})^2},$$

$$\forall \mathrm{n} \in \mathrm{NB}, \mathrm{n} \neq 1, \mathrm{t} \in \mathrm{T} \tag{3.45}$$

where $V_{min,n,t}^{DR}$ and $V_{max,n,t}^{DR}$ are the minimum and maximum voltage magnitude of $n^{th}$ node with DR control at timeslot *t* respectively. Based on UK standards, $V_{nom}$, $V_{min}$, $V_{max}$ are considered as 1, 0.94 and 1.1 respectively.

The objective of RPLI is to minimise the total real power loss of the DN and is defined as:

$$RP\mathrm{LI} = \frac{\mathrm{P_{loss,t}^{DR}}}{\mathrm{P_{loss,t}}}, \quad \forall \mathrm{t} \in \mathrm{T} \tag{3.46}$$

Where, $P_{loss,t}$, $P_{loss,t}^{DR}$ are the total real power loss without and with DR control at timeslot *t*. Generally, power loss between two adjacent branches *n* and *n+1* can be calculated as:

$$P_t^L(n, n+1) = \sum_{n,t} R_{n,n+1} \left[\frac{|V_{n,t} + V_{n+1,t}|}{Y_{n+1,t}}\right]^2,$$

$$\forall n \in NB, n \neq 1, t \in T \tag{3.47}$$

Where $R_{n,n+1}$ is the resistance and $V_{n,t}$ and $V_{n+1,t}$ are the voltages between two adjacent buses *n* and *n+1* at timeslot *t*.

***Constraints:***

The following constraints are defined for the objective function:

$$\mathrm{P_{n,t}^{D}} = \mathrm{P_{n,t}^{G}} + \mathrm{P_{n,t}^{L}} \tag{3.48}$$

$$\mathrm{Q_{n,t}^{D}} = \mathrm{Q_{n,t}^{G}} + \mathrm{Q_{n,t}^{L}} \tag{3.49}$$

$$\mathrm{V_{min}} \leq \mathrm{V_{n,t}} \leq \mathrm{V_{max}} \tag{3.50}$$

$$\mathrm{S_{br,t}} \leq \mathrm{S_{max}} \tag{3.51}$$

$$\Delta P_{min,lv,t} \leq \Delta P_{lv,t}^{DR} \leq \Delta P_{max,lv,t} \tag{3.52}$$

Equations (3.48)-(3.49) denote the typical AC power flow equations. $P_{n,t}^{D}$ and $Q_{n,t}^{D}$ are active and reactive power demand, $P_{n,t}^{G}$ and $Q_{n,t}^{G}$ are active and reactive power generation and $P_{n,t}^{L}$ and $Q_{n,t}^{L}$ are active and reactive power loss at node *n* at timeslot *t* respectively. (3.50) denotes the voltage statutory limit in the DN (±6% in this study); Equation (3.51) is the thermal rate constraint of each branch $br \in BR$ , and $S_{br,t}$ can be calculated through (3.53)-(3.55).

$$S_{br,t} = \sqrt{{P_{br,t}}^{2} + {Q_{br,t}}^{2}} \tag{3.53}$$

$$\mathrm{P_{br,t}} = \sum\nolimits_{\mathrm{n,t}}^{\mathrm{BR(br,1),T}} \mathrm{P_{n,t}^{G}} + \sum\nolimits_{\mathrm{n}}^{\mathrm{BR(br,2),T}} \mathrm{P_{n,t}^{L}} \tag{3.54}$$

$$\mathrm{Q_{br,t}} = \sum\nolimits_{\mathrm{n,t}}^{\mathrm{BR(br,1),T}} \mathrm{Q_{n,t}^{G}} + \sum\nolimits_{\mathrm{n,t}}^{\mathrm{BR(br,2),T}} \mathrm{Q_{n,t}^{L}} \tag{3.55}$$

$$,\forall\ \mathrm{br}\ \in \{\mathrm{BR}, \mathrm{br}'\}, t \in \mathrm{T}, \mathrm{n} \in \mathrm{NB}$$

where $S_{br,t}, P_{br,t}$ and $Q_{br,t}$ are apparent, active and reactive power flow in branch *br* at timeslot *t* respectively. $P_{n,t}^{G}$, $Q_{n,t}^{G}$, $P_{n,t}^{L}$ and $Q_{n,t}^{L}$ are the active power, reactive power, active power loss and reactive power loss fed by branch *br. br′ is* the total number of nodes fed by branch *br*. It should be noted that the active and reactive power of a dispersed generation as well as the reactive power generated by the parallel capacitance in the branch *br* are not considered.

Equation (3.52) denotes the limits of available flexible demands that are provided by the LTA at different LV feeders. Thus, $\Delta P_{lv,t}^{DR}$, should be constrained within the $\Delta P_{min,lv,t}$ and $\Delta P_{max,lv,t}$ as the minimum and maximum DR availability from each LV feeder at timeslot *t*.

- ***Problem Formulation***

The optimisation problem for the objective function (3.43) is described as:

$$\min_{lv,t} f(\Delta P_{lv,t}^{DR}) \quad ,\forall\ lv \in LV, t \in T, \tag{3.56}$$

Subject to: (3.44)-(3.55)

The problem is solved using Genetic Algorithm (GA). Among the evolutionary optimisation techniques, the GA is a well-known method that is widely used in power system, specifically for solving a multi-objective function. If suitable operation techniques are applied, GA can be faster and can perform better compared to Differential Evolution (DE) and Partial Swarm Optimisation (PSO) techniques [212, 213].

Figure 3-11 illustrates the flow diagram for obtaining the optimum DR size for each LV feeder using GA. Each individual is defined as a vector of:

$$[\Delta P_{1,t}^{DR}, \ldots, \Delta P_{LV,t}^{DR}]_{1\times Lv}, \forall \text{ lv} \in \text{LV}, t \in \text{T} \tag{3.57}$$

In order to apply the constraints at the objective function, the fitness function is created using penalty strategies. In this context, the fitness function is composed of penalty terms for large number of violations (3.50)-(3.52).

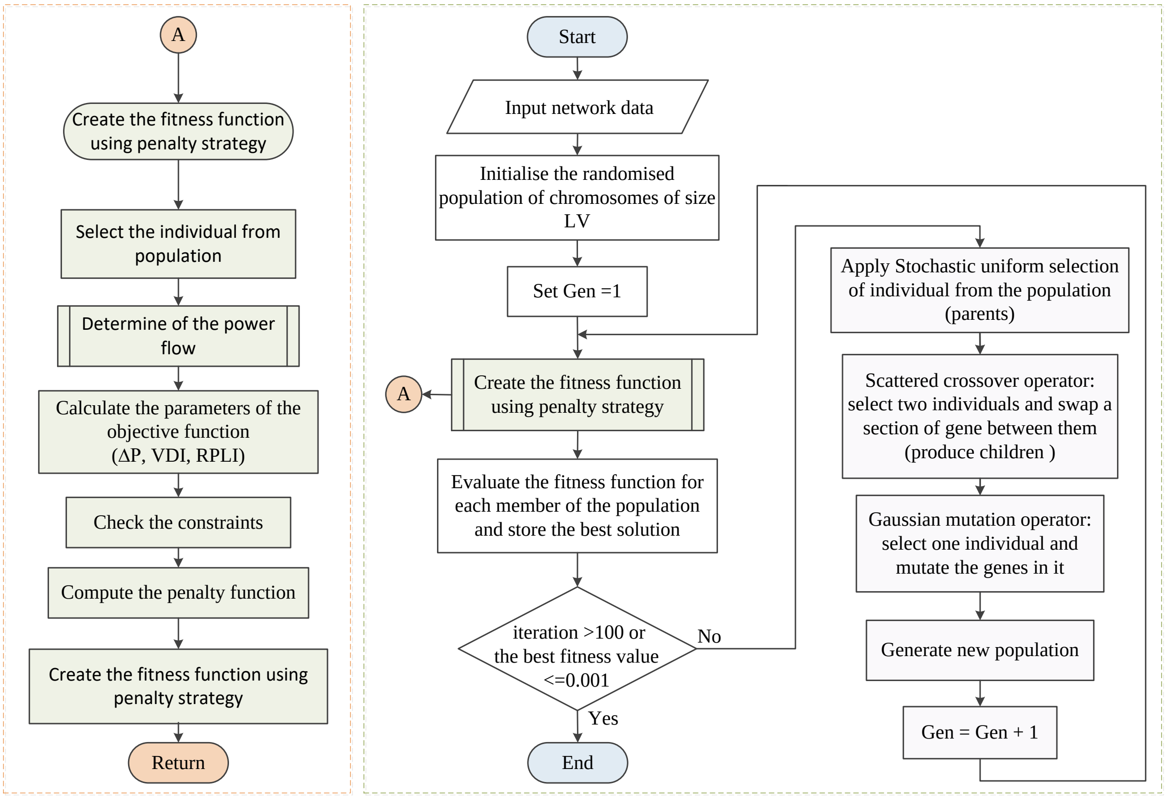



**Figure 3-11:** Flowchart of the Genetic Algorithm implemented to solve the multi- objective function (3.56) to determine the minimum required DR from each LV feeder considering voltage and thermal limits

## 3.4.3 Supplier Agent

The goal and the methodology introduced for SA is similar to the SA in the previous objective (section 3.3.3). However, instead of four, a two-level piecewise linear pricing function as shown in Figure 3-12 is modelled to present the price of electricity in each time interval ($p_{lv,t}$) and is expressed as:

$$P_{lv,t} = \begin{cases} \propto_1 PR^{DR}_{lv,t} + \beta_1 , & \forall \; PR^{DR}_{lv,t} \leq 70\% \\ \propto_2 PR^{DR}_{lv,t} + \beta_2 , & \forall \; PR^{DR}_{lv,t} > 70\% \end{cases}$$

$$\forall \propto_1 < \propto_2, lv \in LV, t \in T \tag{3.58}$$

where,

$$PR^{DR}_{lv,t} = \frac{\Delta P^{DR}_{lv,t}}{\Delta P_{lv,t}} * 100 \tag{3.59}$$

$PR^{DR}_{lv,t}$ is the participation rate, the ratio of the percentage of required DR at each LV feeder *lv*, which is calculated by DRPA ($\Delta P^{DR}_{lv,t}$), and the available DR at each LTA ($\Delta P_{lv,t}$). $\beta_1$ and $\beta_2$ are constant and $\propto_1$ and $\propto_2$ are the slopes of the two segments.

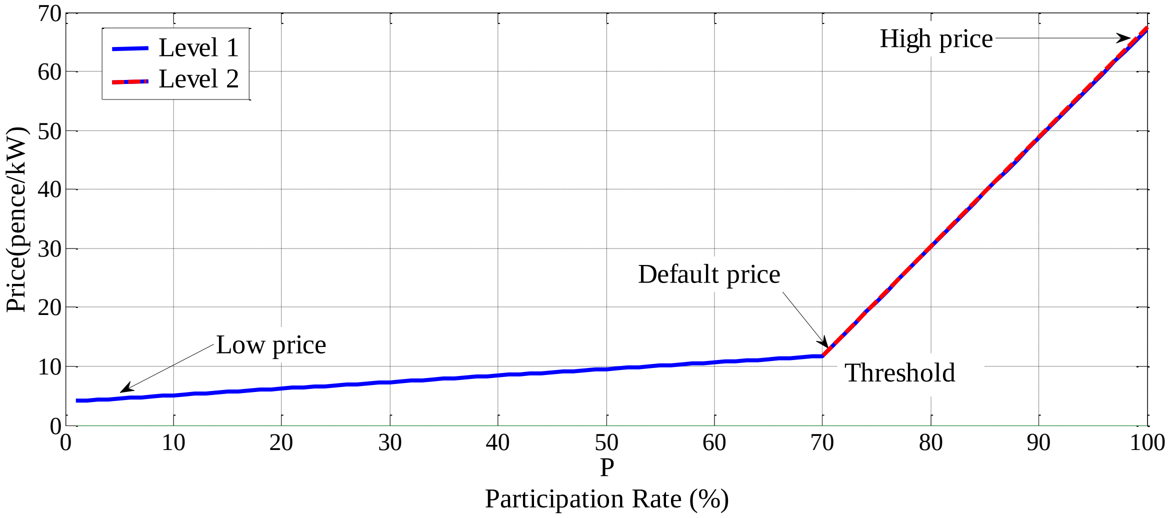



**Figure 3-12** Two-level piecewise linear pricing function

## 3.4.4 Overall DR control

The proposed DR algorithm is presented in the flowchart in Figure 3-13 in which each colour represents one specific agent. The decision-making is applied in timeslot *t-1* for the next timeslot *t*. The DR control mechanism starts by updating data of each agent. Then, the DRPA runs a power flow in order to determine the network parameters such as voltage and power at each bus and current in each branch. Based on the power flow results, the status of the network is assessed to identify if voltage magnitude in any bus or current at any branch exceeds their limits. Since the aim of this paper is to alleviate the MV network constraints by DR provided from LV feeders, the only controllable variable is active power from HAs connected to LV feeders. In case of any network constraint violations, the optimal amount of load curtailment at each LV feeder ($\Delta \mathrm{P}_{\mathrm{lv,t}}^{\mathrm{DR}}$) is determined as explained previously.

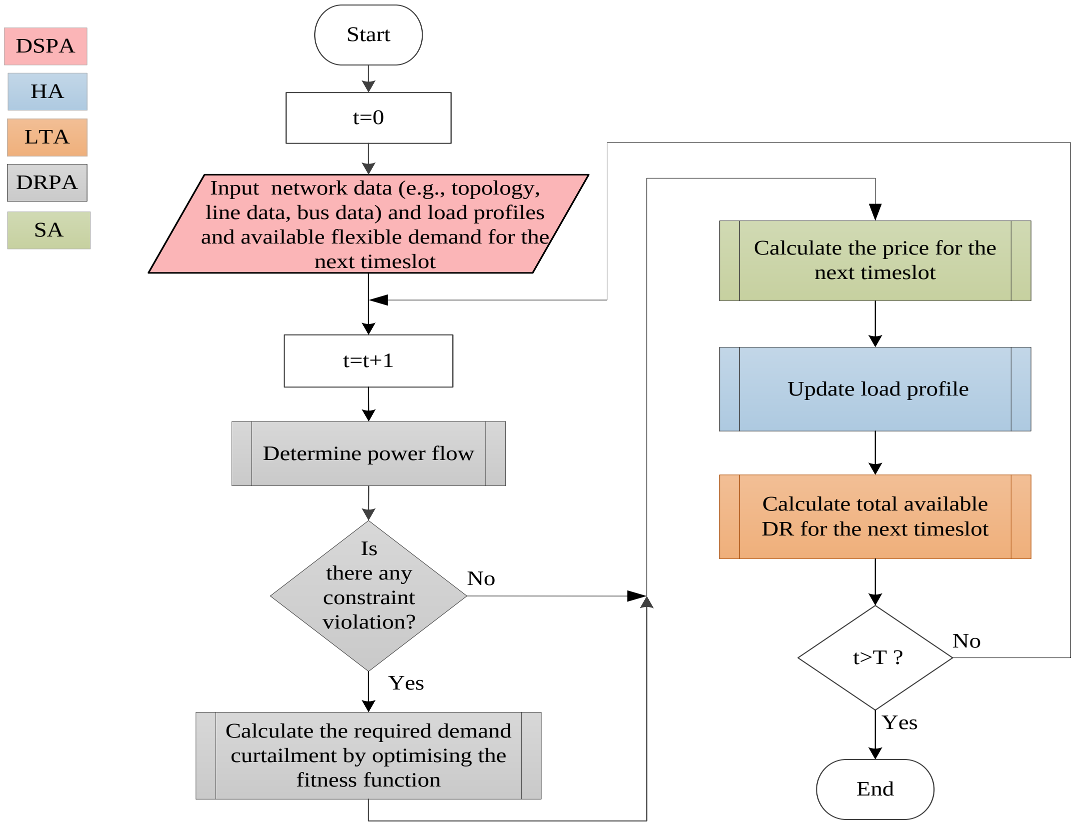



**Figure 3-13:** Overall algorithm of the proposed active MV/LV network management through price-based DR

Receiving the $\Delta P_{lv,t}^{DR}$, the price for the next timeslot *t* is specified by SA through (3.58)-(3.59) Based on the price, HAs decide about their load scheduling for the next timeslot and update their load profiles. Accordingly, each LTA updates its information about its associated HAs.

The actual demand curtailment ($\mathrm{DR_t}$) from aggregation of all LV feeders in the network, at timeslot *t* can then be expressed as:

$$\mathrm{DR_t} = \sum_{lv} (\mathrm{l_{lv,t}^{DR}} - \mathrm{l_{lv,t}}),$$

$$\forall \ \mathrm{lv} \in \mathrm{LV}, \mathrm{t} \in \mathrm{T} \tag{3.60}$$

(3.60) defines the difference between the load profile before ($\mathrm{l_{lv,t}}$) and the new load profile after applying DR mechanism ($\mathrm{l_{lv,t}^{DR}}$) at timeslot *t* of $lv^{th}$ feeder.

## 3.5 MV/LV Network Management (Objective 3)

Unlike the first two DR mechanisms which are price-based, the DR controller in this section aims to activate DR services through incentive-based schemes. The implementation of DR is in real time at LV feeders where two different methodologies are investigated: EDR and Local Community DR (LCDR). In both schemes, load shedding is used in order to curtail households' loads during emergency conditions. DR event can occur due to either LV or MV network demand-supply balancing issues. In this condition, a Demand Curtailment Level (DCL) signal is sent to HAs by LTA. The DCL signal consists of required amount of load curtailment and duration of DR event. In EDR, consumers are in pre-contract agreement for reducing their demands during emergency condition. DRPA has the same functionality as the one discussed in section 3.4.2 with the difference that the required DR curtailment is sent to LTA, instead of SA, for further action. Hence, its methodology is not studied in this section. The structures of DR implementation in EDR and LCDR are presented in Figure 3-14 and Figure 3-15 respectively.

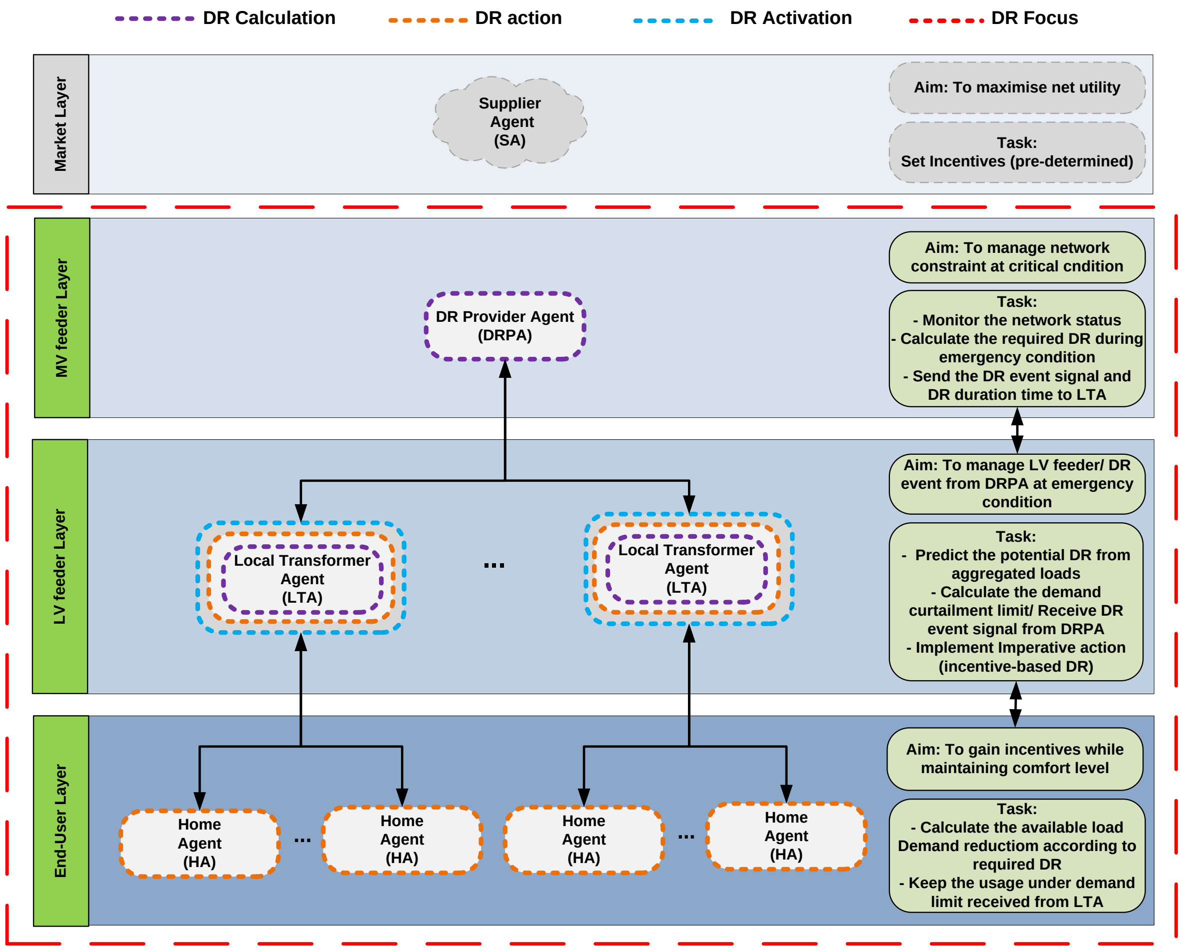



**Figure 3-14:** MAS structure for managing MV/LV networks through Emergency DR

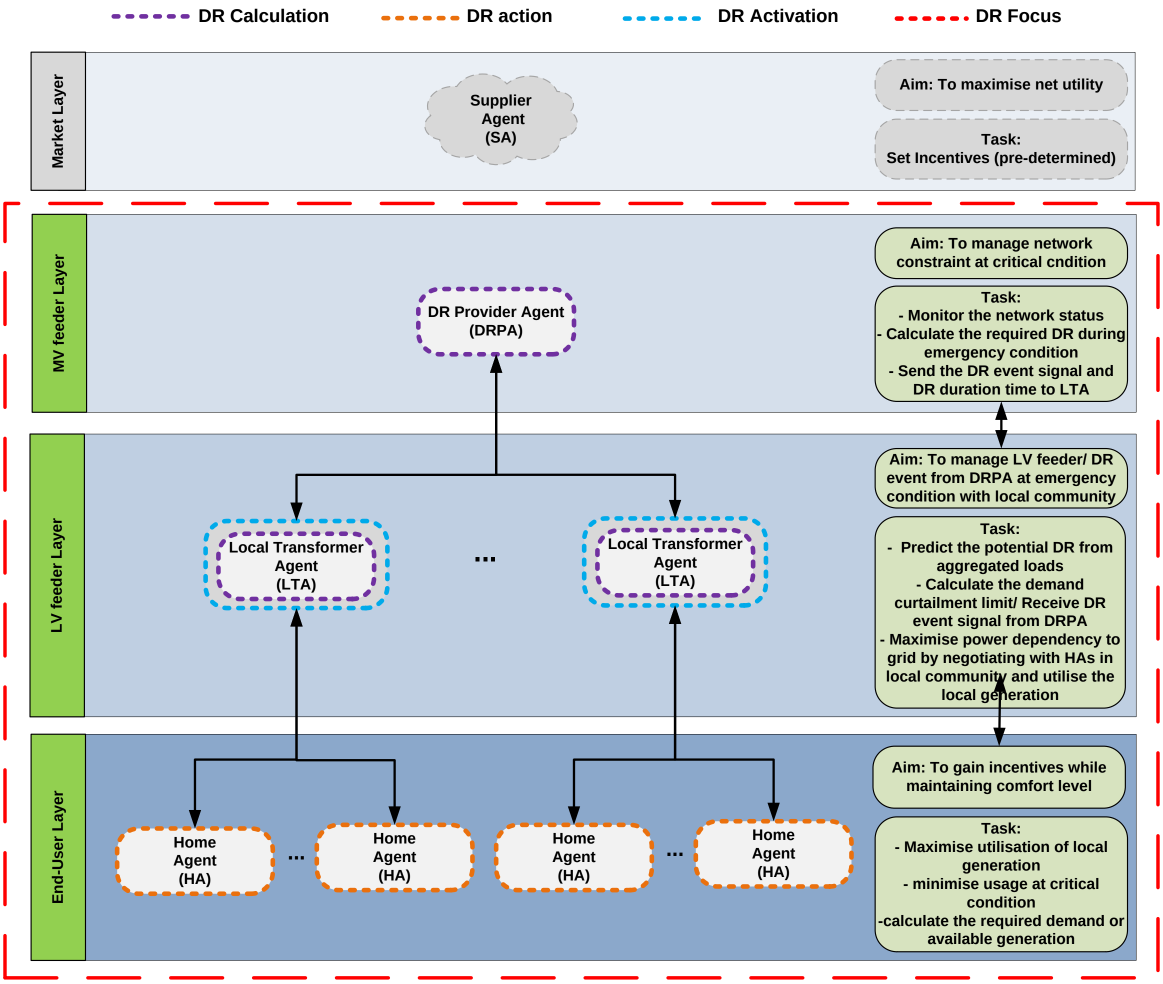



**Figure 3-15:** MAS structure for managing MV/LV networks through Local Community DR

### 3.5.1 Home Agent

The goal of HA is to maximise its economic benefits through incentives resulting from DR participation. Therefore, two parameters are essential in determining the available load reduction: motivation and DR potential.

- ***Emergency Demand Response***

Consumers receive fixed incentives in the form of cash payment for their participation. If a DCL is received from LTA, HA calculates the available demand reduction during DR event as:

$$\mathrm{l}^{LR,max}_{c,h,t} = \mathrm{l}_{c,h,t} - \hat{\mathrm{l}}^{hist,min}_{c,t}, \forall \ c \in C, h \in H, t \in T \quad (3.61)$$

where, $l_{c,h,t}^{LR,max}$ is the maximum load that can be reduced at each time interval $t$ for each household $h$ within $c^{th}$ cluster. $\acute{l}_{c,t}^{hist,min}$ is the mean aggregated of minimum load for $c^{th}$ cluster which is obtained from the historical load profiles.

HA obtains two types of DR signals. Firstly, a $\mathrm{DCL}_{c,h,T'}^{Req}$ which is an initial DR request containing the DCL for specific time interval $T'$ is received. HA calculates $DR_{c,h,T'}^{max}$, the maximum available DR with respect to $\mathrm{DCL}_{c,h,T'}^{Req}$ as:

$$DR_{c,h,T'}^{max} = \begin{cases} 0 & , \forall\ \mathrm{DCL}_{c,h,T'}^{Req} \geq \mathrm{l}_{c,h,T'} \\ \mathrm{l}_{c,h,T'} - \mathrm{l}_{c,h,T'}^{LR,max} & , \forall\ \mathrm{DCL}_{c,h,T'}^{Req} < \mathrm{l}_{c,h,T'}, \mathrm{DCL}_{c,h,T'}^{Req} < \mathrm{l}_{c,h,T'}^{LR,max} \\ \mathrm{l}_{c,h,T'} - \mathrm{DCL}_{c,h,T'}^{Req} & , \forall\ \mathrm{DCL}_{c,h,T'}^{Req} < \mathrm{l}_{c,h,T'}, \mathrm{DCL}_{c,h,T'}^{Req} > \mathrm{l}_{c,h,T'}^{LR,max} \end{cases}$$

$$, \forall\ \ c \in C, h \in H$$

$$T' \in \{\mathrm{t}_{start}, \mathrm{t}_{start}\}, \{\mathrm{t}_{start}, \mathrm{t}_{start}\} \in T \tag{3.62}$$

$l_{c,h,T'}$ is the load at household $h$ before any reduction and $l_{c,h,T'}^{LR,max}$ is the maximum load that can be reduced during period $T'$. It should be noted that HA may accept the $\mathrm{DCL}_{c,h,T'}^{Req}$ only at particular time intervals in $T'$. However, even if the HA cannot meet the requested $\mathrm{DCL}_{c,h,T'}^{Req}$, it calculates and sends the maximum load curtailment that is available. HA then replies to LTA with a proposal of a new load profile after DR curtailment that is expressed as:

$$DR_{c,h,T'} = \mathrm{l}_{c,h,T'} - DR_{c,h,T'}^{max}, \forall\ \ h \in H, t \in T \tag{3.63}$$

$DR_{c,h,T'}$ is the proposal of updated load profile after demand reduction for household $h$ during $T'$.

The second type of DR signal is $\mathrm{DCL}_{c,h,T'}^{Conf}$ in which HA receives a confirmation of DR proposal containing the final DCL for time interval $T'$. Accordingly, it updates its load consumption as:

$$\mathrm{l}_{c,h,T'}^{DR} = \mathrm{l}_{c,h,T'} - \mathrm{DCL}_{c,h,T'}^{Conf} \tag{3.64}$$

$l_{c,h,T'}^{DR}$ is the new load profile after DR implementation for household $h$ at $T'$. It is assumed that when consumers accept a DR request, they will not change their decision.

- ***Local Community Demand Response***

In this scheme, HAs connect to a particular LTA and communicate with each other to create a local community. HA receives a DCL signal in each time interval *t* when it can decide about its participation for the next timeslot *(t+1)*. It is assumed that some households are equipped with roof-top PV panels which enable them to generate local power. The model of PV and related information is provided in the next chapter. The HA has two DR opportunities: maximising its dependency level to power grid and reducing power usage. In the former, HA benefits from energy expenses reduction by maximising its utilisation of its local generation, if it has any. This is expressed as:

$$\Delta_{h,t}^{l,G} = G_{h,t}^{max} - \mathrm{l}_{c,h,t}, \forall\ c \in C, h \in H, t \in T \tag{3.65}$$

$\Delta_{h,t}^{l,G}$ is the difference between the total initial load ($l_{c,h,t}$) and maximum PV generation ($G_{h,t}$). A negative value of $\Delta_{h,t}^{l,G}$ represents the total required demand ($D_{h,t}^{WR}$) as:

$$D_{h,t}^{WR} = \left|\Delta_{h,t}^{l,G}\right|$$

$$, \forall\ \Delta_{h,t}^{l,G} < 0,\ \ h \in H, t \in T \tag{3.66}$$

It is clear that if the household $h$ does not have any PV generation, $D_{h,t}^{WR} = l_{h,t}$. Apart from bill saving, HA can benefit from feed-in-tariff which further increases its economic gain. Feed-in-tariff refers to the payment made to households for local generation and selling electricity to the grid. A positive value of $\Delta_{h,t}^{l,G}$ shows the local available generation that can be provided to the grid from household $h$ ($G_{h,t}^{TG}$) as:

$$G_{h,t}^{TG} = \Delta_{h,t}^{l,G}$$

$$, \forall\ D_{h,t}^{WR} \geq 0,\ \ h \in H, t \in T \tag{3.67}$$

(3.67) indicates that the maximum independency to the grid occurs when $\Delta_{h,t}^{l,G}$ is positive.

In the second opportunity, HA gets rewarded based on its participation in community demand reduction. Further load reduction, is only available for negative value of $\Delta_{h,t}^{l,G}$. The total DR from load curtailment ($D_{h,t}^{R}$) is calculated as:

$$DR_{h,t}^{max} = \begin{cases} DCL_t - D_{h,t}^{WR} & ,\forall\ DCL_t \geq D_{h,t}^{WR},\ \Delta_{h,t}^{l,G} < 0 \\ D_{h,t}^{WR} - \mathrm{l}_{c,h,t}^{LD,max} & ,\forall\ DCL_t < D_{h,t}^{WR},\ \Delta_{h,t}^{l,G} < 0 \\ 0 & ,\forall\ \ \Delta_{h,t}^{l,G} \geq 0 \end{cases}$$

$$,\forall\ \ c \in C, h \in H, t \in T \tag{3.68}$$

The total load reduction depends on the motivation and attitudes of HA in DR participation. Therefore, the total required demand from the grid after applying load reduction ($D_{h,t}^{R}$) is calculated as:

$$D_{h,t}^{R} = D_{h,t}^{WR} - (\delta_h * DR_{h,t}^{max})\ ,\forall\ \ \ h \in H, t \in T \tag{3.69}$$

$\delta_h$ indicates the satisfaction of household $h$ to DR participation and is calculated as:

$$\delta_h = A_h * FM_h \tag{3.70}$$

where $A_h$ and $FM_h$ are the attitudes and financial motivation of each household $h$ to demand reduction schemes. The calculation of these parameters is described in the next chapter. Each HA sends the $D_{h,t}^{R}$ and $G_{h,t}^{TG}$ at each timeslot $t$ to the LTA.

### 3.5.2 Local Transformer Agent

LTA aims to mitigate network constraints by implementing DR during critical conditions. The amount of total load curtailment $DCL_{lv,t}^{total}$ is determined by LTA or DRPA according to previously discussed methodologies. Alleviating network constraints and activating DR is based on the type of DR.

- ***Emergency Demand Response***

In this scheme, The DR notification is sent to HAs in advance, e.g., day or hours ahead based on estimation of the network status. Therefore, when a DR event is detected, LTA needs to allocate an initial DCL to its associated HAs. In this regard, LTA estimates the potential of demand curtailment from all aggregated loads within a cluster of households ($\mathrm{l'}_{c,t}^{DR}$), as shown in Figure 3-16 and using the following equation:

$$l'^{DR}_{c,T'} = \int_{t_{start}}^{t_{end}} \left(l'^{hist,max}_{c,t} - l'^{hist,min}_{c,t}\right) dt$$

$$, \forall\, c \in C, h \in H, T' \in \{\mathrm{t}_{start}, \mathrm{t}_{start\}}\}, \{\mathrm{t}, \mathrm{t}_{start}, \mathrm{t}_{start}\} \in T$$

$$, \forall\, l'^{hist,max}_{c,t} - l'^{hist,min}_{c,t} \geq 0 \tag{3.71}$$

where,

$$l'^{hist,max}_{c,t} = \frac{\sum_h l'^{hist,max}_{h,t}}{H}, \; c \in C, h \in H, t \in T \tag{3.72}$$

$$l'^{hist,min}_{c,t} = \frac{\sum_h l'^{hist,min}_{h,t}}{H}, \; c \in C, h \in H, t \in T \tag{3.73}$$

$l'^{hist,max}_{c,t}$ and $l'^{hist,min}_{c,t}$ are the mean of peak and minimum demands from all households in cluster $c^{th}$.

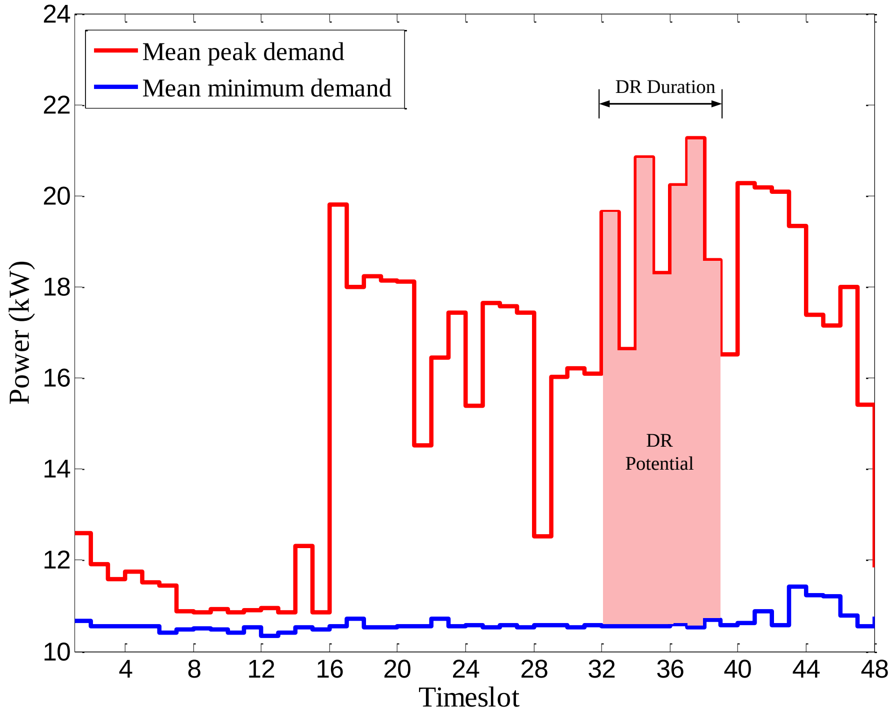



**Figure 3-16:** Illustration of potential of demand reduction for each cluster of customers

The initial DCL is then determined for each cluster of HA based on a merit order. LTA starts with the group of HAs with the highest probability of DR potential and allocates appropriate DCL $^{Req}_{c,h,T'}$, to them. The allocation procedure continues to the next cluster until it meets the overall objectives and maintains constraints of the power network. LTA then sends an initial DR request containing DCL and DR duration to HAs. Receiving the response (proposal) from all HAs, LTA updates its data and sends a final DCL signal to selected HAs taking in to account the HAs DR potential.

- ***Local Community Demand Response***

The main aim of LTA in LCDR is to work with HAs at community level in order to maximise their independency from the power grid in a DR event. This scheme is activated in real time where LTA sends the $DCL_t$ signal to all its associated HAs based on the network status. The same methodology introduced in section (3.3.2) is used to calculate the required DR in each time interval ($\mathrm{DR}_{\mathrm{lv,t}}^{\mathrm{req}}$). The DR event occurs if the total aggregated load at transformer level is greater than its maximum capacity or if a DR signal is received from the DRPA. Each LTA updates its status when it receives the $\mathrm{G}_{\mathrm{h,t}}^{\mathrm{R}}$ and $\mathrm{D}_{\mathrm{h,t}}^{\mathrm{R}}$ from all its associated HAs as:

$$D_{lv,t}^{req} = \sum_{h} D_{h,t}^{R}$$

$$G_{lv,t}^{ava} = \sum_{h} G_{h,t}^{TG}$$

$$, \forall \; lv \in LV, h \in H, t \in T \tag{3.74}$$

$D_{lv,t}^{req}$ and $G_{lv,t}^{ava}$ are the total demand and available generation from all HAs in timeslot *t*. Therefore, $\mathrm{DR}_{\mathrm{lv,t}}^{\mathrm{req}}$ is calculated as:

$$\mathrm{DR}_{\mathrm{lv,t}}^{\mathrm{req}} = TC_{\mathrm{lv,t}}^{\max} - D_{lv,t}^{req} \quad , \forall \; lv \in LV, t \in T \tag{3.75}$$

If $\mathrm{D}_{\mathrm{lv,t}}^{\mathrm{req}} > 0$, LTA needs to maximise local usage of renewable generation. The amount of required generation to meet the demand at timeslot *t* ($\Delta_{\mathrm{lv,t}}^{\mathrm{l,G}}$) is calculated as:

$$\Delta_{\mathrm{lv,t}}^{\mathrm{l,G}} = \mathrm{G}_{\mathrm{h,t}}^{\mathrm{TG}} - \mathrm{D}_{\mathrm{lv,t}}^{\mathrm{req}} \tag{3.76}$$

where the amount of energy that is needed to be purchased from all HAs ($G_{lv,t}^{buy}$) is:

$$G_{lv,t}^{buy} = \begin{cases} \Delta_{lv,t}^{l,G}, & \Delta_{lv,t}^{l,G} > 0 \\ G_{h,t}^{TG} & , \Delta_{lv,t}^{l,G} \leq 0 \end{cases} \tag{3.77}$$

LTA uses a merit order to identify the selected HAs and the amount of energy to be acquired from each HA ($G_{h,t}^{buy}$). Since the purchase procedure is done in local community and also consumers are under the same feed-in-tariff, the order of selecting HAs is based on the highest availability of generation.

### 3.5.3 Overall DR control

- *Emergency Demand Response*

The overall DR algorithm for the EDR scheme is shown in Figure 3-17. At the first step, each agent updates its knowledge about other related agents. In case of any DR event, LTA groups its associated HAs into distinctive clusters. For each cluster, the load profile as well as the potential of DR is predicted by LTA. Then, LTA allocates DCL to selected groups of HAs in a merit order and sends an initial DR request to them. The allocation is updated upon receiving responses from HAs and accordingly the new DCL is sent to selected HAs. The latter reduce their consumption in order to ensure that the total household power usage does not exceed a given DCL.

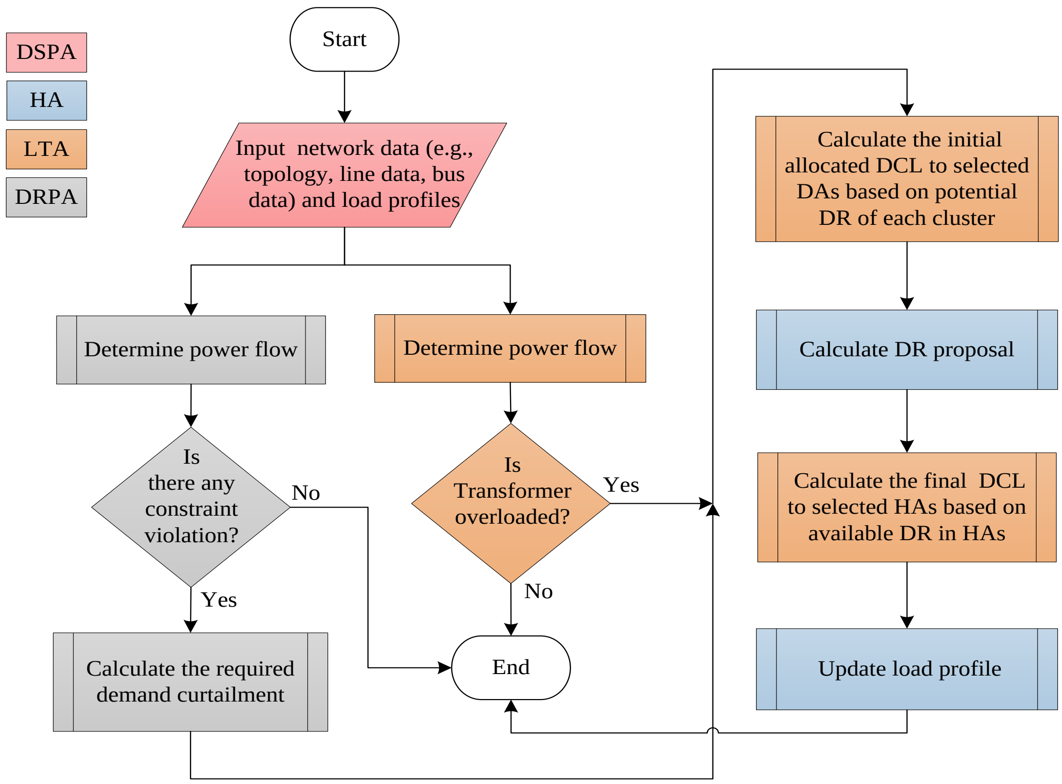



**Figure 3-17:** Overall flowchart of the proposed active MV/LV network management through EDR.

- ***Local Community Demand Response***

In case of critical conditions, the total amount of demand and generation are provided to the households in that community from the LTA. Each household makes a decision to alter its demand dependency on the power grid by changing electricity usage. Then the household submits the updated load profile of its consumption and generation (if they have any) for the next time interval to the LTA. Moreover, LTA provides the required supply by maximising its local usage of renewable generation. A community incentive is allocated to each LTA which they then share to participants according to their reduction. In addition, a pre-determined reward is awarded to the best community with highest total power reduction. The overall DR algorithm for the LCDR scheme is shown in Figure 3-18.

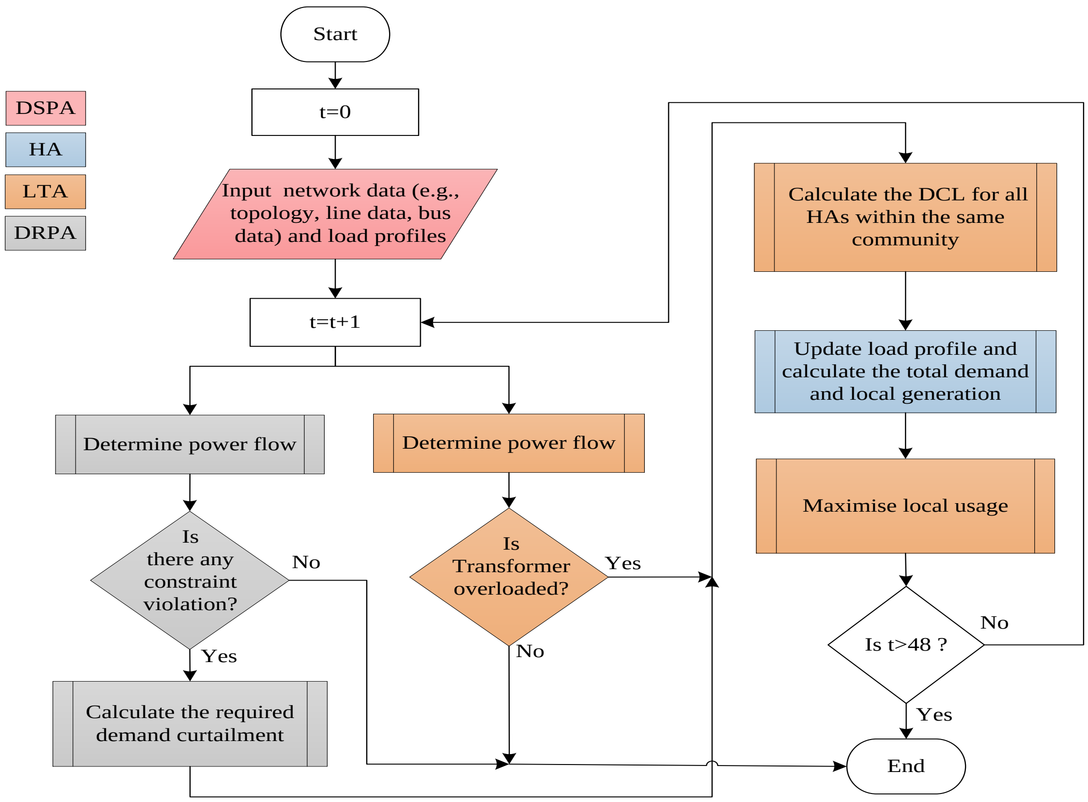



**Figure 3-18:** Overall flowchart of the proposed active MV/LV network management through LCDR

## 3.6 Summary

This chapter provides a detailed description of the proposed MAS framework and architecture. Five kinds of agents are introduced to model a DR-based active distribution network in a virtual agent-based environment. According to the agent's location in the network, four layers are defined; market, MV feeder, LV feeder and end-user layer. For configurability and flexibility, the same MAS platform is used for all three objectives of the thesis and the structures of the DR mechanisms are modelled individually.

The focus of DR in the first and third objectives is on LV network and the second one on MV network. The first two aims are implemented according to price-based DR where the DR activation occurs at SA. In contrast, the last one is incentive-based where DR gets activated at LTAs.

The aim of the DR control algorithm of each HA in the two first objectives is to optimise the load scheduling of shiftable appliances based on different pricing signals set by SA. In contrast, the third objective considers the load curtailment through load shedding. LTAs calculate and estimate the available or required DR size at each time interval. DRPA is responsible for monitoring and assessing the network status. The dynamic pricing tariffs are determined by SA using data received from LTA or DRPA. The overall tasks and methodologies for all agents, except for DSPA, are summarised in Table 3-1.

**Table 3-1:** Summary of the overall methodology for each objective of this thesis

| Obj. | DR type | Agents Tasks | | | |
|---|---|---|---|---|---|
| | | **HA** | **LTA** | **DRPA** | **SA** |
| **1** | **DA-RTP/ ToU** | Optimise shiftable appliances scheduling based on day ahead price signals | Calculate the potential of DR based on probability assessment | Monitor the network status | Set tariffs according to predicted participation rate in day-ahead |
| | **RTP** | - Optimise shiftable appliances scheduling based on a price prediction capability<br>- Calculate available DR at each timeslot in real time basis | Calculate the total DR availability by aggregating the available DR size from all HAs | Monitor the network status | Set tariffs using a four piece-wise linear function based on participation rate in real time |
| **2** | **RTP** | Computationally less demanding decision-making on start-up of shiftable appliances at each timeslot | Calculate the total DR availability by aggregating the available DR size from all HAs | Calculate the total DR requirement from each LV feeder based on the most sensitive buses and potential of DR of each LV feeder | Set tariffs using a two piece-wise linear function based on participation rate in real time |
| **3** | **EDR** | Reduce demand according to maximum DR availability and DCL | Determine the required DCL for each HA based on an initial probabilistic analysis and negotiation with HAs | Determine the required DCL for each LTA in emergency condition | Set pre-determined incentives for each participating HA in EDR |
| | **LCDR** | Reduce demand by maximising local generation usage, and reducing usage according to the maximum DR availability and DCL | Determine DCL and maximise utilisation of local generation at LV feeder | Determine the required DCL for each LTA in emergency condition | Set pre-determined incentives and rewards for each local community |

# Chapter 4 Parameters for Multi Agent System Modelling

## 4.1 Introduction

In the models proposed in the previous chapter, for each of the three objectives of the thesis, the parameters needed to be determined prior to the implementation. This chapter provides information regarding the selection of these parameters. The network simulation environment together with the dataset used is also introduced. The households load profiles as well as their characteristics are described as well. Three objectives are considered in this thesis as described in section 1.3 and in this chapter these are referred to as objective 1 (LV network), objective 2 (MV network) and objective 3 (MV/LV network) as described in chapter 1. For each objective, the simulation modelling along with the simulation set-up is presented.

## 4.2 Power Distribution Network Modelling

The aim of the ADNM developed in this thesis is to control the constraints in the DN through flexible residential loads. Therefore, when designing the physical layer of the MAS framework, the size of the network should be big enough to accommodate large scale DR aggregation. In this regard, a modified IEEE 69-bus 12.66 kV radial distribution network is used as the testing layout of the MAS framework. The one line diagram of the test system is shown in Figure 4-1. The network comprises 8 MV feeders as well as 48 lateral LV feeders. Each LV feeder is fed from a 12.66/0.415kV, 45kVA MV/LV transformer which consists of 19 nodes, each representing two households. Hence, each LV feeder is connected to 38 households and this represents a total of 1824 households in the network. System data including line and transformer parameters are provided in Appendix A.

The same network topology is used for all three objectives. However, depending on the focus of DR mechanism in each objective, the relevant methodology is implemented and tested in the respective area (LV or MV feeders). In addition, the households' features are described individually for each case. The representation of each component in the physical layer and the agents in the cyber layer are modelled and simulated using MATLAB respectively.

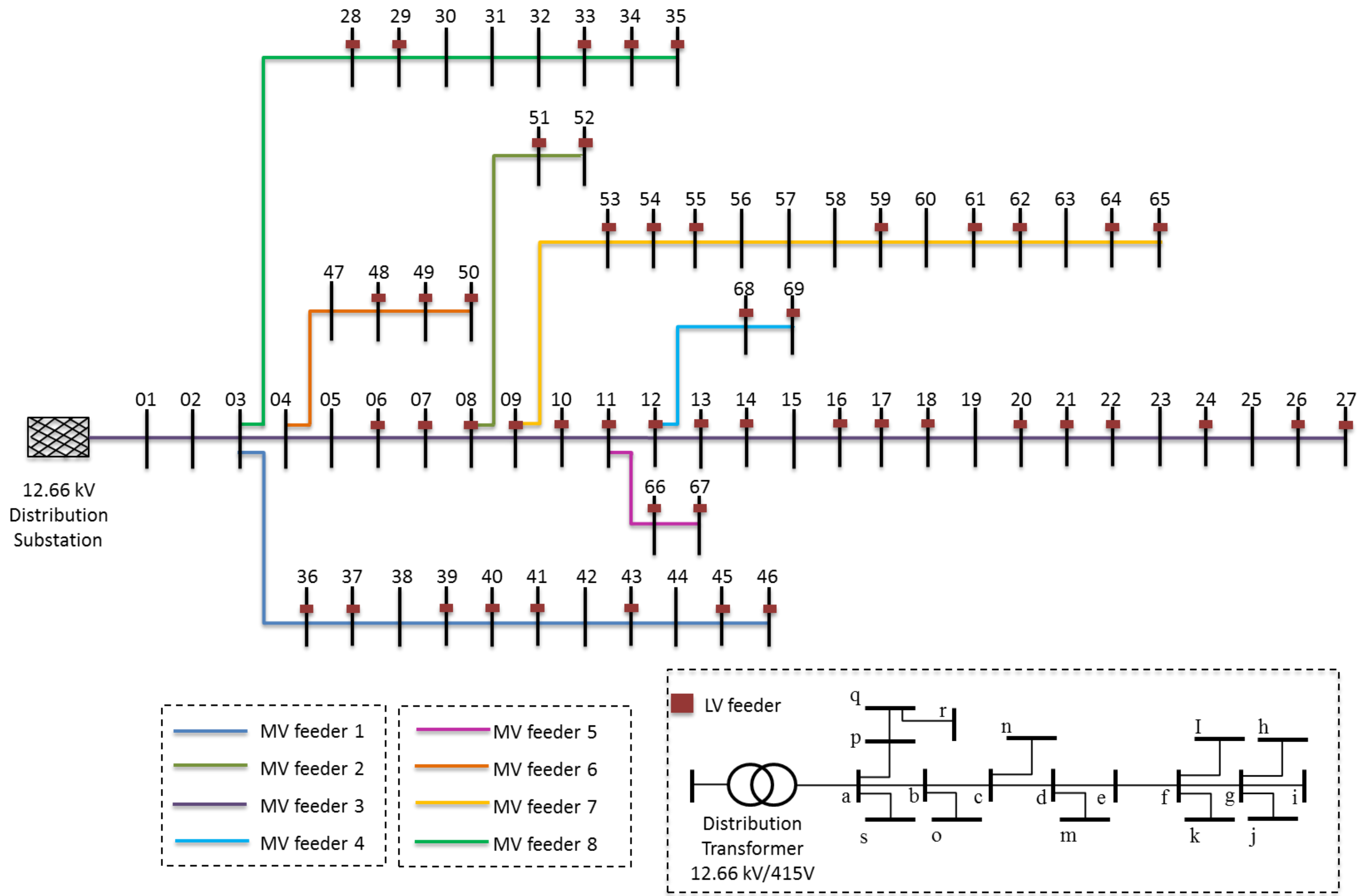



**Figure 4-1**: One line diagram of modified IEEE 69-bus test system with 8MV feeders and 48 LV feeders

## 4.3 Creating Households Load Profile from Dataset

The dataset related to a real trial, IEMST project [214], is used in order to provide appropriate information to determine the load profile as well as characteristics for each household. The programme targeted the electricity consumption (without PV and EV), of 5028 Irish residential customers with half-hourly meter reading resolution. The duration of the trial was split into two timeframes: a six month benchmark period (July- Dec 2009) and a one year test period (Jan-Dec 2010). In the former, all participants were equipped with smart meters and their energy consumptions were measured as normal under fixed price tariffs. In the second period, customers were allocated randomly to different tariff scenarios including five ToU tariffs (labelled A-D) and one controlled group (labelled C). However, the profile of the set of consumers in each trial group was almost the same in terms of behavioural, demographic and attitudinal perspectives. The tariffs and the population allocated in each group are depicted in Table 4-1. The four first price rates are designed according to the time of the day where three pricing bands, day, peak and night time, were defined. In contrast, in the last ToU tariff, the price variation was on the type of the day, weekends/weekday, in order to assess its effect on consumption behaviour. An in-home survey was also taken which provides valuable information regarding characteristics of the residential electricity consumption patterns and behaviours.

**Table 4-1:** Groups and ToU tariffs structure of IESMT [42]

| **Price band** | **Price by tariff group (c/kWh)** | | | | | |
|---|---|---|---|---|---|---|
| | **A** | **B** | **C** | **D** | **W** | **Control** |
| Night (23:00 to 08:00) | 12 | 11 | 10 | 9 | 10 | |
| Day (All other times) | 14 | 13.5 | 13 | 12.5 | 14 | 18 |
| Peak (17:00 to 19:00, Mon | 20 | 26 | 32 | 38 | 38 | |
| weekend (All Weekend) | | | | | 16 | |
| N (households) | 1368 | 511 | 1370 | 509 | 100 | 1170 |

The choice of the dataset used was the availability of meter-reading, in-home surveys and various ToU tariffs for large numbers of residential DR participants.

In order to model the customer flexibility behaviour, synthetic load profiles for households are created and applied in the network analysis. To achieve more accurate results, the data related to only weekdays for a summer month, July, is considered in the analysis. That is due to the fact that the type of the day and month can highly affect the consumption patterns, consumers' behaviour and the price elasticity of energy demand [215, 216]. The meter readings for the benchmark period, where all households are in the same tariff, are utilised. The data used in the simulation was for a total of 23 days, resulting from July having 8 non-weekdays. The first timeslot (t=1) represents 00:00:00-00:29:59 hrs. The Knowledge Discovery in Databases (KDD) process is employed for generating the load profiles of households.

### 4.3.1 Pre-processing

The aim of this step is to minimise the percentage of error in data reading due to anomalous readings, meter faults, loss of supply or other interruptions. This is done in two phases: clearing and cleaning data, and replacing the missing data with appropriate values. Applying the former process improves the accuracy and quality of the result.

***Phase1-Clearing and cleaning data:*** Any meter reading value which meets the following conditions is removed from the original dataset. All missing values were considered as 0 which were replaced with the appropriate values in the next phase.

- Negative or zero values or higher than 10kW
- Any repeated data with the same time stamp
- Value higher than the sum of the mean and three time the Standard Deviation (SD) of the energy values for that specific day (value > mean(value) + 3δ)

For each customer, all readings for a complete day which belong to any of the following categories are removed.

- Days with less than ten different values in the meter readings
- Days with less than 43 time interval in the meter readings (1/8 of total reading per day)
- Day with three continuous missing timeslots (1.5 hour or about 0.06% of total reading)
- Day with two pairs of two continuous missing timeslots (two different of 1hour missing values)

***Replace missing data with appropriate values*:** The missing energy values at specific timeslots were replaced with available data obtained from their mean of readings at previous and next timeslots. If the first time interval (t=1) or last time interval (t=48) were missed, their replacement were done by averaging the readings of timeslot (t=2) and (t=3) and (t=46) and (t=47) respectively.

A comprehensive study on missing meter data impact on clustering and characterisation of their load profiles was investigated [217] but since this was not the focus of this thesis, it will not be discussed in depth. The results showed that although replacing larger percentage of missing values provides a larger sample size, it will also affect the quality and accuracy of clustering results. In this regard, customers with more than one missing day in their meter readings were removed. The missing days were replaced with the data available for similar day in that month. It should be noted that, only consumers who's meter readings were available in both control and trial periods are considered. After cleaning and clearing data, 3990 customers remained in this study. This filtering ensures the quality of the dataset.

### 4.3.2 Normalisation

The purpose of clustering consumer load profiles is to investigate a similarity in their consumption patterns. Hence, prior to clustering, firstly, the average monthly usage of each household is calculated as:

$$\overline{l_h} = \frac{\sum_{N_d} l_{h,N_d}}{N_d}, \forall\, h \in H, N_d = [1, 23] \tag{4.1}$$

where,

$$l_{h,N_d} = \sum_t l_{h,t}\,, \forall\, h \in H, t \in T \tag{4.2}$$

where, $\overline{l_h}$ is the average load consumption of household $h$ during all weekdays of July ($N_d$) and $l_{h,N_d}$ is the average usage in ${N_d}^{th}$ day. Then, a linear normalisation process is used to normalise and transform each of the averaged value of the load profile using the following equation:

$$l_h^{norm} = \frac{\overline{l_h} - \min(l_{h,N_d})}{\max(l_{h,N_d}) - \min(l_{h,N_d})}$$

$$, \forall\ h \in H, N_d = [1, 23], t \in T \qquad (4.3)$$

$l_{h,t}^{norm}$ and $l_{h,N_d}$ are the normalised load and meter reading data for $h^{th}$ household, at day $N_d$. The maximum value of the load curve $\left(max\left(l_{h,N_d}\right)\right)$ can be assumed as a reference value for the normalisation.

### 4.3.3 Clustering

The quality of clustering results significantly relies on the applied algorithm. In this regard, three clustering techniques are used and implemented for the electricity meter data for comparison purposes.

***K-means algorithm:*** This is one of the most common clustering algorithms which has been extensively implemented [218]. Each observation allocates to one specific cluster with the nearest mean. The segmentation method, based on Euclidean distance within all clusters, depends on the number of clusters. The disadvantage of this algorithm is the need of pre-determination of the number of clusters by users.

***Fuzzy K-means:*** This is similar to the K-means technique with the difference that each sample can belong to more than one cluster. For each observation, a weighted centroid method is applied to determine the grade of membership to other clusters [219]. The inputs of the algorithm are the number of clusters and membership criteria. Stable partitions are obtained by repeating the procedure.

***Dirichlet Process Mixture Model (DPMM):*** The DPMM is a Bayesian non-parametric statistical model that hierarchically combines Dirichlet and Multinomial distributions [220]. In fact, electricity load profiles are represented as draws from Multinomial distributions. The advantage of the model is that, unlike the K-means and Fuzzy K-means algorithms, the number of clusters does not need to be pre-determined.

**Evaluation:** For the studied dataset, scanning the unique model parameter (concentration parameter of a Dirichlet distribution), the DPMM algorithm converges in a partition with six clusters. For the first two clustering algorithms, the clustering was repeated for 2-14 numbers of clusters in order to investigate the impact of the number of pre-determined clusters. In addition, the performance of the results for all clustering techniques regarding the quality and composition of clusters were assessed. The evaluation was verified by Davies-Bouldin index

(DBI) which is based on a ratio of within-cluster and between-cluster distances [221] and the results are illustrated in Figure 4-2. The smallest DBI value represents the optimal clustering number. As can be seen, the distribution of all algorithms follows a similar trend although the DBI values for DPMM are slightly higher. However, comparing the results, the optimal number of cluster by DBI evaluation is similar to DPMM. A comprehensive comparison between DPMM and various clustering techniques presented in [220] demonstrate the high accuracy of this technique. The optimal number of clusters was determined as six with DPMM, to represents variability distribution of demand profiles. The centroid of each created clusters is shown in Figure 4-3 and the average power consumption as well as population within each cluster is illustrated in Table 4-2.

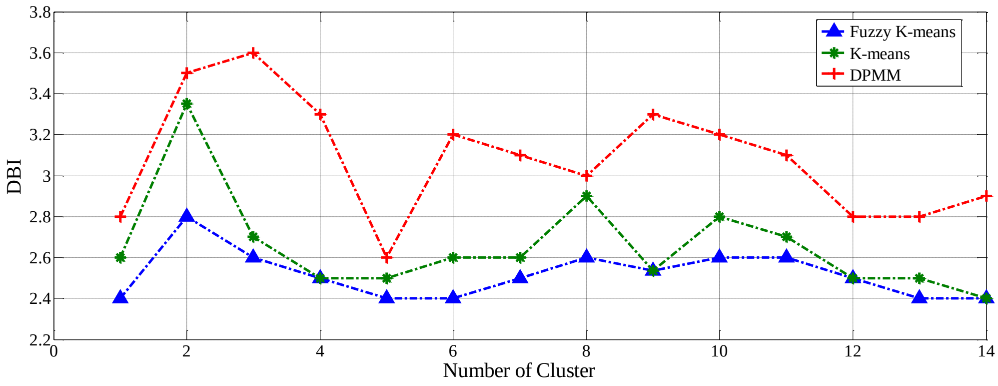



**Figure 4-2:** DBI for different clustering methods

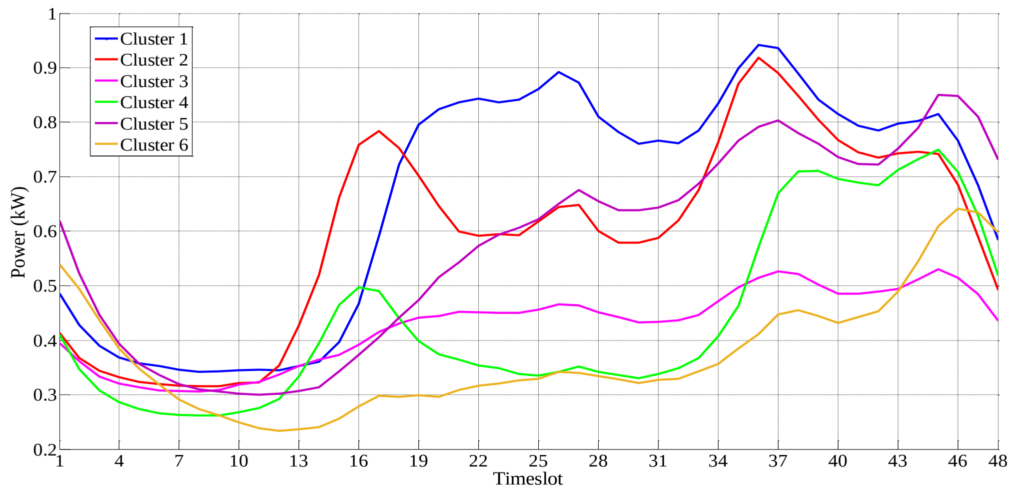



**Figure 4-3:** Centroid of the 6 clusters resulting from DPMM

**Table 4-2:** Population and average power consumption in each cluster

| Cluster No. | No. of Customers | Population (%) | Mean Consumption (kWh) | Mean Consumption (%) |
|---|---|---|---|---|
| 1 | 799 | 20 | 394.10 | 25.08961 |
| 2 | 625 | 16 | 362.80 | 23.09695 |
| 3 | 757 | 19 | 55.75 | 3.549215 |
| 4 | 533 | 13 | 200.32 | 12.75298 |
| 5 | 931 | 23 | 197.45 | 12.57027 |
| 6 | 345 | 9 | 360.35 | 22.94098 |

### 4.3.4 Synthetic Data

1824 synthetic load profiles were created based on the clustering results. Firstly, for each cluster, the mean aggregated minimum and maximum loads values were calculated. Then, the load profiles were randomly created with a normal distribution around the centroid of that cluster. The percentage of synthetic load profiles created in each cluster is kept constant for all clusters in the dataset. The synthetic data extracted from clustering results is shown in Figure 4-4. The generated load profiles are distributed randomly in the network.

## 4.4 Classification of Dataset

Data classification is an effective tool for dealing with the residential loads challenges regarding their intermittency and uncertainty nature. A characterisation-based clustering technique is used to study the various aspects of customer characteristics in each cluster.

Using a multinomial regression model, the correlations between dependent variables (customer's characterisation) and independent variable (mean usage) within each cluster is studied. Table 4-3 summarises the main features which can have an effect on the power usage. The household features include the size of household and the number of bedrooms.

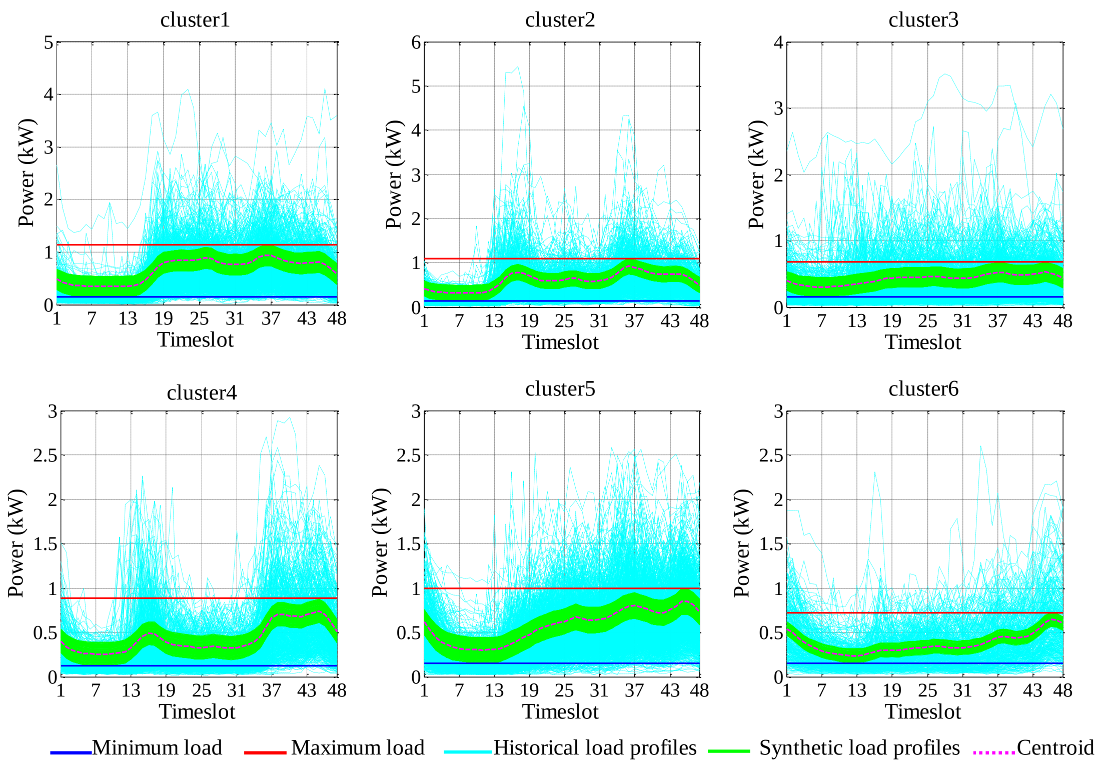



**Figure 4-4:** Load profiles of HAs created based on 6 cluster results (1824 profiles)

**Table 4-3:** Customers characterisation within each cluster

| Cluster No. | Household feature | Occupancy level | Educational level | Economic level |
|---|---|---|---|---|
| **1** | 6.842898 | 3.834268 | 6.512359 | 4.584632 |
| **2** | 4.573384 | 1.992343 | 4.635458 | 3.401898 |
| **3** | 4.822042 | 2.147352 | 5.115433 | 2.812393 |
| **4** | 1.839991 | 3.472032 | 6.397739 | 4.031594 |
| **5** | 1.839991 | 1.216999 | 1.904661 | 1.425251 |
| **6** | -1.57424 | -0.15855 | -1.71991 | -1.46396 |

The characteristics of clusters 1 and 2 have the highest effect on their usage. On the other hand, cluster 6 which have relatively high mean usage although all its characteristics have low values. This indicates the possibility of this cluster consisting of wealthier customers. It can be observed that household features and educational level are the characteristics having the most effect on DR potential. The analysis of Table 4-3 is provided along the rest of the chapter as appropriate.

#### 4.4.1.1 Willingness to Participate in DR Schemes

Consumers are grouped according to their attitudes towards DR participating. The clustering is performed using K-means algorithm as explained previously. Hence, each individual household is assigned to a cluster of households with similar willingness to engage in DR. The clustering results are evaluated by DBI and Calinski-Harabasz Index (CHI), which is based on a variance ratio of within and between clusters, as shown in Figure 4-5. Unlike DBI, the best clustering result in CHI is obtained for maximum values. Three optimal number of clusters are obtained with different attitudes, highly motivated, less motivated and doubter, and these are summarised in Table 4-4.

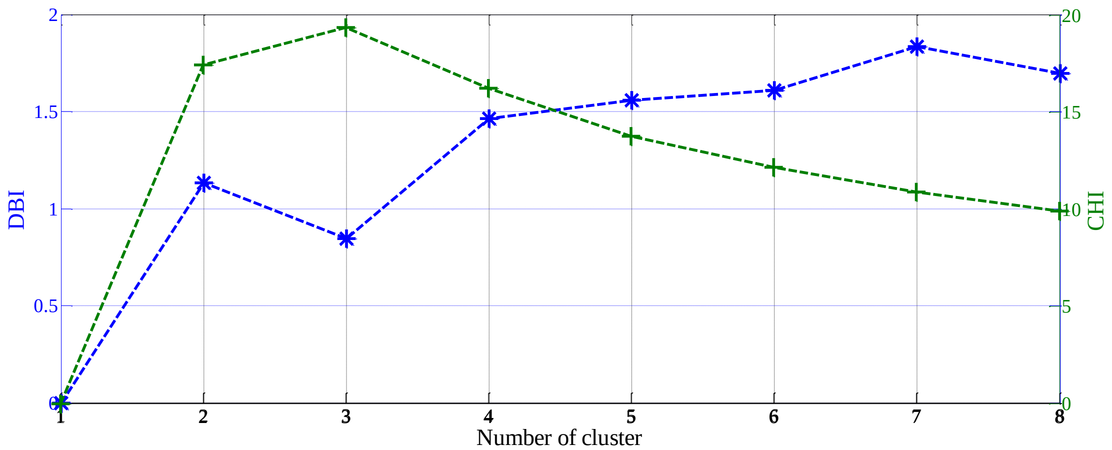



**Figure 4-5:** DBI and VRC for evaluating clustering of households

**Table 4-4:** Social segmentation of the customers

| Cluster No | Attitude [%] | | |
|---|---|---|---|
| | Highly motivated | Less motivated | Doubter |
| **1** | 58.2 | 37.7 | 4.1 |
| **2** | 31.8 | 61.8 | 6.4 |
| **3** | 31.7 | 65.8 | 2.5 |
| **4** | 19.8 | 77.4 | 2.8 |
| **5** | 46.4 | 46.3 | 7.3 |
| **6** | 41.9 | 48.6 | 9.5 |

The value of $A_h^t$ in all objectives is assumed to be 1 and 0 for the highly motivated and doubter groups respectively and a random number between 0 and 1 is allocated to the less motivated group. $A_h^t$ remains unchanged during the whole simulation period for each HA.

### 4.4.1.2 Price Elasticity of Demand

The data related to trial period is investigated together with the benchmark period in order to determine the coefficients of the price elasticity. Appendix B presents the Ratio of Cost (RC) values which is the ratio of each trial tariff in respect to the fixed tariff (control group). The percentage of demand reduction is also shown for different cluster of customers based on the time the day. Figure 4-6 shows the total energy usage before and after applying DR. These plots depict the PED which is dependent on the time of day. It can be deduced that reduction in power consumption in each cluster does not necessarily have a linear relationship with price. Moreover, the granularity of PED is different for various ToU tariffs in each group. Considering Table 4-3, although the RC value for tariff A is higher, not all customers are likely to be elastic to this tariff. It can also be observed that the potential of DR does not necessarily depend on population within a cluster. For instance cluster 3 has the lowest mean power usage Figure 4-6 and cluster 1 has the highest but the elasticity in cluster 3 is higher than cluster 1. This is because of the different characteristics of consumers in regards to economic aspects, convenience, comfort level and awareness amongst others. It is evident from the results in table SD where the DR potential results from a combination of on power consumption as well as individual household characteristics.

Linear regression model was used to model the correlation between different pricing bands and demand reduction for each cluster as illustrated in Figure 4-7. The effects that various ToU bands have on household clusters is presented. Using the regression results in Figure 4-7, the elasticity coefficients from equations (3.7) and (3.39) are obtained and summarised in Table 4.5.

**Table 4-5:** Setting coefficients of parameters $\boldsymbol{\varepsilon_c}$and $\boldsymbol{b_c}$ (6) in the simulation for each cluster

| **Cluster No.** | $\varepsilon_c$ | $b_c$ |
|---|---|---|
| **1** | 0.5485 | - 0.4009 |
| **2** | 0.807 | -0.2799 |
| **3** | 0.556 | -0.1926 |
| **4** | 0.6759 | -0.2342 |
| **5** | 0.4294 | -0.1488 |
| **6** | 0.39 | -0.1072 |

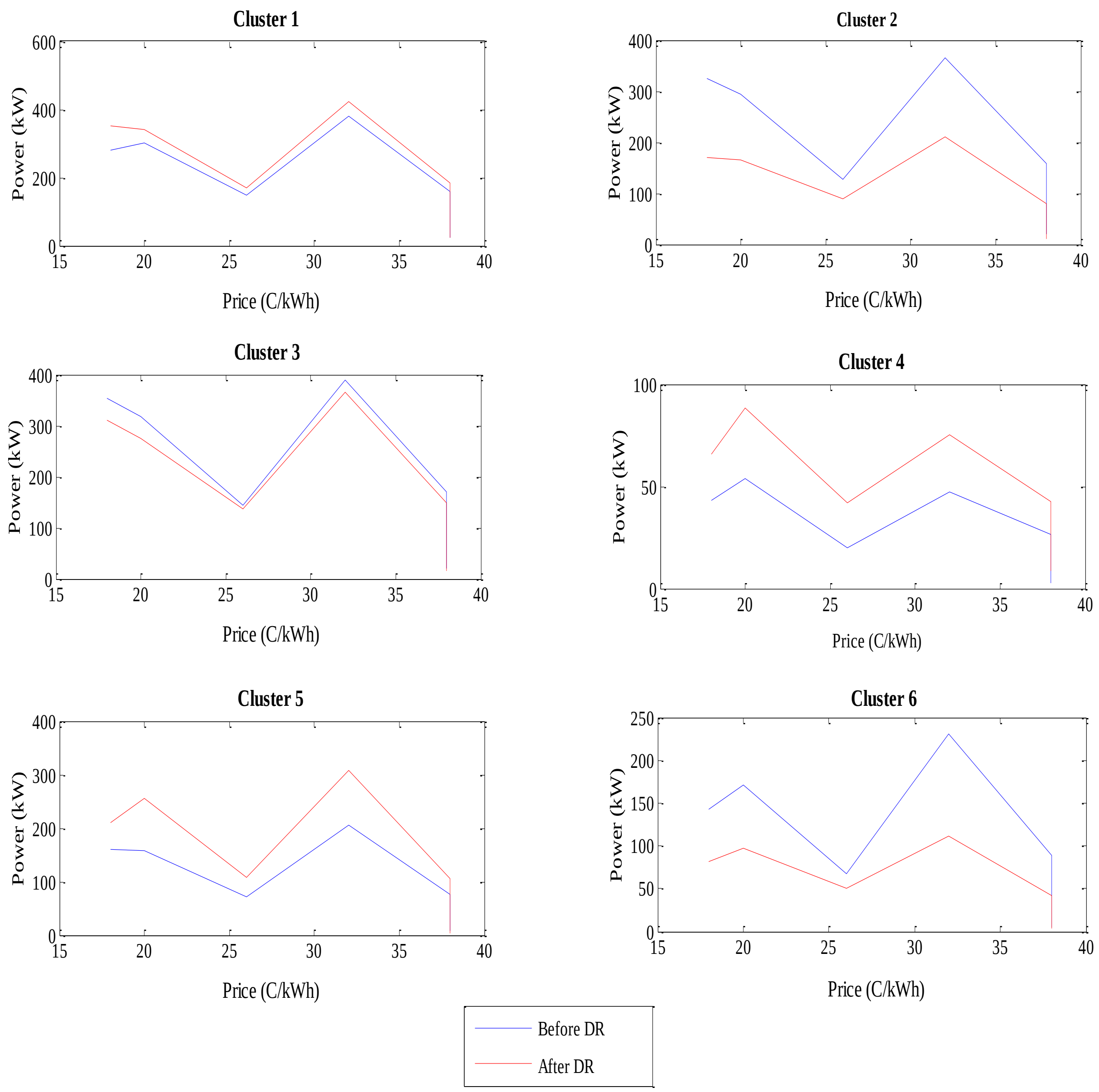



**Figure 4-6:** Mean power usage/price elasticity of each cluster to different tariffs

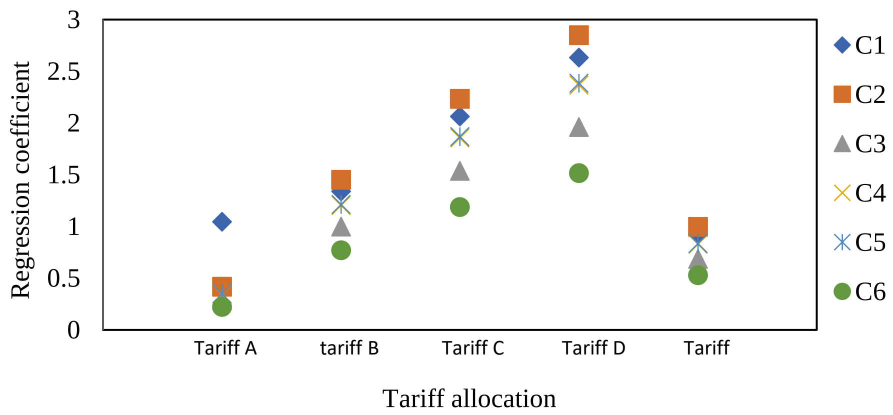



**Figure 4-7:** Regression coefficients for different tariffs allocation and different groups of customers

## 4.5 Load Modelling

### 4.5.1 Wet Appliances model

The shiftable loads have flexible time delays, fixed cycle lengths and power consumption in each phase of their operation. The length of operating cycle of each appliance depends on the operating parameters and temperature. The appliances from Figure 3-4 (b) are described in the following with regard to their characteristics.

***Dishwasher (DW)*:** A typical dishwasher has an operating length of 75 minutes [222, 223] and consists of three cycles: wash, rinse and dry. The power consumption for each cycle is between 0.2kW and 2.8kW and averaging around 1.19kWh. A typical demand profile for such an appliance is shown Figure 4-8.

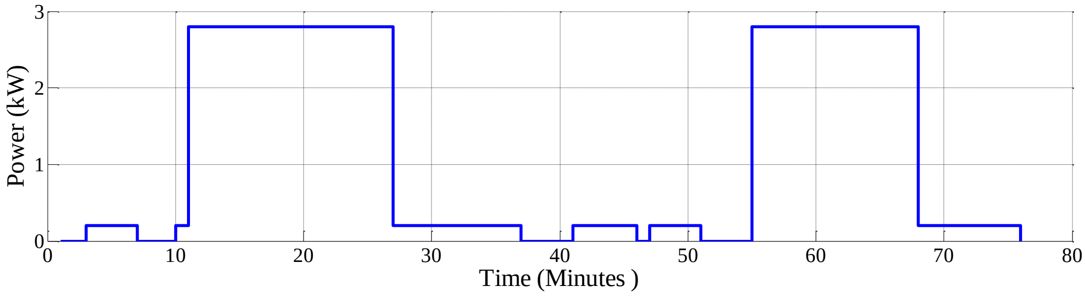



**Figure 4-8:** Typical consumption of a dishwasher [222]

***Washing Machine (WM):*** The operation of a WM comprises mainly of washing and drying cycles, lasting approximately 75 minutes [222, 223]. It has similar power consumption as DW with an average of 1.5kWh per cycle. A typical consumption profile for such WM is shown Figure 4-9

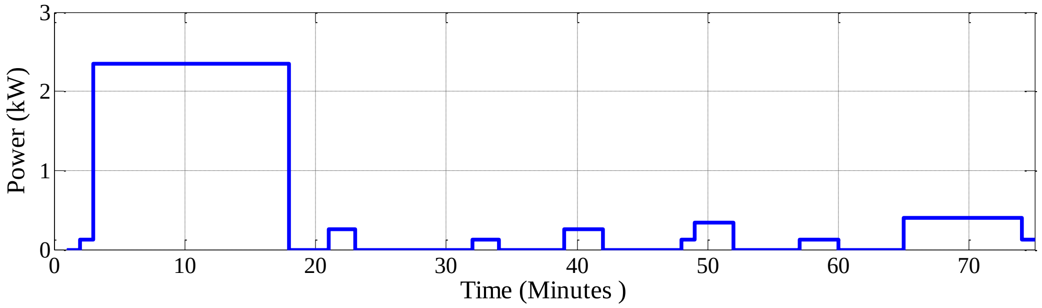



**Figure 4-9:** Energy consumption of a washing machine [222]

***Tumble Dryer (TD):*** This has operating cycles of approximately 52 minutes [222, 223]. Typical values for power usage are around 0.2kWh to 2.6kWh with an average of 1.2kWh as depicted in Figure 4-10.

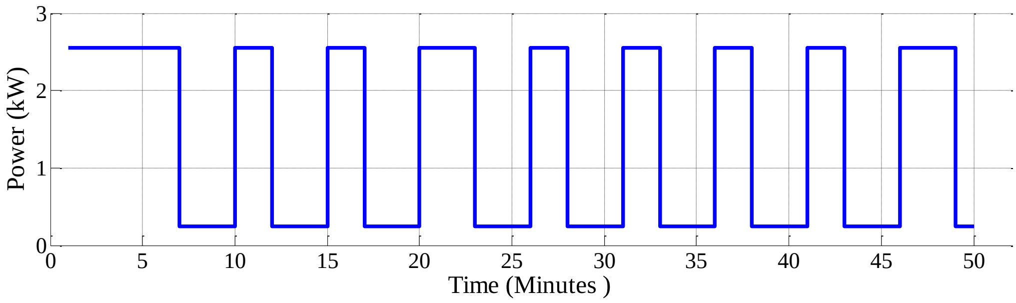



**Figure 4-10:** Energy usage of a typical tumble dryer [222]

One assumption made is that all these appliances have integrated timers or electronic control mechanisms which enable planned shifting of the start time based on timeslots.

### 4.5.2 PV Model

The output of a typical PV was required for considering the local generation at household level to model the LCDR scheme (objective 3). The typical characteristics of the PV model used are shown in Table 4-6.

**Table 4-6:** PV panel properties

| **PV Model** | **Suntech STP250S** | |
|---|---|---|
| **Electrical Characteristics** | Number of panel | 8 |
| | Standard Test Condition power rating | 250 W |
| | Optimum Operating Voltage | 30.7 V |
| | Optimum Operation Current | 8.15A |
| | Peak Efficiency | 15.4% |
| **Mechanical Characteristics** | Solar Cell | Monocrystaline Silicon |
| | No. of Cells | 60 (6x10) |
| | Dimensions | 1640x992x50mm |
| | Weight | 19.1 kgs |

A typical summer day, 19th July, was arbitrarily chosen for the PV data. The weather condition for that specific day is given below.

**Table 4-7:** Weather condition used for PV model

| **Date** | | 19th July 2017 |
|---|---|---|
| **Temperature** | Low | 15.8° C |
| | High | 20.7° C |
| **Wind** | Average | 6.0 mph |
| | High | 23 mph |
| | Direction | SW |
| **Rain** | | 4.10 mm |

The distribution of the solar output with respect to timeslots is depicted in Figure 4-11

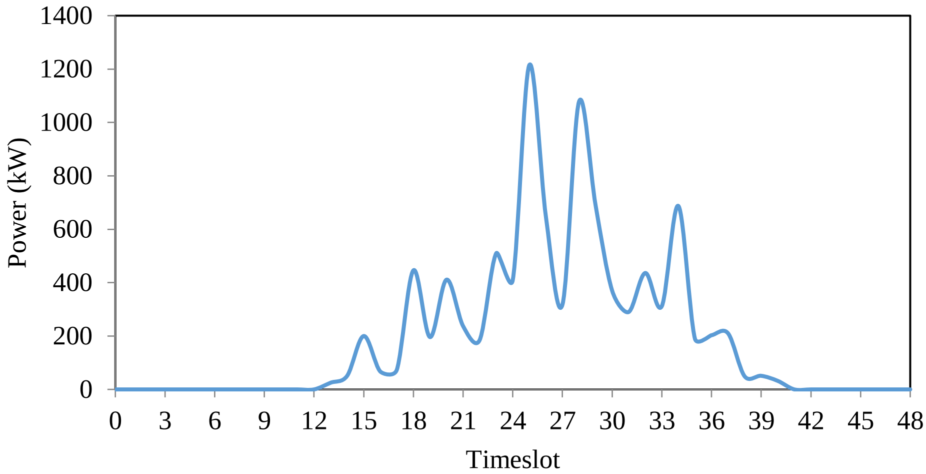



**Figure 4-11:** Solar output power

# 4.6 LV Network Modelling

## 4.6.1 Simulation Model

The first objective of this thesis is the LV network management (without) considering any DR event in the MV network. The proposed methodology is implemented and the simulation results are evaluated for one LV feeder as shown in Figure 4-1. A total number of 38 households are considered for the simulation over a one-day period for all case studies in this thesis. In order to examine the performance of the proposed methodology, the synthetic load profiles are distributed in the network, keeping the same proportion of household clustering. This is depicted in Figure 4-12, where each household is presented with an arrow having different colour representing the cluster of that household. Each bus is connected to two households in a different cluster.

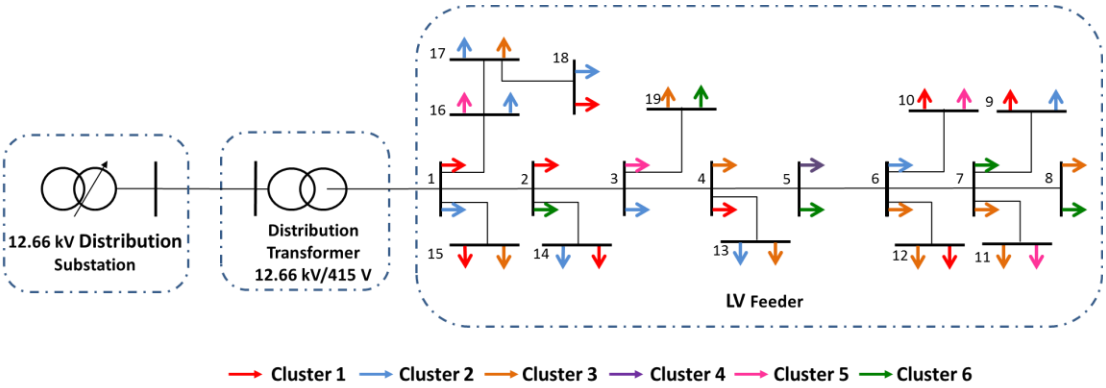



**Figure 4-12:** One-line diagram of the test system for LV network modelling with the distribution of cluster of households.

### 4.6.2 Simulation Set up

***Home Agent:***

Detailed parameters of the shiftable loads are summarised in Table 4-8. It is assumed that each appliance uses equal proportion of the total required energy for completion of its operation ($l_{h,t}^{sh} = \frac{E^{sh}}{\Delta t^{sh}}$). The background load for each household is determined as the difference between the load profile and the power consumption of each operating appliance.

**Table 4-8:** Parameters characteristics of the shiftable loads

| | **Ownership rate** | $\mathbf{l_{h,t}^{sh}}$ | $\mathbf{\Delta t^{sh}}$ | $\mathbf{E^{sh}}$ |
|---|---|---|---|---|
| **Washing machine** | 98% | $^{1.2}/_{3}$ kW | 3 | 1.2 kW |
| **Dish washer** | 95% | $^{1.19}/_{3}$ kW | 3 | 1.19 kW |
| **Tumble dryer** | 89% | $^{0.9}/_{2}$ kW | 2 | 0.9 kW |

The user's allowable window $\left(\Delta \mathrm{t}_{\mathrm{h,t}}^{\mathrm{sh,pref}}\right)$ is determined for each cluster of households, from equation (3.24), in which the operating status of each appliance $(x_{C,h,t}^{sh})$ is set to 1 if $\left(P\left(Z_{C,t}^{sh}\right)\right) \geq 0.5$. Then, the start time of each wet appliance $\left(t_{h,t}^{sh}\right)$ for each household is deduced based on a random selection from their $(\Delta t_{h,t}^{sh,pref})$. This is illustrated in Figure

4-13. The values of $\Delta t_{h,t}^{sh,pref}$ are provided in the LTA parameter setting. The coefficients for the price prediction model in equation (3.15) are set the same as the RTP of SA as depicted in Table 4.5.

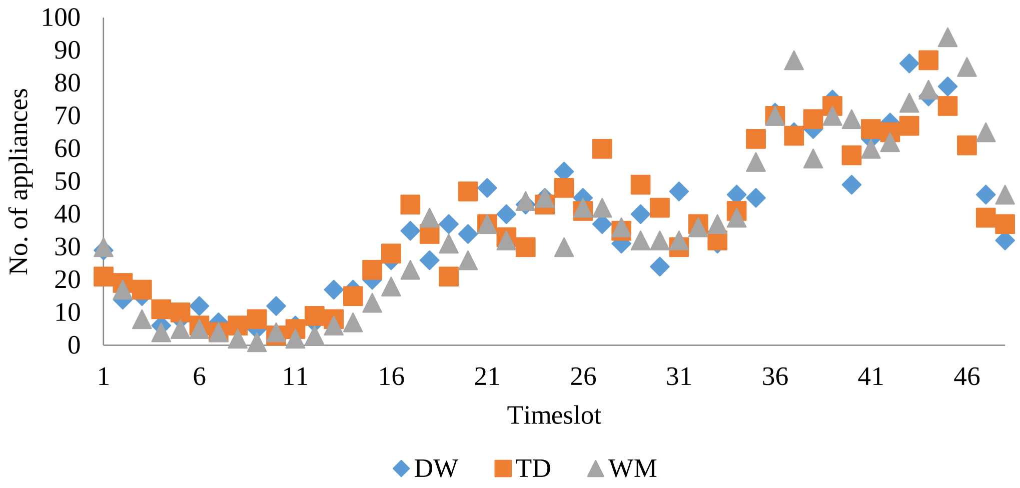



**Figure 4-13:** The random-base selection of start-up time of shiftable appliances before DR implementation

***Local Transformer Agent:***

The results from the methodology proposed in section 3.3.2, to estimate the potential of shifting wet appliances, are provided. The simulation is performed for one-day period using historical load profiles from the dataset.

$\boldsymbol{Y_{c,h,t}^{sh}}$**:** The ownership rate of different controllable appliances along with their daily frequency usage for each cluster of consumers is shown in Figure 4-14. While most households own washing machines, the highest ownership rate for dish washer and tumble dryer are from clusters 1, 2 and 3.

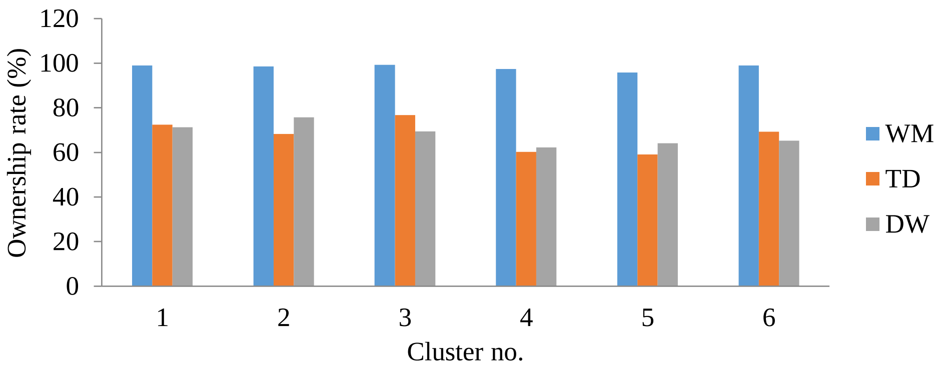



**Figure 4-14:** Appliances ownership rate (%) for each group

The probability of starting time of appliance in each cluster during a typical weekday is determined using equation (3.25).  This is shown in Figure 4-15 for washing machine and for all appliances in Table 4-9. It should be noted that in order to determine the maximum DR availability, the wet appliances are considered to be run once during one day simulation for those households that own them. As can be observed, the probability of start-up of the appliances in each cluster is direct correlation with its peak demand.

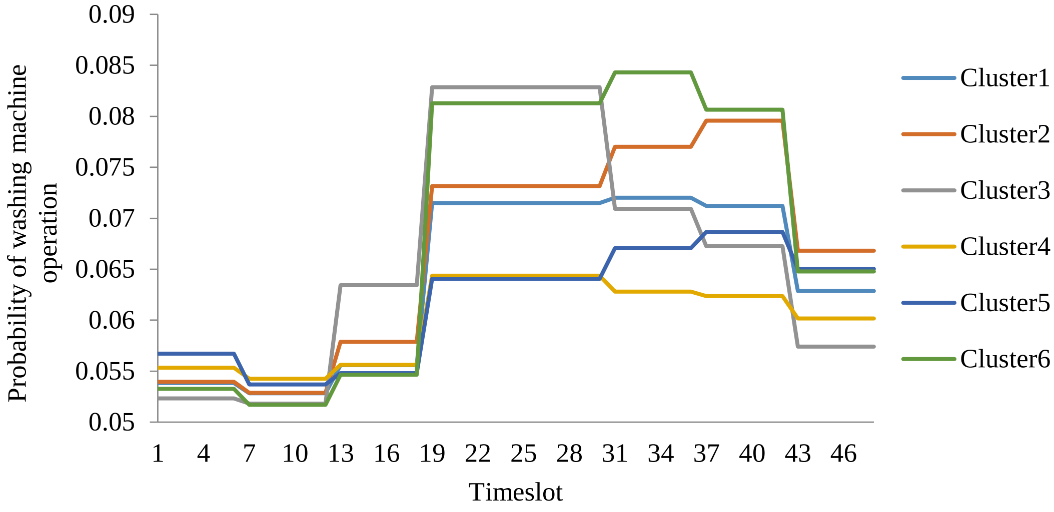



**Figure 4-15:** Probability of operating of washing machine for all clusters of consumers

**Table 4-9:** The preferable time windows for shiftable appliances in each cluster of consumers

| | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** |
|---|---|---|---|---|---|---|
| $\Delta t_{h,t}^{WM,pref}$ | 1-48 | 13-47 | 14-48 | 13-48 | 1-3, 16-48 | 1-2, 34-48 |
| $\Delta t_{h,t}^{DW,pref}$ | 1-48 | 1-47 | 14-48 | 1, 13-48 | 1-3, 16-48 | 1-2, 34-38 |
| $\Delta t_{h,t}^{TD,pref}$ | 1-2, 15-48 | 14-47 | 14-48 | 14-20, 33-48 | 1-2,17-48 | 1-2, 36-48 |

$\acute{l}_{c,t}^{DR,pot,total}$ **:** The potential of demand shifting from all aggregated households within each cluster during a typical day is plotted in Figure 4-16.

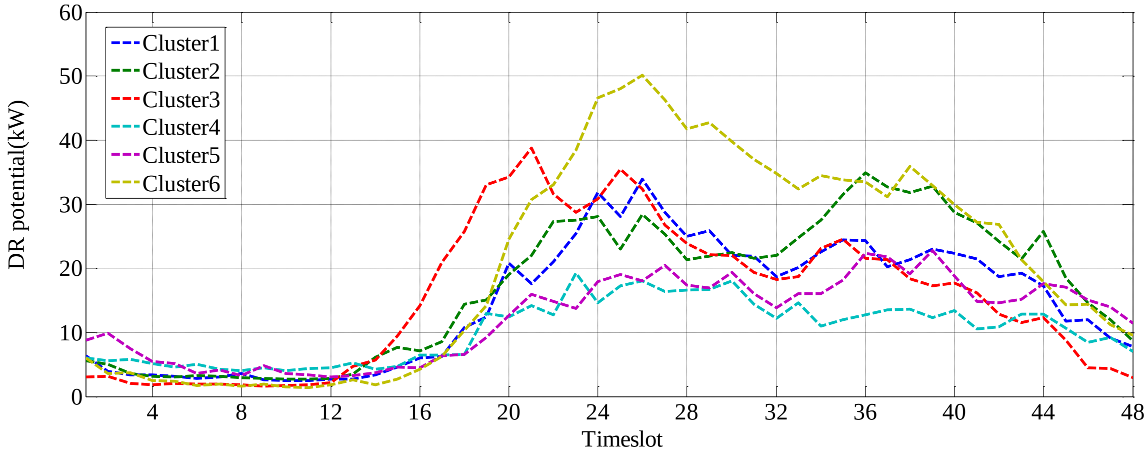



**Figure 4-16:** The potential of DR arising from shiftable appliances in all clusters

As can be seen, the potential of responsiveness demand over time varies in each cluster which is dependent on the load profile of that cluster.

***Supplier Agent:***

At the time of writing this thesis, to the author's knowledge no RTP tariff were implemented in UK. Hence, the coefficients in equation (3.58) were obtained by using the price data of the first dynamic ToU tariffs in GB (Low carbon London trial), as explained previously in section 2.6.1. Three price bands were determined by EDF Energy supplier [39]: as High: 67.2 pence/kWh, Default: 11.76 pence/kWh and Low: 3.99 pence/kWh. Accordingly, the price coefficients that are used to design either DA-RTP or RTP, are presented in Table 4-10. The three pricing bands are also used for ToU tariff as presented in Table 4-11. The fixed price in all cases is considered to be 14.22 pence/kWh.

**Table 4-10:** Parameters determined for four-level piecewise linear pricing function in (3.30)

| **Parameter** | **Value** | **Parameter** | **Value** |
|---|---|---|---|
| $\propto_1$ | 0.0253 | $\beta_4$ | -118.8 |
| $\beta_1$ | 3.99 | **Min. price** | 3.99 p/kWh |
| $\propto_2$ | 0.338 | **Max. price** | 67.2 p/kWh |
| $\beta_2$ | -8.52 | **Threshold 1** | 5 p/kWh |
| $\propto_3$ | 0.912 | **Threshold 2** | 11.76 p/kWh |
| $\beta_3$ | -42.96 | **Threshold 3** | 40 p/kWh |
| $\propto_4$ | 1.86 | | |

**Table 4-11:** ToU tariff designed by SAs for HAs in objective one

| ToU tariff | Day | Peak | Night |
|---|---|---|---|
| **Price** | 11.76 | 67.2 | 3.99 |
| **Timeslot** | 17-34<br>39-46 | 35-38 | 1-16<br>47-48 |
| **Hour of day** | 8.00-17.00<br>19.00-23.00 | 17.00-19.00 | 23.00-8.00 |

## 4.7 MV Network Modelling

### 4.7.1 Simulation Model

This objective deals with objective 2 as explained in section 3.4, which aims to manage the voltage and thermal constraints at MV network level while considering normal operating status at LV feeder. The network shown Figure 4-1 is utilised for the implementation and evaluation of the proposed framework. The numbering of LV feeders, where the households loads are connected, and their position at the network is summarised in Table 4-12.

**Table 4-12:** LV feeders numbering

| LV feeder No. | Bus No. | MV feeder No. | LV feeder No. | Bus No. | MV feeder No. | LV feeder No. | Bus No. | MV feeder No. |
|---|---|---|---|---|---|---|---|---|
| **1** | 6 | 3 | **17** | 26 | 3 | **33** | 49 | 6 |
| **2** | 7 | 3 | **18** | 27 | 3 | **34** | 50 | 6 |
| **3** | 8 | 3 | **19** | 28 | 8 | **35** | 51 | 2 |
| **4** | 9 | 3 | **20** | 29 | 8 | **36** | 52 | 2 |
| **5** | 10 | 3 | **21** | 33 | 8 | **37** | 53 | 7 |
| **6** | 11 | 3 | **22** | 34 | 8 | **38** | 54 | 7 |
| **7** | 12 | 3 | **23** | 35 | 8 | **39** | 55 | 7 |
| **8** | 13 | 3 | **24** | 36 | 1 | **40** | 59 | 7 |
| **9** | 14 | 3 | **25** | 37 | 1 | **41** | 61 | 7 |
| **10** | 16 | 3 | **26** | 39 | 1 | **42** | 62 | 7 |
| **11** | 17 | 3 | **27** | 40 | 1 | **43** | 64 | 7 |
| **12** | 18 | 3 | **28** | 41 | 1 | **44** | 65 | 7 |
| **13** | 20 | 3 | **29** | 43 | 1 | **45** | 66 | 5 |
| **14** | 21 | 3 | **30** | 45 | 1 | **46** | 67 | 5 |
| **15** | 22 | 3 | **31** | 46 | 1 | **47** | 68 | 4 |
| **16** | 24 | 3 | **32** | 48 | 6 | **48** | 69 | 4 |

The results are obtained from the aggregation of 1824 households' demand profiles. Figure 4-17 illustrates the distribution of different cluster of customers in each LV network. The distribution of households along LV feeders and their willingness to participate in DR schemes is presented in Figure 4-18.

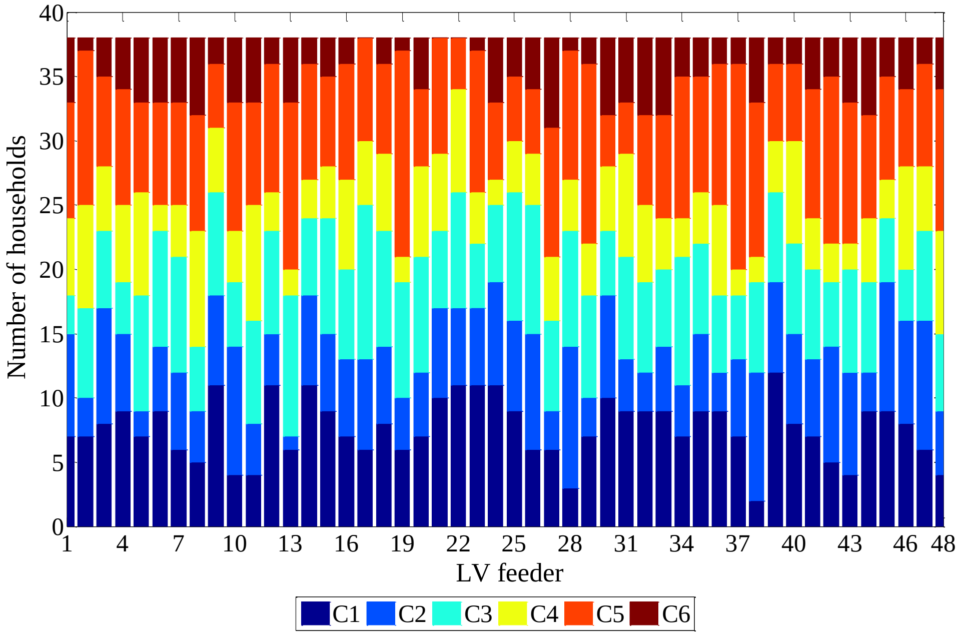



**Figure 4-17:** Distribution of clusters of customers in each LV feeder

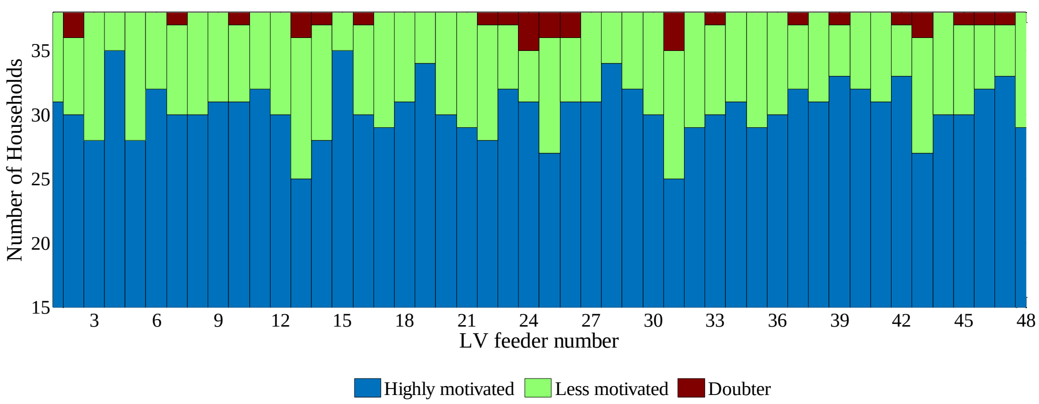



**Figure 4-18:** Number of households in each LV fodder regarding their attitudes towards participating in DR programmes

### 4.7.2 Simulation Set up

***Home Agent:*** The parameters regarding appliances performance for each household is set according to its cluster, and using a similar approach to the previous section. The initial start-up time of wet appliances ($\mathbf{t}_{\mathbf{s\,h}}^{\mathbf{sh}}$) and the appliances ownership rate are normally distributed along LV feeders.

***Supplier Agent:***

The minimum and maximum price bands are similar to LV network (equation 3.30), for comparison purposes. However, the number of threshold is 1 instead of 3, Figure 3-12, as shown together with the other parameters in Table 4-13.

**Table 4-13**: Parameters determined for two-level piecewise linear pricing function in (3.58)

| **Parameter** | $\propto_1$ | $\boldsymbol{\beta_1}$ | $\propto_2$ | $\boldsymbol{\beta_2}$ | **Min. price** | **Threshold** | **Max. price** |
|---|---|---|---|---|---|---|---|
| **Value** | 7.77 | -3.78 | 55.44 | -43.68 | 3.99 p/kWh | 11.76 p/kWh | 67.2 p/kWh |

***DR Provider Agent:*** The required input parameters for calculating the fitness function for the objective function introduced in equation 3.56, are either static or dynamic. The former refers to pre-determined parameters including weighting factors, setting parameters in GA algorithm and voltage sensitivity of buses. On the other hand, the dynamic parameters including VDI and RPLI are obtained by running the power flow at the network in real time.

- ***Weighting Factors:*** These are considered to be equal as expressed below:

$$w_1 = w_2 = w_3 = \frac{1}{3} \tag{4.4}$$

- ***Voltage Sensitivity*:** This is usually obtained from the inverse of Jacobian matrix in the load flow study ($J^{-1}$) as expressed in:

$$\begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix} = J^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{4.5}$$

where, $\Delta\theta$ and $\Delta V$ are vectors of voltage angle and nodal voltage variations respectively. Due to the variability of the coefficients in (4.5) to the network operating point [224], they need to be recalculated and updated constantly, hence a time consuming process. Since the objective function of DRPA is to keep the voltage magnitude within allowable limits in a radial MV/LV network, the voltage angle of buses is not studied. In order to tackle the complexity and computational burden of the classical method, a direct approach [225] was applied. This method is dependent on the topology of the network instead of the network operating points and the sensitivity coefficients are defined as:

$$\frac{\partial V_m}{\partial Q_n} = -R_{m-1,n-1} \tag{4.6}$$

where, the voltage sensitivity is a matrix of $(m \times n)$ presenting the voltage sensitivity of bus $m$ in respect to the active power variation at bus $n$. Since the voltage at bus slack is always constant:

$$\frac{\partial V_1}{\partial Q_n} = 0 \tag{4.7}$$

The result is shown in Figure 4-19.

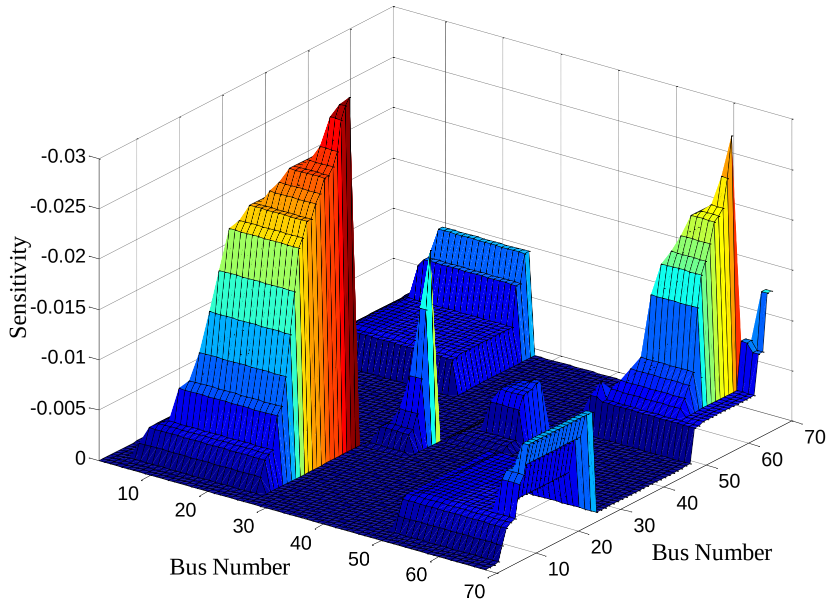



**Figure 4-19:** Voltage sensitivity coefficients of all buses to the active power variation in other buses at the network

After determining the voltage sensitivity matrix, the maximum sensitivity of each bus to the changes of the power in other buses is considered in the objective function.

***Setting Parameters in GA:*** The GA problem in equation (3.56) is solved using the Global Optimisation toolbox of MATLAB. The GA parameters for solving the objective function are presented in Table 4-14.

**Table 4-14:** GA parameters

| Population size | Selection method | Crossover | Mutation | Termination condition |
|---|---|---|---|---|
| 100 | Stochastic uniform | Scattered | Gaussian | - Maximum number of generation>100<br>- Best fitness value <=0.001 |

The penalty function parameters are considered as 3000, 5000 and 5000 for voltage, thermal and maximum DR availability constraints respectively.

## 4.8 MV/LV Network Modelling

### 4.8.1 Simulation Model

The focus of this objective is on managing the MV/LV network where all DR events from DRPA or LTA are sent to HAs by LTA. DR is activated in LTA and the implementation is done by consumers. Therefore, the simulation is performed on one LV feeder.

### 4.8.2 Simulation Set up

***Home Agent:*** In both schemes, $l_{c,h,t}^{LR,max}$ is extracted from the dataset for each cluster. It is assumed that the participants will always meet the available demand reduction in LCDR. In EDR the demand reduction is based on requested load curtailment from LTA. In LCDR, various financial motivations, participation rates and PV penetration rates for HAs are considered. For EDR it is assumed that only highly motivated groups of households participate and this amounts to 81.58% or 31 HAs in the LV feeder.

***Local Transformer Agent:***

The obtained results of predicted and actual DR during a typical day are shown in Figure 4-20. The former is defined according to the equation (3.26). Furthermore, $\acute{l}_{c,t}^{hist,max}$ and $\acute{l}_{c,t}^{hist,min}$, the average minimum and maximum power consumption from all households within each cluster, are also presented. It should be noted that the DR is calculated according to the total load reduction from all households without considering their trial tariff allocations. However this is considered reasonable since a normal distribution is applied to allocate the population in different ToU tariffs. The results show a high accuracy in the prediction.

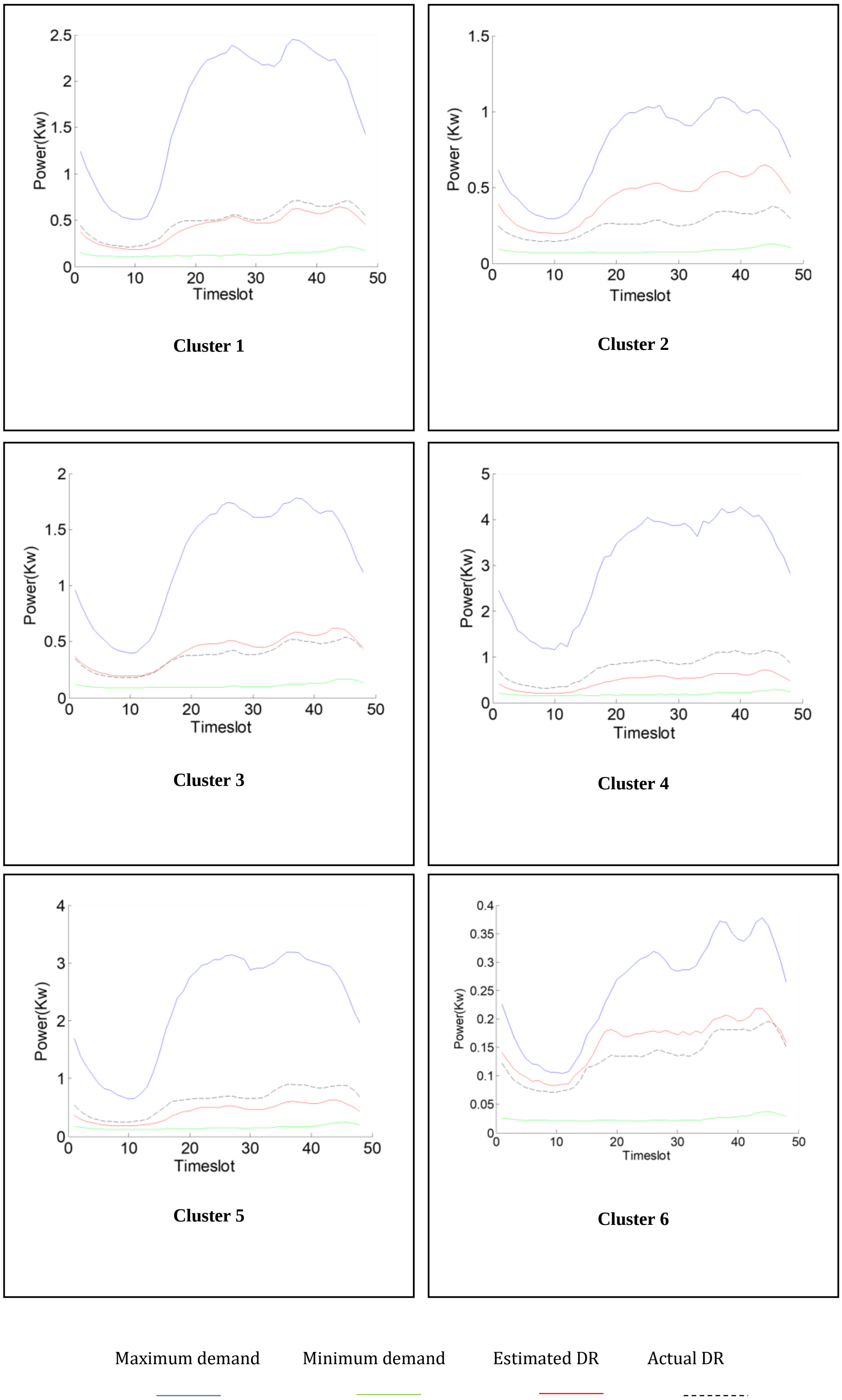



**Figure 4-20:** Demand response within each cluster

## 4.9 Summary

This chapter deals with the simulation parameters required for implementing the proposed MAS framework. The physical layer and the distribution network are first introduced. The dataset used in the analysis for all case studies is then presented. The procedures to generate the synthetic load profile for households from the data set are explained together with the simulation results. A characterisation-based clustering technique is used and each household is allocated to one of the 6 resulted clusters. Consumer's characteristics including price elasticity of demand as well their attitudes towards DR participation were extracted from the dataset. The technical model of the controllable appliances used in this thesis is also described.

Three case studies are considered: LV, MV and MV/LV network management in accordance with the objectives of this thesis. The simulation environment and the distribution of each cluster of household within the network are explained. In each scenario, as discussed in the previous chapter, the set-up parameters for modelling agents are provided.

The price coefficients for designing price-based tariffs are also defined. For each cluster of HAs at LV and MV level, the ownership of appliances, their start-up and time preference are provided. Similarly, the potential of shifting demand from wet appliances for the two first scenarios as well as the potential of load shedding from HAs at MV/LV level are presented.

# Chapter 5 Simulation Results and Discussions

## 5.1 Introduction

In this chapter, the proposed DR-MAS-based ADNM frameworks which are discussed in chapter 3, are implemented to assess their feasibility and applicability. For each objective of the thesis, one case study is investigated with different scenarios. These include Fixed, ToU, DA-RTP and RTP for the first objective, fixed and RTP for the second objective and EDR and LCDR for the third one. An analytical discussion of the simulation results is provided. Considerations affecting the results, such as household characteristics, financial motivation and participation rate amongst others, are also explored. The advantages of the proposed framework are discussed. It should be noted that the simulation environment and the setting parameters are described in the previous chapter. It is also assumed that no communication failure occurs during the simulation period and that the distribution constraints are met.

## 5.2 LV Network

In order to show the impacts of the proposed decentralised local DR as well as the application of the DR-MAS-based ADNM framework, four different scenarios are simulated and compared. The first scenario is considered as a reference case point. The others are the models for diverse pricing tariffs discussed previously. The initial load profiles of households are the same as scenario 1. However, households make the decision about their appliances performance individually at different time basis.

***Scenario 1- Case with Fixed Tariff:*** This case is a comparison benchmark in order to illustrate the advantages of implementing DR in the other cases. The same fixed electricity rate is assigned to all HAs. Therefore, this case simulates a situation where the potential of DR is not taken into account and HAs do not schedule their loads. The simulation is performed with HAs having initial load profiles.

***Scenario 2- Case with ToU Tariff:*** In this scenario a three-band ToU tariff is allocated to all HAs. They work independently to schedule their appliances at the start of the day. Since the price is fixed during each time-interval, the optimisation problem has one solution for each day. Therefore, it cannot reveal the actual potential of DR in managing the network and is suitable for peak load reduction.

***Scenario 3- Case with DA-RTP Tariff:*** This case is similar to scenario 2, but HAs are informed about the price one day ahead and are charged with the announced prices. HAs make decision about their scheduling once at the start of the day and this is updated each day according to the price. This case simulates a condition in which DR potentials are enabled through time-varying sale prices. The variation in prices during different time intervals provides a better insight about network operation.

***Scenario 4- Case with RTP Tariff:*** In this case HAs receive prices on a half an hour-basis in a typical day. Unlike other scenarios, the prices dynamically change to reflect the network status and the required DR from households aggregated demands. HAs have the capability to forecast the RTP prices. According to the price prediction, they make decision about their load scheduling at the start of the day and update their load scheduling on receiving new prices during the day.

### 5.2.1 Simulation Results

This section describes the results of simulation for each case study. A detailed analysis and discussion is provided in section 5.2.2.

#### 5.2.1.1 Scenario 1: Fixed Pricing

Figure 5-1 shows the simulation results in scenario 1, reference, where the SA sets a fixed price and HAs do not control any of their flexible loads. The power consumption from all background and controllable appliances during simulation period is plotted. The red dashed-lines show the electricity price. The total energy consumption is 1740.66 kW which is similar for all case studies. That is explained as the DR is performed only through shifting/delaying the shiftable appliances. Hence, the households loads can be only temporarily reduced but in practice no load shedding occurs. The PAPR and the standard deviation of the load profile are 1.26 and 2.6kW respectively. It is clear that the peak demand is relatively high during afternoon peak time period (timeslot 35-37). In addition, the transformer voltage magnitudes, presented in Figure 5-2, illustrates that the voltage at those timeslots exceeds the lower boundary limit.

The total electricity payment of all HAs is 24766.12 pence/kW and the average payment of each HA is 592.74 pence/kWh. The maximum and minimum electricity bill is 1213.58 pence/kWh and 286.95 pence/kWh respectively.

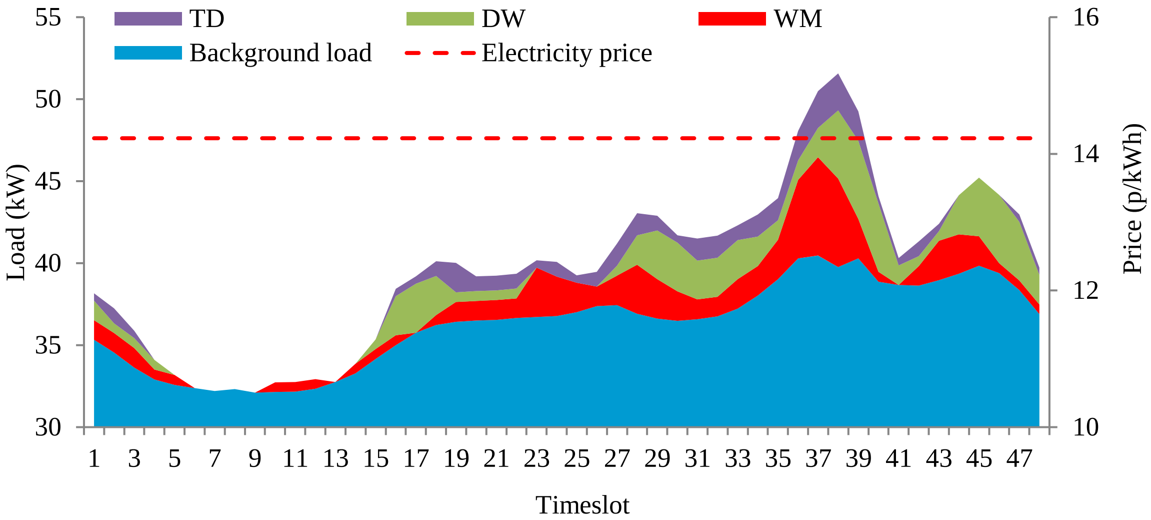



**Figure 5-1:** Distribution transformer load from aggregation of 38 HAs and electricity prices in scenario 1

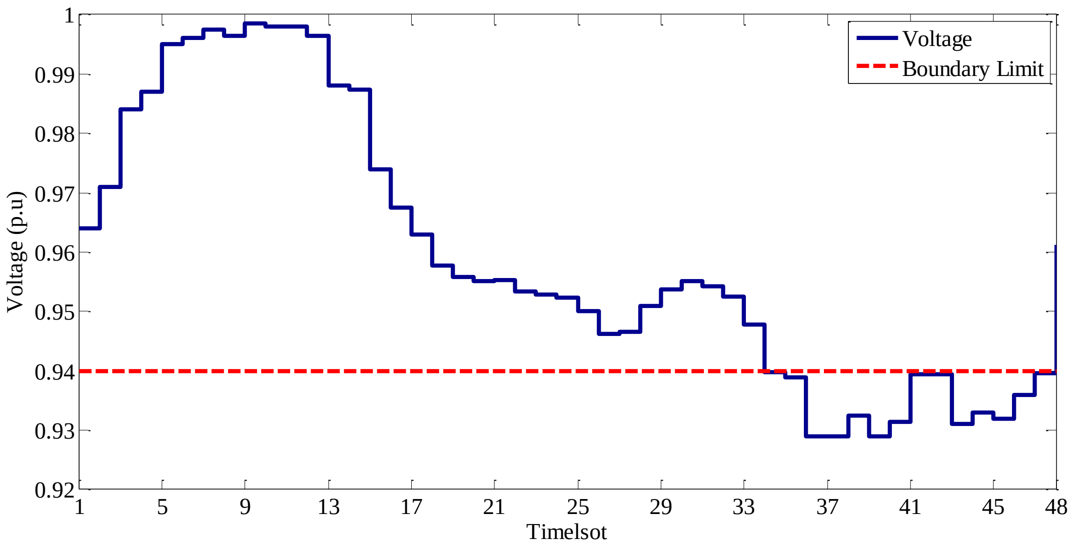



**Figure 5-2:** Voltage profile at distribution transformer in scenario 1 (fixed tariff)

### 5.2.1.2 Scenario 2: ToU Pricing

The electricity price in this scenario has pre-defined fixed tariff bounds. Hence, the optimisation results of HAs for different days are similar. The transformer loading for the one day simulation is depicted in Figure 5-3, showing the aggregation of different types of loads from all connected HAs in the LV network. ToU prices are shown with red dashed-lines. Compared to the previous scenario, the demand is shifted mostly from peak times to non-peak hours. The most reduction is 34.54kW between timeslot 35-39 and the most demand increment is 52.04kW during timeslot 7-13. Therefore, the PAPR does not change significantly. However, the standard deviation of the load profiles is reduced by 0.6kW, thus showing an improved load profile. Figure 5-4 shows the transformer voltage magnitudes before and after DR. The voltage at morning peaks exceeds the allowable lower limit but is improved in other times.

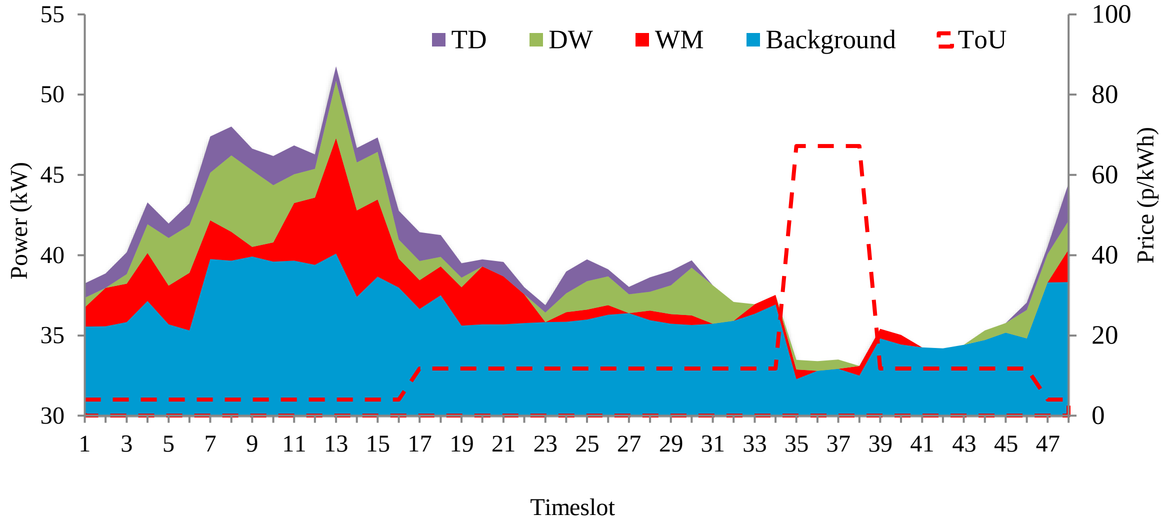



**Figure 5-3:** Distribution transformer loading from aggregation of 38 HAs and electricity prices in scenario 2.

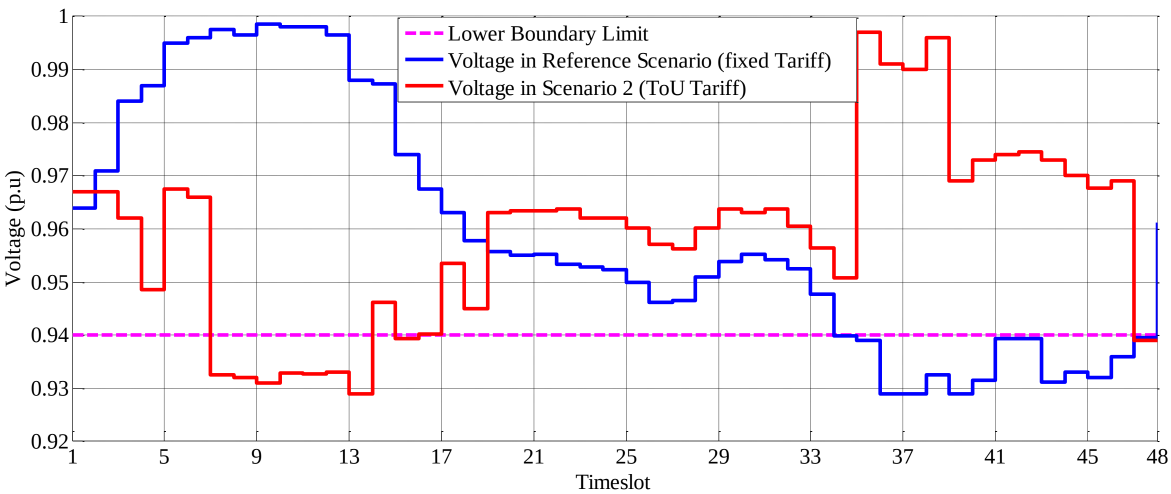



**Figure 5-4:** Voltage profile at distribution transformer in scenarios 1(fixed tariff) and 2(ToU tariff)

It should be noted that only 2 HAs have not contributed in DR and the total electricity payment of all HAs is 22388.6 pence/kW. The average, maximum and minimum individual bill payment of each HA is 531.24 pence/kW, 1063.4 pence/kW and 266.05 pence/kWh, respectively. These analyses indicate that overall financial gain of HAs from this tariff comparing to the fixed one by 2377.53 pence/kW (9.6%). However, a more coordinated load scheduling is needed to improve the network status. Here, HAs do not consider PAPR and the only way to manage the constraint and increase the quality of the network is to set dynamic tariffs as discussed in scenarios 3 and 4.

#### 5.2.1.3 Scenario 3: DA-RTP

In this scenario the electricity payment calculation is based on the prices announced a day ahead regardless of actual price in the next day. Accordingly, HAs solve the optimisation of controllable appliances scheduling problem. Figure 5-5 presents the instantaneous active power at transformer after simulation. The red dash-dotted line shows the electricity price of the day-ahead which is calculated using predicted available DR during the next day. The green dashed-line is the updated price in real time reflecting the network status. It is worth to clarify that the total power consumption, the blue line, does not show the types of loads for a better illustration. The voltage profile is depicted in Figure 5-6 showing the comparison to the reference scenario.

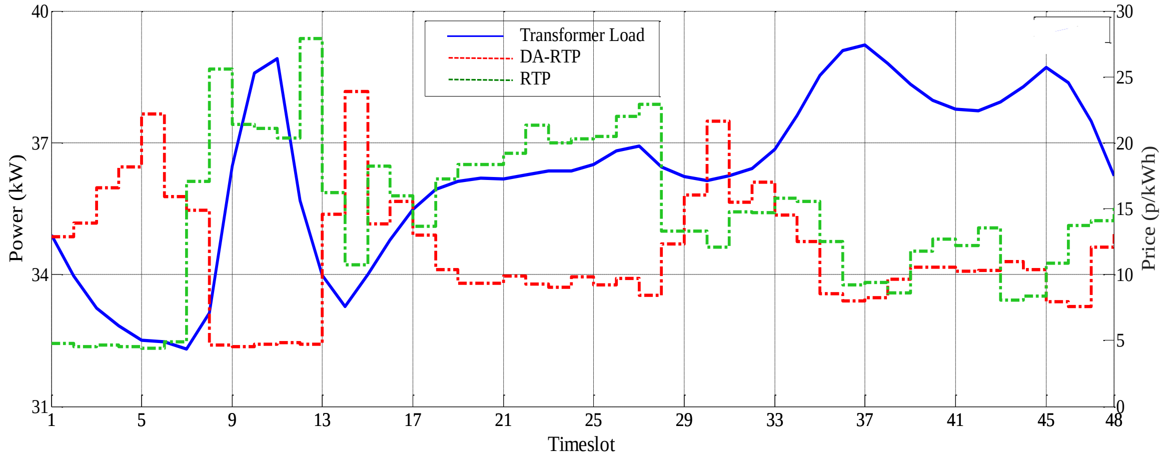



**Figure 5-5:** Distribution transformer loading from aggregation of 38 HAs, DA-RTP and real time price signals in scenario 3

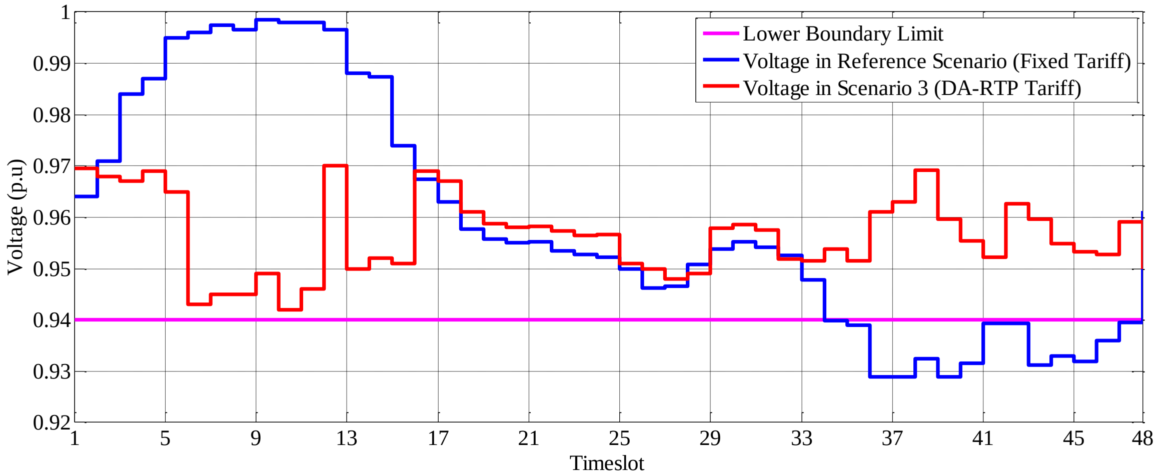



**Figure 5-6:** Voltage profile at distribution transformer in scenarios 1 and 3

As can be seen, the overall voltage at the transformer side is improved with all values above the lower limit. However, higher new peaks are generated where the price is lower.

Compared to scenario 2, the duration of morning peaks decreases and the amount of maximum load also reduces by 0.87kW. PAPR is 1.20 which is 3.64% and 2.24% less than scenario 1 and 2 respectively. The standard deviation is 1.95kW which is less than the first two scenarios.

All HAs have participated in DR but with various scheduled limited number of controllable appliances. The real time pricing is set according to transformer and network status and is calculated similar to RTP. The total electricity payment of all HAs is 20106.79 pence/kWh. The average, maximum and minimum individual bill payment of each HA is 510.67 pence/kW, 1014.26 pence/kWh and 249.27 pence/kWh, respectively. This shows profits of 18.81% compared to scenario 1 and 10.19% compared to scenario 2. If HAs were charged according to real time price signals, the difference in total payment of all HAs would increase by 26%. Therefore, this tariff cannot reveal the real pricing of the network and even if SA does not consider its own benefit, it is still not budget balanced.

#### 5.2.1.4 Scenario 4: RTP

HAs in this scenario have the capability to predict the prices for the upcoming day and also update them with the prices in real time. Hence, their load scheduling is dynamically changed according to the price, to minimise their electricity payment. SA sets the prices according to available and required DR at each timeslot to keep the transformer status and voltage within their limits. The simulation result of transformer loading is shown in Figure 5-7. The blue line, and the red and pink dashed-lines present the load aggregation of HAs, RTP and predicted price by HAs. It should be noted that the results of price estimation is similar for all HAs and all of them have participated in this scenario. The voltage profile of distribution transformer compared to the reference scenario is presented in Figure 5-8.

Similar to scenario 3, the voltage is maintained within statutory limits during simulation period. The price is set higher where the voltage decreased to motivate the consumers to shift more demands. As a result, the voltage improves relatively. PAPR is reduced by 5.79%, 7.9% and 9.22% in comparison to scenarios 1, 2 and 3 respectively. This implies that although the load flattening is not considered directly in the load scheduling optimisation problem of HAs, it is achieved in the RTP. The maximum peak demand is 38.60kW which is 4.59%, 3.72% and 1.6% less than scenarios 1, 2 and 3 respectively. The standard deviation is 1.03kW which is also reduced in comparison with other scenarios.

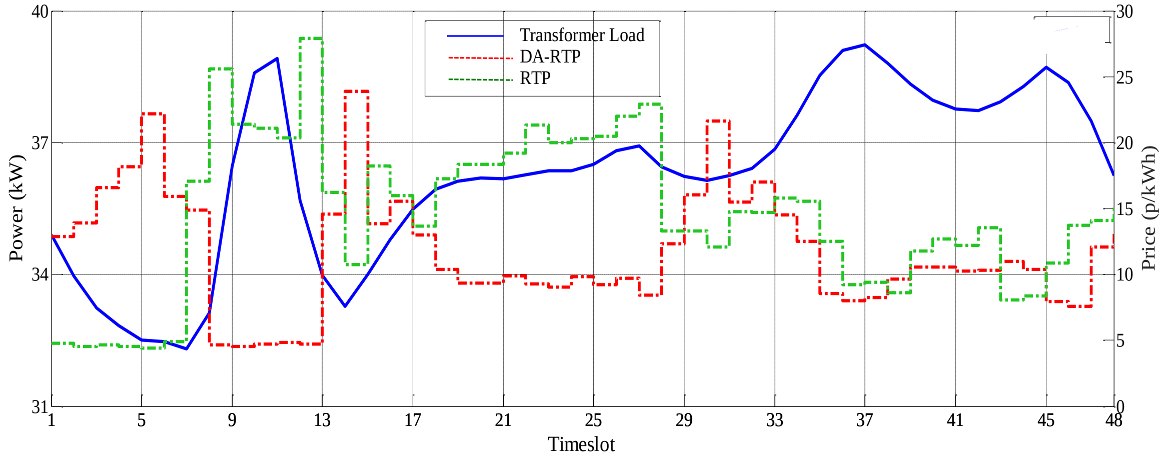



**Figure 5-7:** Distribution transformer loading from aggregation of 38 HAs, RTP and predicted price signals in scenario 4

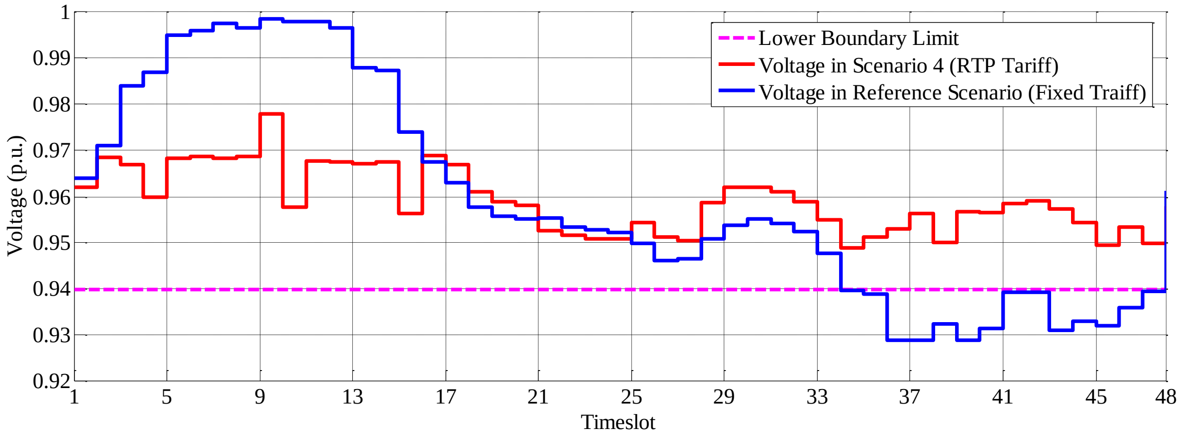



**Figure 5-8:** Voltage profile at distribution transformer in scenario 1 and scenario 4

The Mean Absolute Percentage Error (MAPE) of the estimated price by HAs and the real defined RTP is 12.71%, which shows a high accuracy for the proposed model. The electricity price for all HAs reduces by 12.08% compare to reference scenario. The average electricity payment of the HAs is 525.10 pence/kWh, a reduction of 11.41%. The maximum payment of HAs is reduced by 13.39% and the minimum payment by 8.35%.

### 5.2.2 Analysis of Results

This section compares and discusses the four scenarios. An in-depth analysis of the results is first provided, followed by the investigation of the long term benefit of applying RTP DR. For the latter, the simulation period as well as the scale of the network is expanded in order to further examine the effect of DR in larger scale and in longer time duration. This provides a better view of the real DN in order to evaluate the effectiveness of the proposed framework.

The performance of all scenarios is analysed from a technical and financial perspective. A summary of the percentage reduction in terms of technical characteristics, including PAPR, the standard deviation and peak demand is presented in Table 5-1 for all scenarios. The voltage profile for all case scenarios are illustrated in Figure 5-9 using boxplots. All values were obtained considering scenario 1 as the benchmark.

**Table 5-1:** Comparison of the technical features for all case scenarios

| Scenario | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **PAPR Reduction (%)** | - | 1.42 | 3.64 | 9.27 |
| **Peak Usage Reduction (%)** | - | 0.90 | 3.05 | 4.59 |
| **Standard Deviation Reduction (%)** | - | 23.27 | 25.01 | 60.19 |

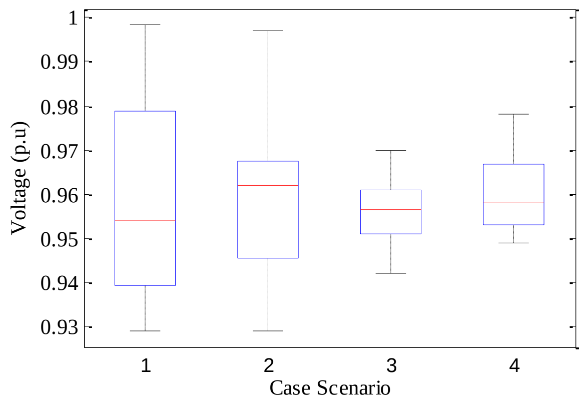



**Figure 5-9:** Comparison of the distribution of voltage magnitudes in all scenarios

It can be observed that RTP presents a greater reduction compared to other scenarios especially for standard deviations of the load profiles. This shows that the aggregated demands scatter over time providing almost flattened load. The standard deviation in scenarios 2 and 3 are close to each other but DA-RTP acts better in reducing PAPR and peak demand value. The voltage magnitudes at both scenarios 3 and 4 are kept within allowable boundary limits at all timeslot with higher values in the latter. The technical aspects are the targets of the network operators, LTAs or DRPA.

On the other hand, financial profits of SA and HAs are other important considerations in the performance of the framework. These factors, including the total electricity payment of all HAs and the average, maximum and minimum bill payment of each HA, are summarised in Table 5-2.

**Table 5-2:** Summary of the percentage bill saving of HAs in all scenarios

| Scenario | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Total payment (%)** | - | 9.56 | 18.81 | 12.08 |
| **Average payment (%)** | - | 10.37 | 13.84 | 11.41 |
| **Maximum payment (%)** | - | 12.37 | 16.42 | 13.38 |
| **Minimum payment (%)** | - | 7.28 | 13.13 | 8.35 |

In contrast with fixed tariff, the greatest reduction in energy expenses is achieved in scenario 3. This illustrated that HAs were successful in finding the optimal scheduling time of their controllable loads with the price variations. However, although individual electricity payment of all HAs can be reduced, this scheme does not necessarily provide the best financial gains for SA. Referring to section 5.2.3, SA has to pay the balancing difference between DA-RTP and actual price rates of the network, which states that in practice this scheme is not an economically viable plan. It is also the same for scenario 2 where HAs' profits increased by 9.96% whereas the real price of SA is higher.

Comparing the improvement of the network quality and the bill saving of HAs, it can be concluded that among all scenarios, RTP results in better demand reduction and in maximising the social welfare of all agents at the network. The bill saving of HAs is not the same due to the differences in their financial and technical constraints discussed previously. However, all HAs benefit from price changes defined in each scenario, regardless of their controllable or background power usage. This demonstrates that even if some HAs are equipped with higher demanding appliances such as EV, the fairness of using the proposed DR mechanism is still valid for all users.

One of the advantages of the proposed framework is that coordination among HAs is not required since they all work individually and in parallel to achieve the network goal. This decreases the data communication complexity as well as processing time. Moreover, the optimisation strategy of HAs does not require revealing their consumption data to other HAs thus keeping the privacy concern of households.

### 5.2.3 Long Term Benefits of RTP

In all previous scenarios, the simulation is performed and analysed for one LV feeder. This section describes and analyses the performance of RTP-DR in a larger scale, at MV network. The aim is to assess the long term benefits of RTP where a new satisfaction factor is introduced for HAs in loads shifting. This is referred as Bill Saving Satisfaction (BSS) in the thesis and is based on the total bill saving as presented in Table 5-3. For each of the 6 clusters of households, a specific BSS factor is considered.

**Table 5-3**: BSS factor for all cluster of households

| Cluster No. | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| BSS | 40% | 100% | 60% | 80% | 20% | 0% |

The simulation is performed for one-month period (30 days). Each HA firstly runs the optimisation of their controllable appliances similar to scenario 4. Then they calculate their total bill saving from the first day. They confirm the load scheduling if the bill saving is attractive and take no action otherwise. For instance, if the simulation day is 4, the total saving of the specific HA is calculated from the sum of the savings from day 1 to 3. If the calculated value is higher than its BSS factor, it starts taking part in DR programme. It should be noted that RTP allocated to each HA within the network is considered the same.

The total bill saving of all HAs in the network is depicted in Figure 5-10 and is based on the cluster and is shown for one month simulation period. It can be clearly seen that HAs with lower BSS take part in DR from the start of this scheme. Hence, their total saving is higher than others. However, the contribution of HAs is improved over time as all consumers can benefit from implementing DR services. The voltage profile of each MV feeder on the first and last day of the simulation period is illustrated in Figure 5-11. The overall improvement at all MV feeders shows the effect of long-term advantages of RTP on the quality and management of the DN. However despite the improvement in the MV feeder 3, the voltage magnitude is still below the allowable limit at timeslot 22 after the simulation.

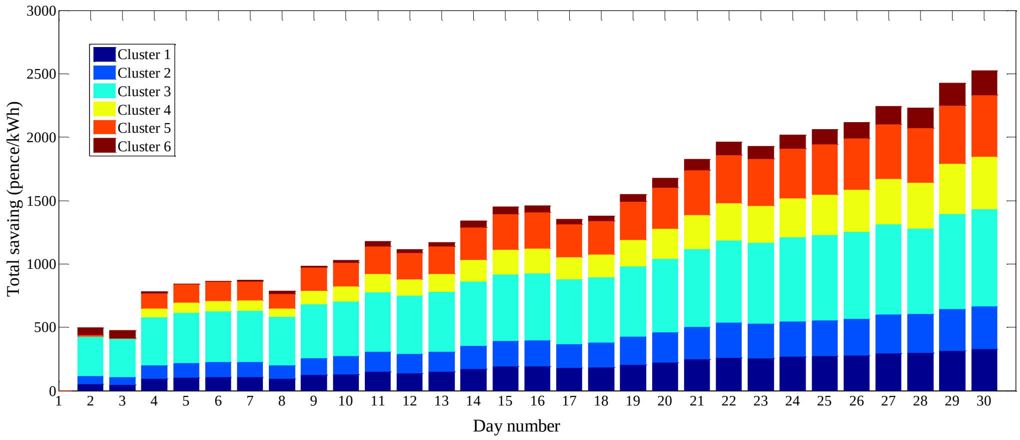



**Figure 5-10:** Total bill saving of HAs based on different bill saving satisfaction factor

In this scenario the significance of the contribution of each LTA in improving the network status is not considered in the design of RTP. Moreover, the price is set without taking into account the potential of responsiveness demand from each LTA. The demand reduction at specific LV feeders does not always affect the voltage at some other feeders. Designing tariffs requires the consideration of both the potential of DR provision at each LV feeder as well as its effectiveness on the overall network operation.

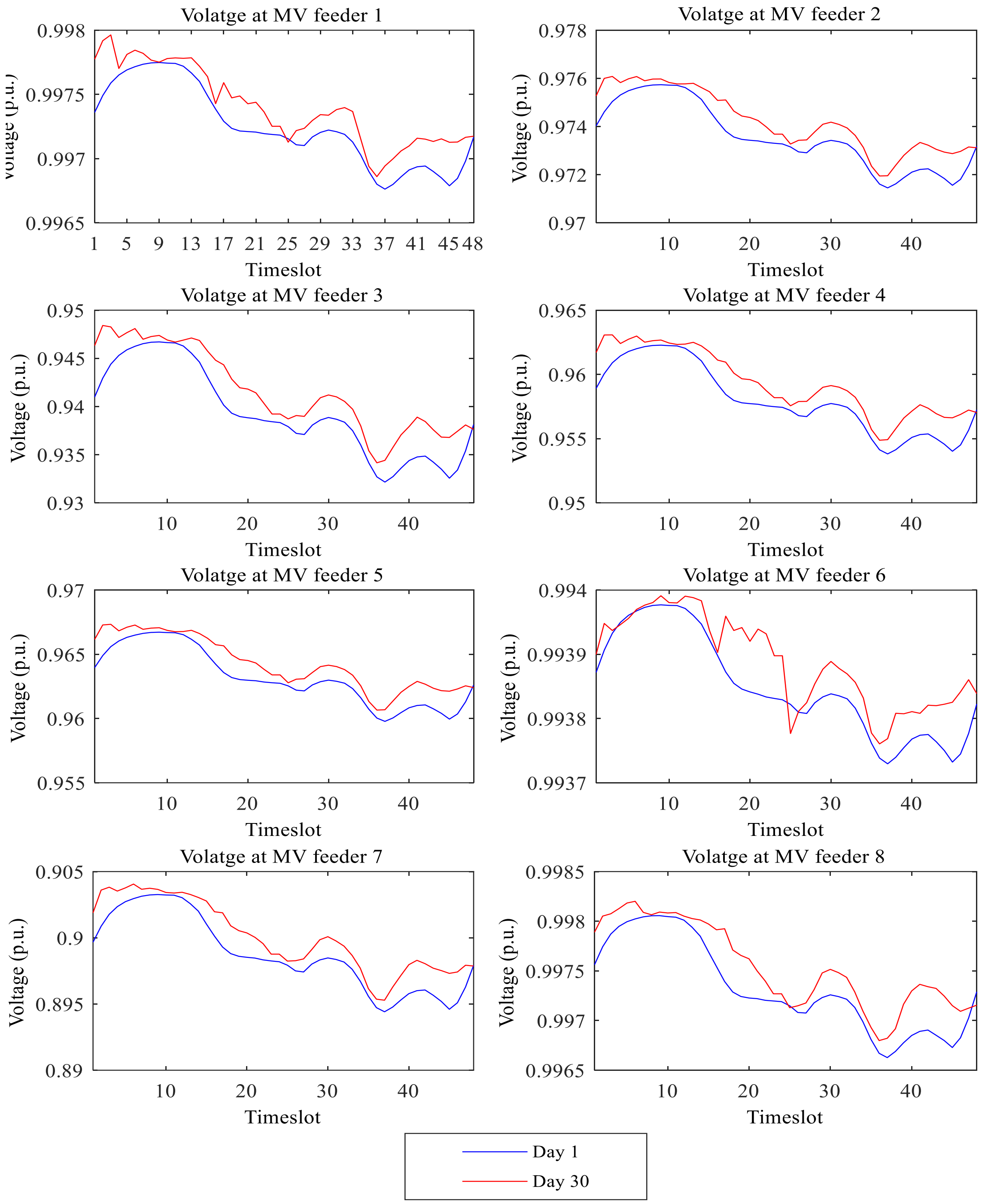



**Figure 5-11:** Voltage profiles along MV feeders on day 1 and day 30

## 5.3 MV Network

This section presents the simulation results for two scenarios. The first, without load control, is considered as a reference case point. The second scenario, with RTP, is the proposed model. Simulations are performed separately for both scenarios and the results are compared and discussed to evaluate the effectiveness of the proposed model.

**Scenario 1: Without DR**

This case study assumes that no DR mechanism is applied in the network. The synthetic data is distributed in the test system. Since no DR action is considered, the results are achieved by running the load flow and obtaining the network status during simulation period. All households are in the same fixed daily time electricity price.

**Scenario 2: With DR**

This case is based on the proposed method where HAs receive prices in real time. The pricing scheme is similar to scenario 4 in LV network but applied to MV network. However, the prices are allocated differently to each LV feeder while they remain the same for all customers within that feeder. The initial load profiles of households are the same as scenario 1. Households make the decision about their appliances performance individually at each timeslot.

### 5.3.1 Simulation Results

The simulation results for defining the dynamic pricing in the proposed method along with the aggregation load profiles of all HAs in both scenarios are shown in Figure 5-12. In Figure 5-12(a) the scattering of the RTP in each timeslot for all LV feeders is presented. In parallel, the total system demand in reference scenario, blue line, and scenario 2 (with RTP), red-dashed line, are depicted in Figure 5-12(b). In each timeslot, the price for each LV feeder is individually updated based on the system status, DR potential and voltage sensitivity of that bus.

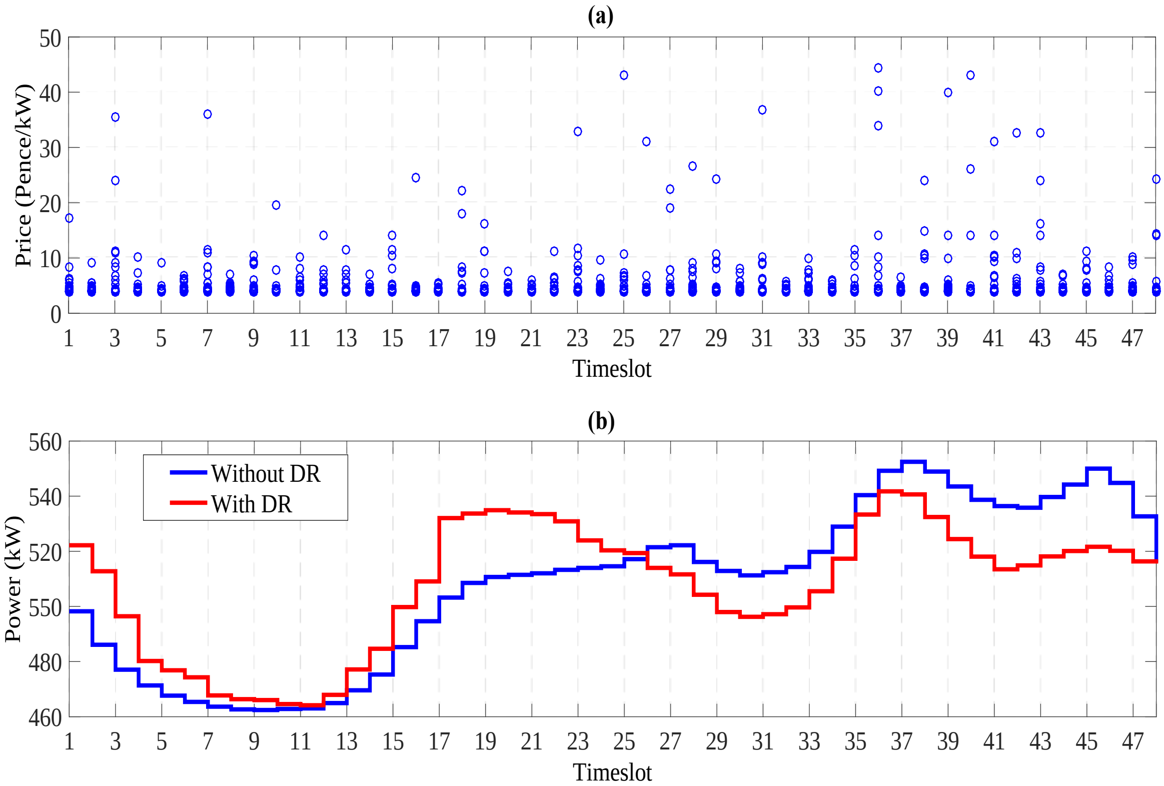



**Figure 5-12:** Electricity price for the proposed model in scenario 2 with RTP (a), Load profiles of the aggregation of all HAs in the test network in both scenarios (b)

For each LV feeder, the overall percentage of power changes after applying DR, is depicted in Figure 5-13. It can be observed that the demand mostly shifted from evening peak-times to morning off-peak times. Minimising the PAPR, with the aim to flatten the total loads of the system is not considered as an objective of this work. This is because the aim of the proposed model is to deploy the DR for relieving constraint in the DN. Thus, the PAPR did not changed significantly. However, the standard deviation in scenario 2 (with RTP) is reduced by 25%.

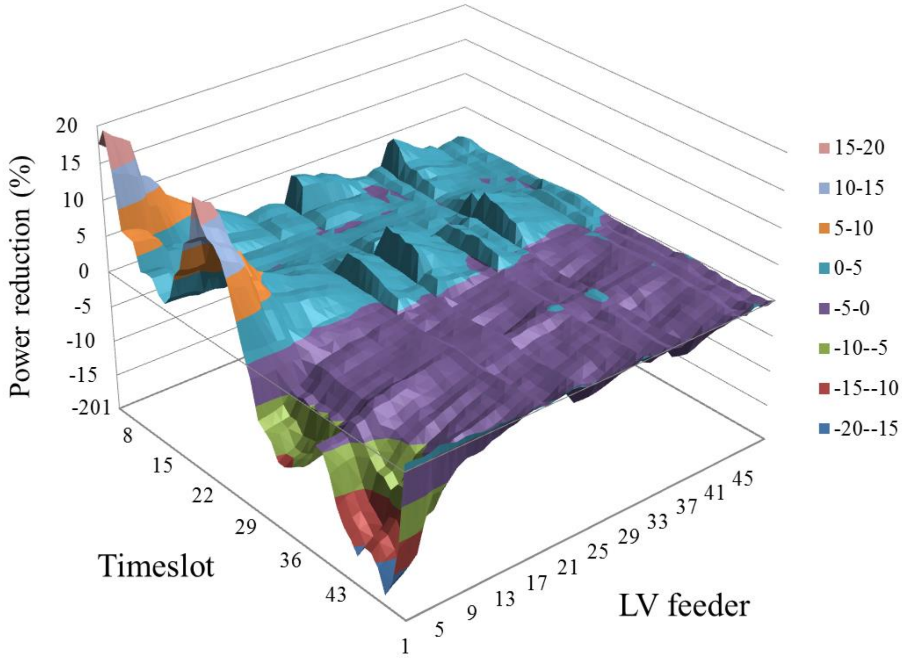



**Figure 5-13:** Power reduction along each LV feeder

The voltage profile at MV connection points in both scenarios are presented in Figure 5-14 using boxplots. This includes the voltage magnitude of all buses over the 48 timeslot simulation periods within each MV feeder.

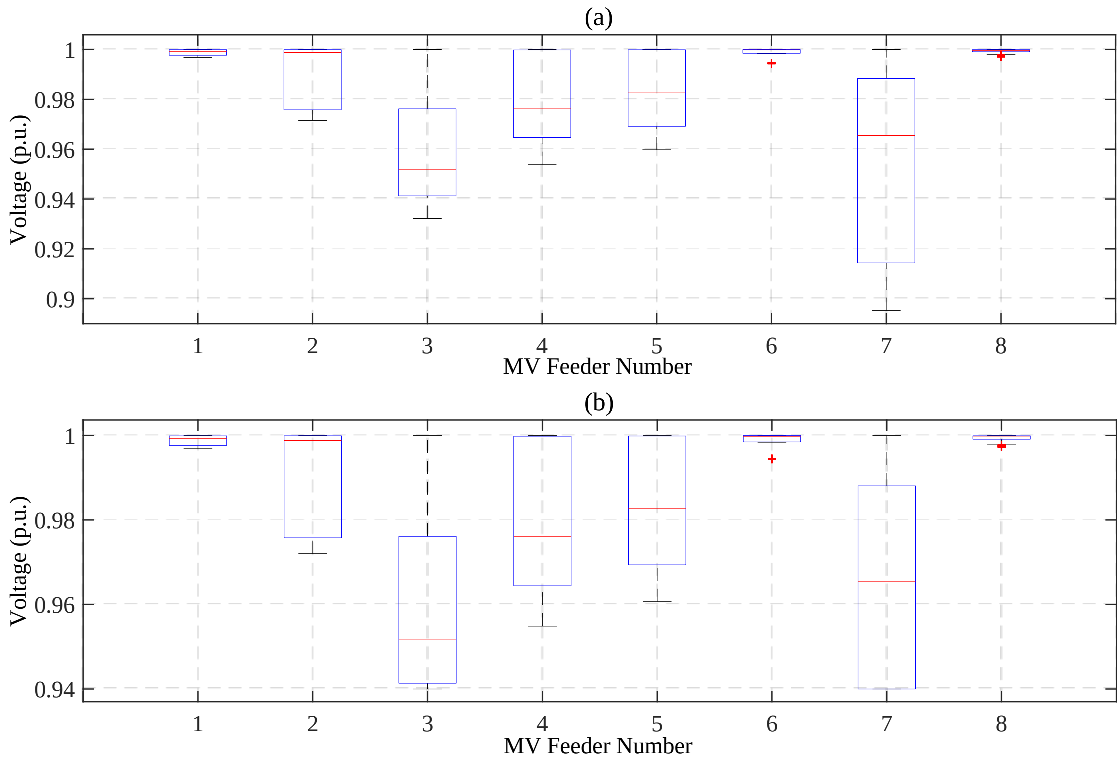



**Figure 5-14:** Voltage levels at the MV connection points in reference scenario (a) and scenario 2 with RTP (b)

It can be seen that in scenario 2 (with RTP), not only was the voltage in the network kept within the statutory limit (here $V_{min}$ = 0.94), but the overall network voltage also has improved. This is also well illustrated in Figure 5-15, where the minimum voltage of all buses in the test system is drawn for both scenarios. However, although the voltage was decreased at some timeslots, e.g., 17-21, the voltage level was still within acceptable bands. The VDI for both scenarios are compared in Figure 5-16 which shows the overall reduction of voltage deviation from the nominal voltage for all LV buses in the network. This demonstrates the effectiveness of the optimisation of the objective function of DRPA in minimising the VDI.

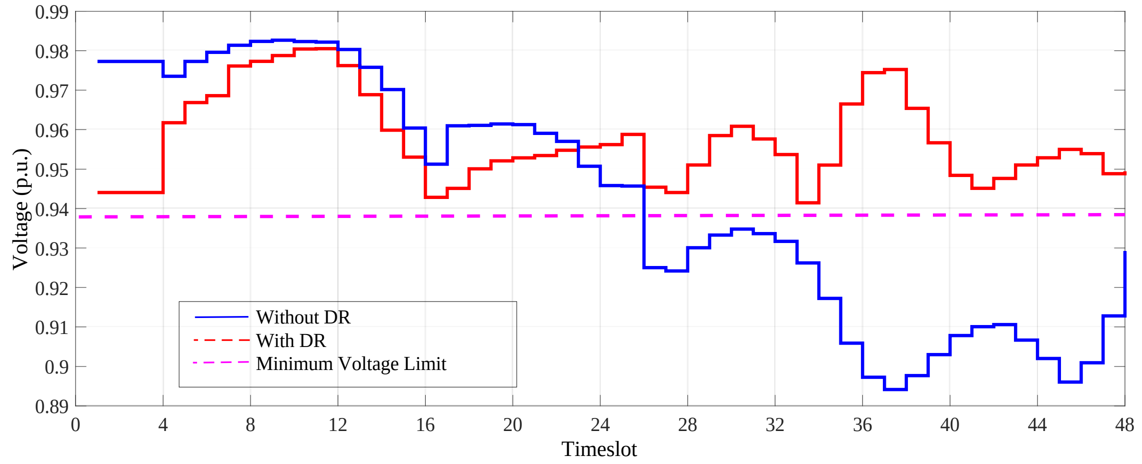



**Figure 5-15:** Minimum voltage profile of the test system before and after DR during one day simulation period

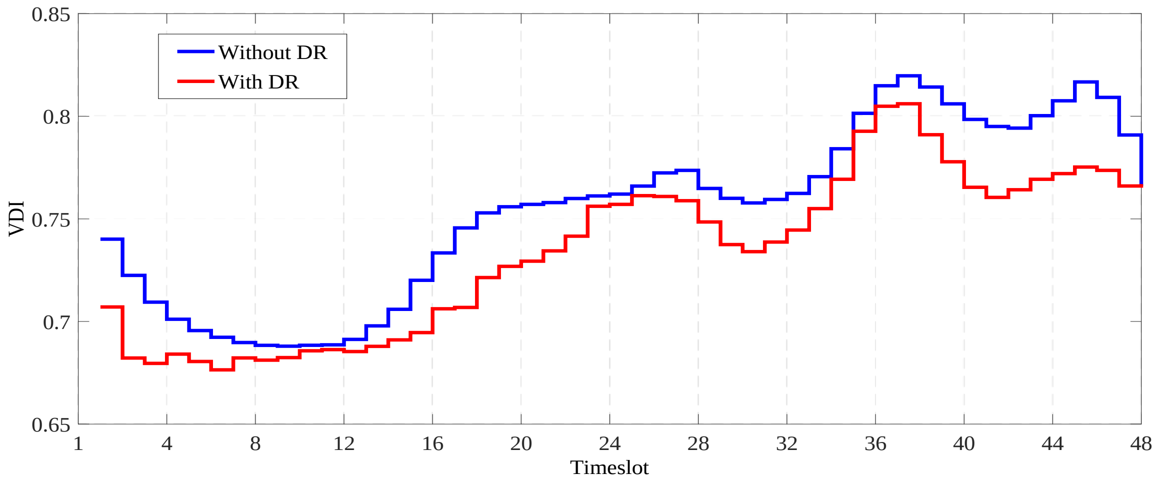



**Figure 5-16:** VDI for both scenarios for each LV bus

The total power loss during the simulation day is shown in Figure 5-17. The power loss increased slightly in scenario 2 (with RTP) at some timeslots due to peak aggregation of loads. However, the sum of the total power loss was reduced by 0.28kW. In addition, RPLI achieved after deploying DR, shown in Figure 5-18, is decreased between timeslot 25-48 where the total demand is reduced. For other time periods where the total demand rose, the RPLI did not increase significantly.

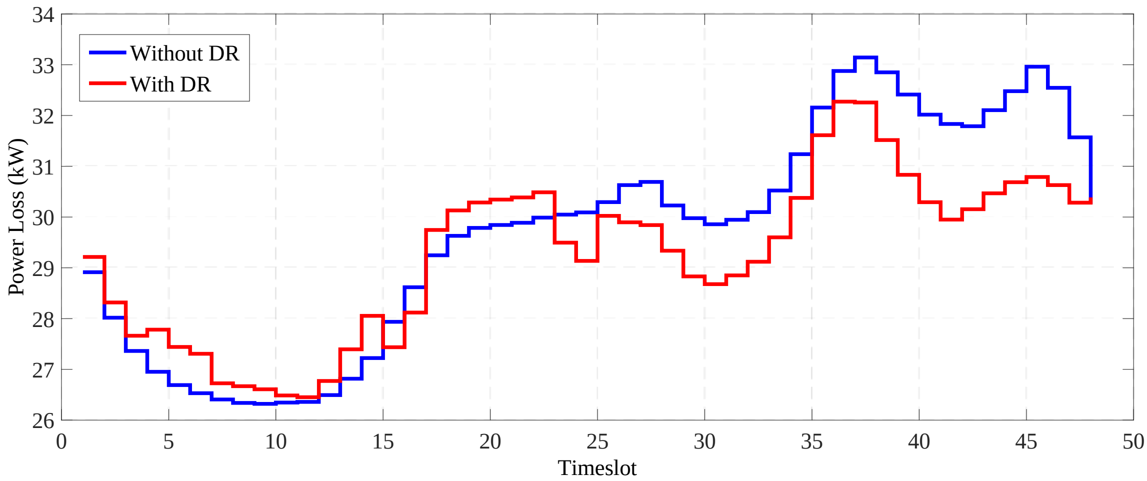



**Figure 5-17:** Total system power loss before and after DR

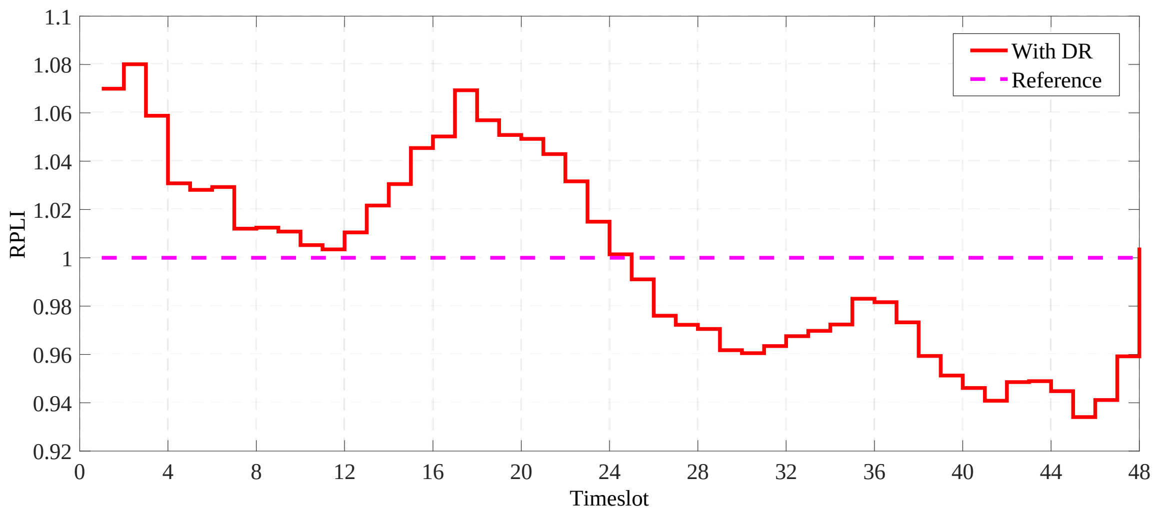



**Figure 5-18:** RPLI after applying the proposed DR control over simulation time

### 5.3.2 Analysis of Results

This section provides an in-depth discussion of the results along with the different features of the proposed MAS framework, with emphasis on how different pricing schemes can effect energy use reduction.

The worst case scenario is studied in order to analyse the computation procedure for the implementation of RTP pricing in the proposed method. For this purpose, MV feeder 7, the most critical feeder in terms of voltage levels in the test network as depicted in Figure 5-14 (a), is chosen. The voltage profile along the feeder during the simulation period is plotted in Figure 5-19 and it illustrates that the voltage is improved and maintained in the allowable limit. The minimum voltage before implementing DR was at timeslot 37 (6:00 pm) and therefore this timeslot is selected for this study. The voltage level at each LV bus along the feeder at timeslot 37 is shown in Figure 5-20. The buses at the end of the feeder experienced lower voltages. The voltage levels at the last 9 buses are below the allowable limits before implementing the DR. Therefore, a DR control mechanism is needed to improve the voltage in order to be within statutory band. The optimal locations for implementing DR are in the buses with the most voltage sensitivity. However, since some technical factors together with some constraints are considered in the objective function, the maximum magnitude of required DR is not necessarily allocated to those buses. For instance, in this case study, the highest kW reduction is computed for LV feeder 59 where the voltage sensitivity is lower than buses 61-65. Accordingly, the highest price is determined for bus 62 which has the maximum ratio of DR requirement to available DR.

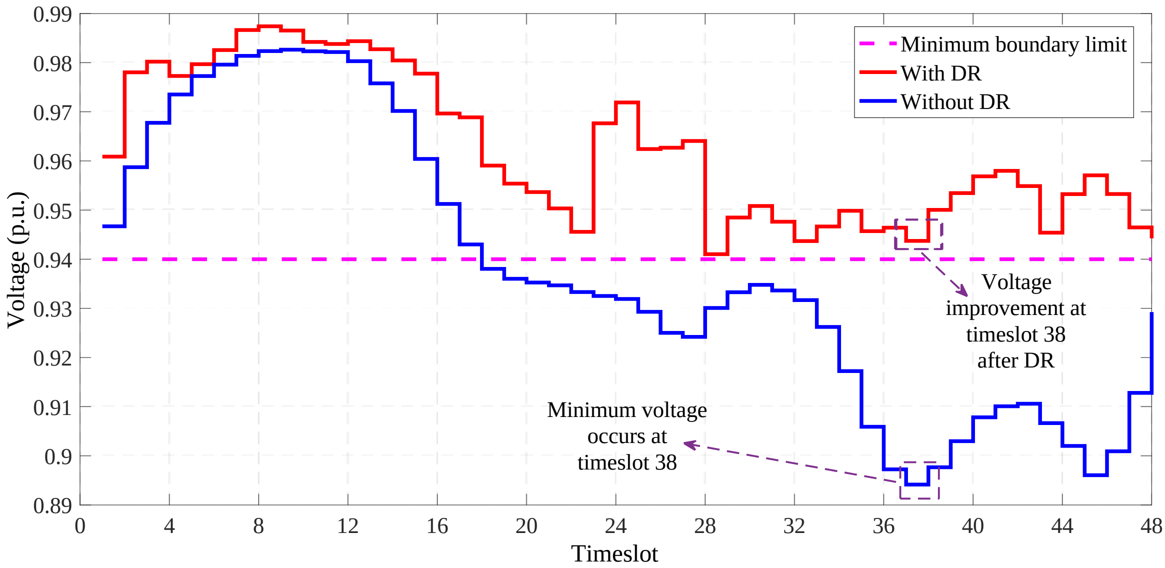



**Figure 5-19:** Voltage profile along MV feeder 7 over simulation time

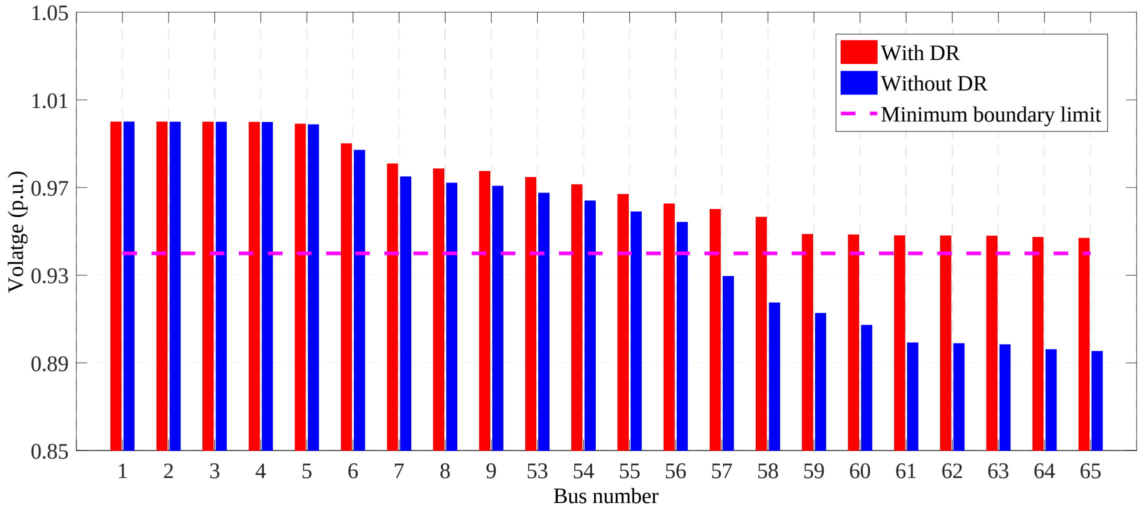



**Figure 5-20:** Voltage profile of each bus along MV feeder 7 at timeslot 37

Table 5-4 illustrates the computed values for parameters required to implement the proposed DR. Since the DR is only available through LV buses, only the buses connected to LV feeders are presented (12 buses). The overall available DR is 21.312 kW and the DR requirement, calculated from equation (3.56), is 14.80 kW. The price for each LV feeder is calculated based on the participation rate as in equation (3.59). The total power reduction after implementing DR is 14.77 kW, thus demonstrating the accuracy and applicability of the proposed method.

**Table 5-4:** Computed values for implementing DR at MV feeder 7 at timeslot 37

| LV feeder No. | Voltage Sensitivity | Available DR (kW) | Required DR (kW) | $(\Delta \acute{P}_{lv,t}^{DR})$ (%) | Actual DR (kW) | Price (Pence/kWh) |
|---|---|---|---|---|---|---|
| **6** | 0.0018 | 0.03 | 0 | 8.11 | 0.019 | 4.89 |
| **7** | 0.0020 | 0.19 | 0.09 | 46.27 | 0.05 | 9.13 |
| **8** | 0.0021 | 2.38 | 0.748 | 31.38 | 1.03 | 7.47 |
| **9** | 0.0031 | 1.96 | 0.871 | 44.33 | 1.16 | 8.91 |
| **53** | 0.0024 | 3.48 | 2.765 | 79.43 | 2.043 | 29.19 |
| **54** | 0.0025 | 4.36 | 3.596 | 82.46 | 3.26 | 34.78 |
| **55** | 0.0027 | 0.97 | 0.717 | 74.06 | 0.953 | 12.21 |
| **59** | 0.0041 | 0.51 | 0.379 | 74.96 | 0.198 | 20.92 |
| **61** | 0.0043 | 2.02 | 0.634 | 31.33 | 0.688 | 15.24 |
| **62** | 0.0043 | 1.86 | 1.63 | 87.70 | 1.79 | 44.47 |
| **64** | 0.0045 | 1.14 | 0.94 | 82.10 | 1.07 | 34.12 |
| **65** | 0.0056 | 2.68 | 2.291 | 85.38 | 2.539 | 40.18 |

It should be noted that it is assumed that all loads in the test system have constant power factors and hence a proportional amount of reactive power is also reduced along with the real power.

### 5.3.3 Scalability of the proposed MAS framework

Implementing the proposed framework shows how different players at the network can communicate, negotiate and collaborate with others in the system to meet the overall system goal. Therefore, the computational burden for the proposed DR strategy is distributed among all participants in DR and is consequently minimised overall. The DSO only needs to optimise the required amount of DR from each LV feeder while assessing and visualising the network status. Predicting the price elasticity or responsiveness demands is not the obligation of the DSO. The aggregators, here referred as LTAs, are responsible for estimating the potential of available DR from their corresponding HAs in each feeder. In addition, considering the price sensitivities and determining appropriate prices for different consumers with distinctive attributes, are undertaken by the SA. Consequently, the proposed MAS simplifies the communication as well as mathematical analysis among agents. In other words, despite the fact that some agents need to negotiate and convey the information to one or more agents, the least computation time is required.

Increasing the number of households or integrating new loads or generations, e.g., EVs and DGs, does not significantly affect the simplicity or time process of the DR mechanism. That can be explained by the following reasons:

1) At the DSO level, the input data for calculations e.g., required demands, available level of flexible loads or generation, are considered as aggregations from each LV feeder. Therefore, the number of loads does not have a consequential influence.

2) With the LTA, the prediction of available DR is based on statistical or probabilistic methods. Since no optimisation is involved, the processing time does not increase.

3) The load scheduling proposed in this research is based on decision-making at each time-interval individually. Hence, no optimisation is required. However, even if an optimisation method is applied in order to schedule the household appliances taking into account a set of prices for a specific period, e.g., next few hours and next day, the time processing is minimal. That is because the optimisation is done in parallel for each household.

4) In the optimisation algorithm of DSO, the iteration number is dependent mostly on the constraints and status of the DN rather than the size of the network or the number of variables.

The above discussions demonstrate the flexibility of the agents in the framework to undertake additional tasks, for instance adopting new types of loads. Therefore, it can be deduced that the presented MAS framework can be readily extended.

## 5.4 MV-LV Network

The simulation results for implementing the two incentive-based DR in the MAS platform are presented and discussed in this section. Unlike the above two case studies, the aim is to provide load reduction through load shedding instead of shifting. In addition, these case studies consider both MV and LV network status. According to the participation motivation, there are two main differences in LCDR and EDR. Firstly, in EDR scheme, consumers are in a contract for reducing the required load shedding, received by LTA, whereas in LCDR all DR engagement is voluntary and can be decided upon request. Secondly, EDR participants get equal incentives for their reduction and hence each HA makes load reduction decision based on its own profit. On the other hand, in the LCDR scheme, HAs within a community are rewarded based on their individual as well as the overall community load reduction.

It should be noted that for both case studies two scenarios are considered: without DR control and with DR. The former one is the reference scenario which, similar to the previous case study, is implemented by applying initial load profiles. In the latter, the proposed methodology and algorithm is implemented. It is assumed that in all scenarios, HAs are charged by the same electricity tariff as the interest of consumers are prompted from the incentives offered by SA. Moreover, as explained in chapter 4, in the LCDR scenario, consumers are equipped with PV in order to investigate the effect of local generation on community load reduction.

### 5.4.1 Simulation Results – Local community Demand Response

The proposed methodology is first implemented for one community in order to assess the feasibility and effectiveness of the proposed framework and algorithm. Then, it is expanded to involve more communities, each having different characteristics, for comparison purposes.

In chapter 3, it was discussed that DR can be achieved in LCDR through three ways. These are dealt with in this chapter as scenarios with DR. An overall of four scenarios are thus studied for the LCDR case study as this also includes one without DR.

***Scenario 1:*** HAs take part in DR reduction scheme through maximising their local PV generation. It is assumed that all HAs are equipped with the PV panel and have the same generation profile. Hence, this scenario results in the highest possibility of load reduction. It is worth to clarify that HAs with PV will always participate in LCDR.

***Scenario 2:*** In this scenario, apart from providing DR from scenario 1, HAs provide further reduction by lowering their demand. Those HAs that have no PV or have higher demands than their generation can take part in this scheme. It is assumed that all HAs are involved and reduce their power consumption up to their required minimum power.

***Scenario 3:*** The trade in of extra available generation from HAs to the community is modelled in this scenario. This scenario considers the required demand after employing scenario 1 and 2.

In the two first scenarios, the contributors are rewarded per kW reduction whereas in the third one they are paid feed-in-tariff rate for each kW generation. The incentive rates are equal for all HAs. It is assumed that DR participation rate as well as the available DR from each HA is maximum. It is worth to clarify that in scenario 2, the Demand Curtailment Limit (DCL) requested from each HA is their maximum available load reduction. The principal aim of this objective is to demonstrate the advantages of the MAS in implementing DR mechanism. The load profiles of the simulation results for all scenarios in the community are presented in Figure 5-21.

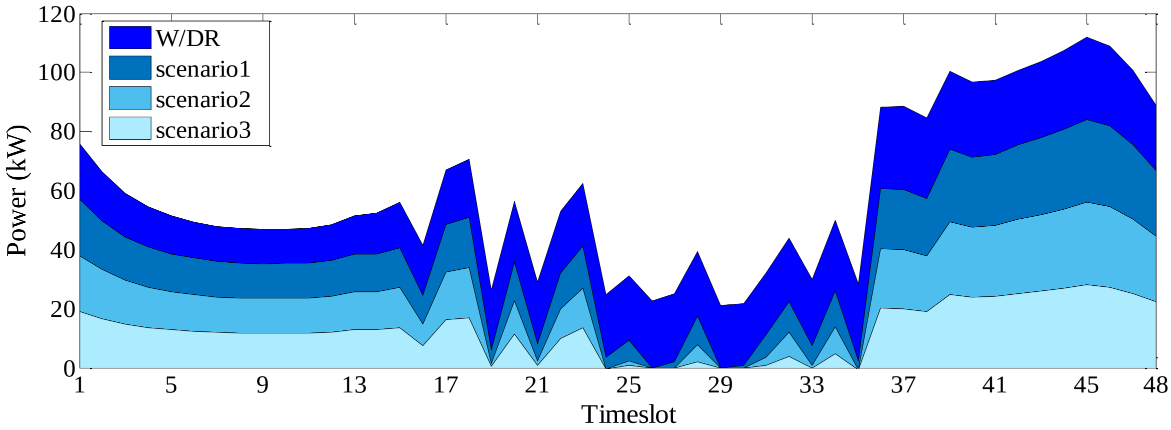



**Figure 5-21:** Load profile of aggregation of all HAs in one community in LCDR for all scenarios

It can be observed that the load profile for all scenarios follows a similar pattern. During no generation period, the power reduction is the same for all DR scenarios as the DR is only available from load shedding. The dependency of the community to the power grid decreases. Moreover, the minimum aggregated load profile during the day occurs with implementing all possible DR scenarios. The maximum percentage of load reduction provided from each scenario is depicted in Figure 5-22. The overall load reduction is 25.68%, 67.8%, and 26.3% in scenarios 1, 2 and 3 respectively. It is clear that scenarios 1 and 3 are dependent on the PV generation and is possible only during day time.  As a result, the highest DR is achieved at the peak generation profile of PV at timeslot 26. In contrast, scenario 2 can be considered as an alternative for all-day DR provision. However, the level of DR size over time depends on the load profile of each HA.

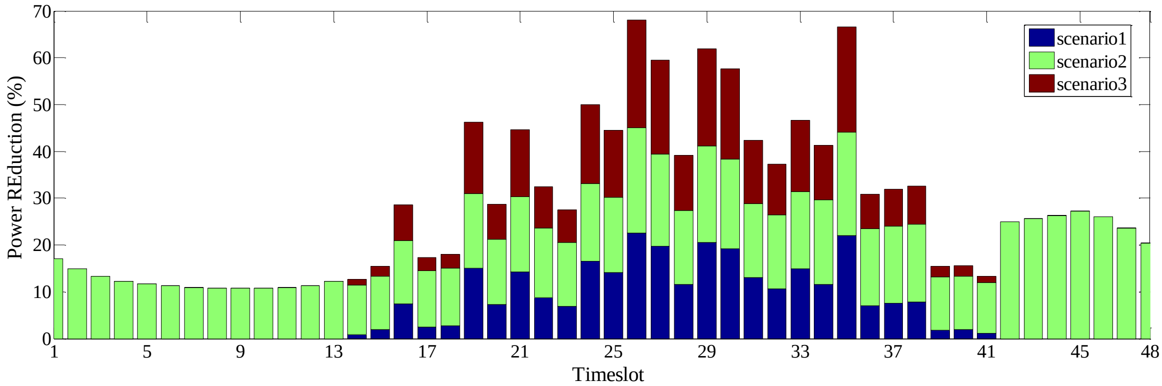



**Figure 5-22:** Overall load reduction of each community in LCDR for all considered scenarios with DR

The effect of LCDR in the voltage profile of the network is shown in Figure 5-23. It can be deduced that the voltage profile significantly improves during day time when the PV can generate power. However, in all timeslots, the DR resulted from scenario 2 increases the voltage magnitude.

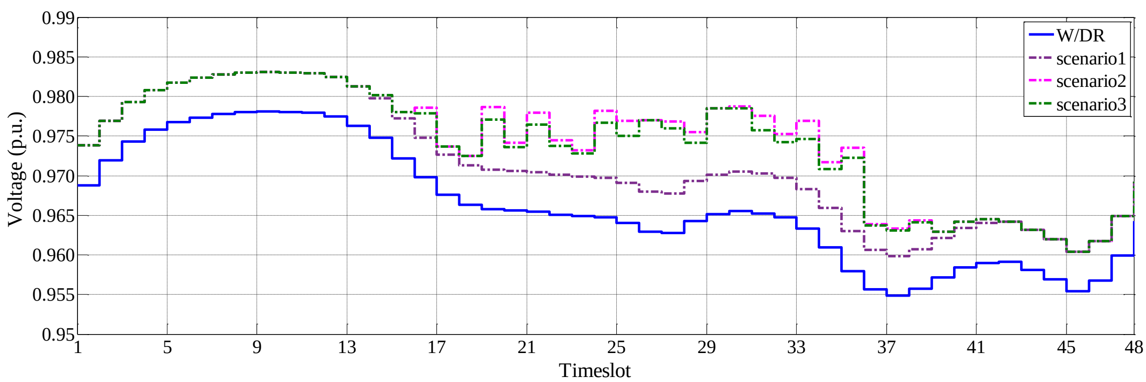



**Figure 5-23:** Voltage Profile before DR and after implementing each scenario with DR Discussion

### 5.4.2 Analysis of Results

This section assesses the effect of the key attributes of consumers in the overall demand reduction. In this regard, several communities are considered having different setting parameters and characteristics. First, the impact of PV penetration as well as participation rate on the total power reduction in each community is investigated. The effect of participation rate on the overall community demand reduction was investigated for various PV penetration percentages. The simulation outcomes are shown in Figure 5-24. The results followed a similar trend and the increase in reduction is relative to the depth of PV penetrations. The maximum reduction is 69% occurs for a PV penetration of 100%. As expected, the higher the penetration, the more reduction is yielded. It should be observed that even with no participation rate, there is still a small amount of DR.  For instance for 20% PV penetration without any participation rate, there is a reduction of 6.5%. This is attributed to the fact that scenario 2 comprises both PV generation and available load reduction. Participation rate is considered for HAs involved in the latter.

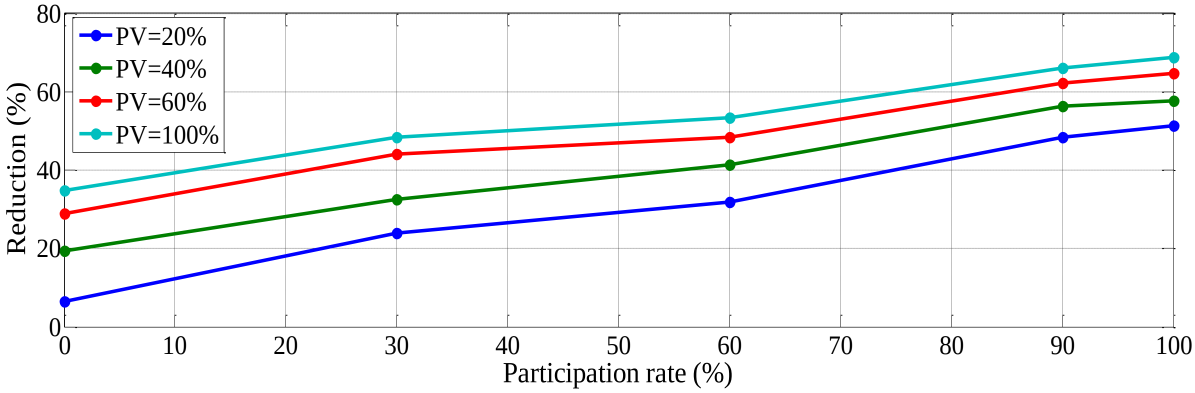



**Figure 5-24:** Impacts of participation rate and PV Penetration on the overall power reduction of community

Secondly, the effect of increasing financial motivation (FM) on participation rate was investigated. This study involved 11 communities and the incentive values were obtained from a UK pilot [226] studying the reduction in peak electricity demand in households. The financial motivation defined between 0% to 100% was allocated to each community with an increasing step of 10%. The incentive was then varied from 6 pence/kWh for community 1 to 15 pence/kWh for community 10. The result is shown in Figure 5-25 where it is clearly evident that increasing the financial motivation results in a surge in the participation rate. As expected, the maximum participation rate resulted from community 10 which had the highest incentive, coupled with the 100% financial motivation.

In case of a community reward scheme, the community with the highest reduction, based on its consumption is chosen and get incentive. This reward is then shared among the contributors within the community. This competitve commnunity energy reduction game can provide a better motivation for DR participation. Agents in one community will work together to achieve the community's goal, which is an advantage of MAS implementation. Referring to Figure 5-25, the successful communities are less sensitive to the incentive rates. This means that HAs should have the maximum participation rate. However this is not only the case since the available DR from each HAs and accordingly the total community is not always comparable to the other communities.

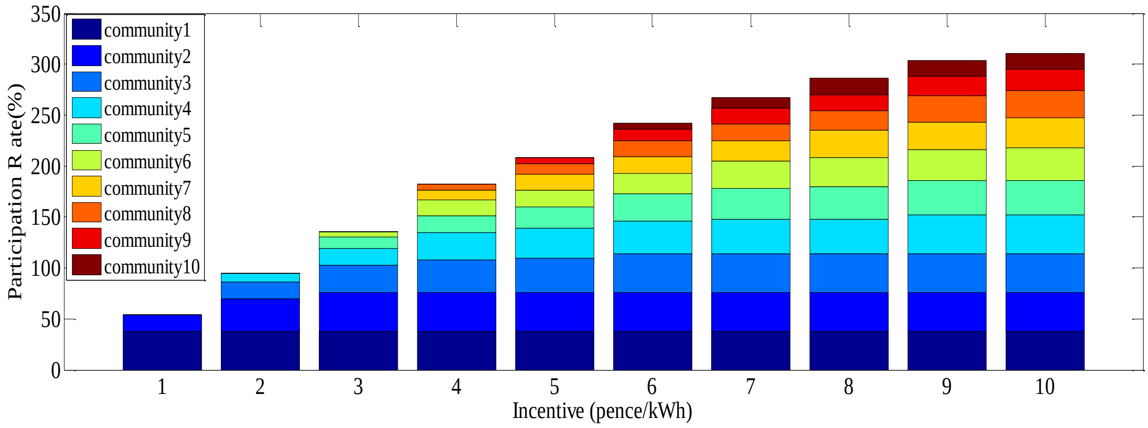



**Figure 5-25:** Effect of financial motivation on DR participation

### 5.4.3 Emergency Demand Response

In this case study, the DR is activated by LTA during emergency condition when system is under stress condition , e.g., transformer overloading or upon receiving any DR event signal from DRPA. In order to simulate such state of the network and test the proposed EDR mechanism, DR signal from DRPA is studied in this section. It is assumed that a 30kW demand boundary limit is sent to LTA from DRPA. The simulation result with and without DR scenarios is depicted in Figure 5-26. The latter is considered as the reference point in order to evaluate the performance of the DR algorithm.

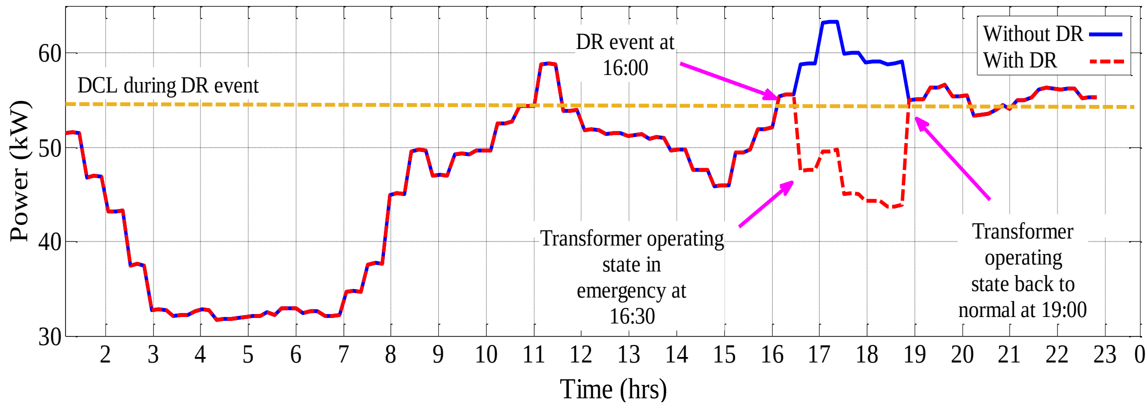



**Figure 5-26:** Instantaneous Power at the LTA with and without DR

It can be seen that with the proposed DR algorithm, the instantaneous power at LTA is decreased and is below the DCL at all timeslots. The simulation procedure is discussed in detail below:

- LTA checks its status continuously to ensure that the transformer load is kept below the boundary limit at any given time. Up to timeslot 33 (16:00hrs), the transformer status is normal and no DR action is needed.

- At time 16:30hrs (timeslot 34), the aggregation loads at the transformer exceeds the maximum limit and continues up to 17:00hrs (timeslot 39). The transformer operating status changes to emergency and a DR event for duration of 2.5 hours is detected.

- LTA calculates and sends the allocated loads to selected HAs based on the methodology explained in chapter 3.

A comparison of the transformer voltages, with and without DR, is depicted in Figure 5-27 An improvement in voltage at peak times can be observed and this is attributed to load reduction. The contribution of each cluster of customers in EDR during DR event is illustrated in Figure 5-28. It can be concluded that to meet the need for higher curtailment, more customers' participation is required. A better degree of DR flexibility can be achieved with an aggregation of more customers, with a view to improving the reliability and efficiency of the power network. The proposed methodology ensures that the DR request is sent to customers according to their potential when necessary. This implies that to meet the requirement of the network, not all clusters have to take part and fewer customers are involved, thus maintaining their comfort level. This can be observed for timeslot 37, 38 and 39 where the demand curtailment is met without the participation of all clusters.

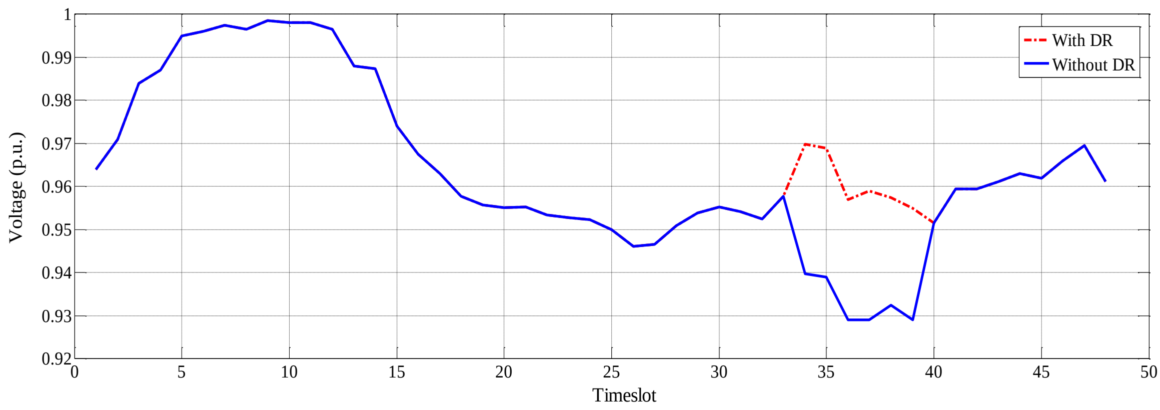



**Figure 5-27:** Voltage (p.u.) of the DT in each bus during DR event

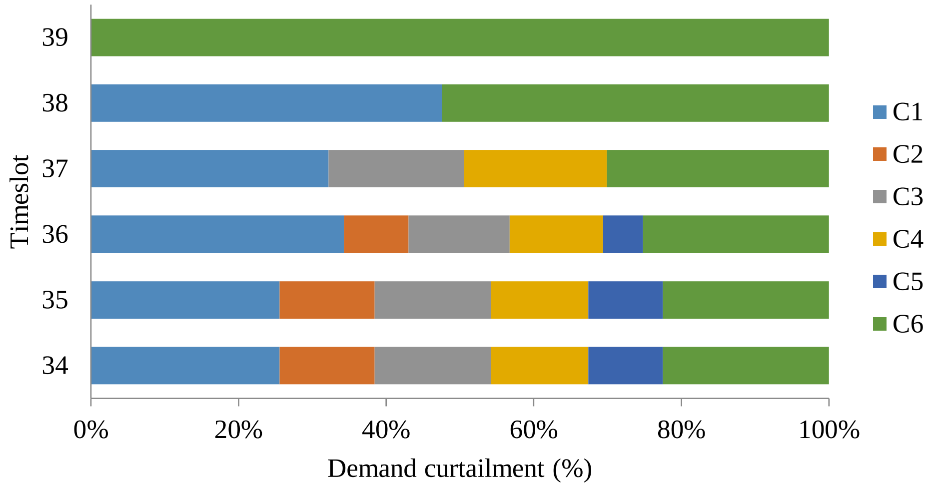



**Figure 5-28:** Percentage of demand curtailment for each cluster in each time-interval during DR event

One of the advantages of EDR is that although customers are under contractual obligation for DR provision, their decision making will be updated upon receiving DR request. This means that when those who have accepted to participate in DR receive a request, they will calculate the available DR size and send it to the LTA. Their proposal would be either accepted or rejected based on their potential. Therefore they only get penalised if they do not meet their accepted proposal. In contrast to other incentive based DR such as DLC, this will guarantee the maximum comfort level of households while maintaining power supply balancing issues at the network.

In LCDR the demand reduction is voluntary and will be decided by HAs at each time interval. Therefore this scheme can provide greater customer satisfation including the benefit of bill saving. In longer term LCDR provides better DR where as EDR is appropriate in temporary load reduction during network stress conditions.

## 5.5 Summary

This chapter implements the MAS framework and demonstrates its advantages. Similar to chapter 4, each objective was studied as an individual case study and these were LV, MV and MV/LV network. Different price-based DR mechanisms were considered for assessing the feasibility and effectiveness of case study 1 and 2. In the third case study, two incentive-based DR schemes were employed.

For each scenario in the LV network, the overall performance of load scheduling at household level and their economic benefits are explained. In addition, the effect of shifting loads under different tariffs on the improvement of the technical characteristics of the network including the voltage, PAPR, standard deviation is shown. An in-depth analytical comparative study of these schemes concluded that RTP is the optimal option for social welfare maximisation of all agents in the system. The work was then expanded to MV network level, with the introduction of a new satisfaction factor, BSS, in order to investigate the long-term benefits of RTP from both households and network perspectives.

The simulation of the MV case study is performed without DR as a reference benchmark and with RTP. The first one was selected as the reference scenario. A significant improvement in the voltage magnitude of the network and VDI is observed at all simulation period. The process of price calculation for each LV feeder is also described. A comprehensive discussion demonstrating the ease of scalability of the proposed scheme is also provided.

Finally, at MV/LV network, the simulation results are presented for the two scenarios, LCDR and EDR. In the former, various factors such as participation rate, PV penetration and financial motivations are considered for each community. The results are then compared and discussed.

# Chapter 6 Conclusion and Future Research

## 6.1 Conclusions

A novel MAS-based framework for DR-based active management for the DN has been investigated and implemented. The proposed platform employs demand responsiveness from both load shifting and shedding in order to mitigate possible overloading issues in MV/LV distribution networks. Two advantages of this system are the capability of merging centralised and decentralised DR control mechanisms and integrating both price-based and incentive-based DR. Unlike many previous attempts [123-130], the consideration of both temporary and long-term benefits of applying DR in the DN is performed. A summary of this research together with the main achievements and contributions are presented in the following. Suggestions for future work are provided in section 6.2.

The future GB distribution network is facing many challenges caused by the increase in penetration of DGs and new responsive loads. The DNOs are transforming to DSOs in order to take an active role in managing the power-demand balancing issues in the DN. Optimising the modern DN, the significance of DR schemes on power balancing across the DN is getting more emphasised. These programmes can be considered as alternative solutions to costly and time-consuming investments in upgrading the network infrastructure.

Therefore, this requires a thorough examination of the potential of DR in relieving the constraints in the DN. However, the quantification of available flexible and dynamic loads has not been addressed in depth in the literature. Having an understanding of available DR sources can significantly improve the outputs of DR strategies during the planning phase. Moreover, due to small responsiveness loads at household level, a large aggregation of peak demands is required to achieve sufficient DR if required. The arising complexity from wide-area DR implementation necessitates the introduction and employment of a control framework that integrates different entities with distinctive attitudes and objectives. In this way, flexible demand from residential consumers can ensure network security and reliability while satisfying all DR players' goals.

A comprehensive review of the relevant background and researches on the residential DR strategies and mechanisms to manage the DN is provided in chapter 2. These studies have proven the effectiveness of residential DR utilisation from both technical and economic aspects. DR mechanisms are divided into consumer and network levels where the key players consist of energy users, network operators, electricity retailers and aggregators. In designing DR algorithms, the focus has been on solo entity, single house or local feeder, or on aggregated level, multiple houses or MV network. At household level, HEMS are classified into three categories including smart, conventional and advanced. The two first systems have similar functionalities with the difference of embedding a price prediction capability in advanced HEMS. Among the proposed models for DR participants' interaction, MAS is one of the most prevalent control methods that provides a distributed and intelligent framework. A number of trials have been reviewed and the outcomes demonstrated that providing DR to DN could be considered as an alternative to defer network reinforcement. Several attributes, opportunities and challenges in consumer participation in DR were investigated.

The proposed MAS framework, consisting of the physical and cyber layer, is introduced in chapter 3. This model comprises four main kinds of agents. These are HA, LTA, DRPA and SA representing households, MV/LV transformers, DSO and energy supplier. An additional agent, DSPA, is used to model the DCC in the GB distribution network. Accordingly, the architecture of MAS-DR-based ADNM presents four different layers as market, MV feeder, LV feeder and end-user, based on the location of defined agents in the network.

One of the advantages of this model is the configurability feature which enables connecting new agents with different goals, tasks and access level to other agents' information. Even after implementation, the overall layout can still be adjusted and the attributes, tasks and access level of each agent can be modified. This framework characteristic allows the employment of one unique platform for all three objectives of this thesis. Only the DR algorithms for each agent and MAS structure are adapted appropriately to model these objectives, which are on LV, MV and MV/LV networks.

For the LV network, an optimisation problem is formulated for solving the load scheduling of households. The innovative aspect of the proposed algorithm is the methodology which considers both minimisation of consumers' energy expenses and maximisation of their satisfaction level. The satisfaction factor is obtained for end users according to their attitudes towards DR engagement as well as the elasticity of their demand to changes in electricity prices. The algorithm is then developed to include the price prediction for RTP scheme. This novel price predictor uses the information regarding the required as well as available DR predicted one day-ahead by LTA. The prices are updated upon receiving new price signals in real time. In the aim of presenting a less computationally demanding technique, a novel decision-making algorithm is proposed and implemented for MV network. This is based on selecting the start-up of the controllable appliances in real time, taking into account the available appliances and the attractiveness of the RTP. The proposed methodology does not involve any optimisation process and is suitable for RTP-based DR. Unlike the first two objectives, HA decides about load shedding instead of shifting in MV-LV network. The size of available DR is dependent on the available local generation at each household and the minimum critical loads that must be run. The financial motivation of consumers is also considered in their decision-making.

The LTA is responsible for calculating the potential and available DR at the LV and MV networks respectively. Although it does not perform any action, its information is crucial for DRPA to calculate the total required DR at each feeder. Additionally, SA utilises this data to set the tariffs in DA-RTP or RTP. This also needs to be provided for HAs to enable them to decide about their next day load scheduling in RTP. The LTAs create a more distributed DR as the information are gathered at each local feeder for further decision making in upper feeder. In the MV-LV feeder, LTA takes a more active role in calculating and sending the DCL or amount of purchased local generation to and from HAs. This is due to the incentive-based DR where the DR action are implemented by local feeders even if DR occurs at MV feeders.

The role of DRPA is limited to monitor and assess the network status taking into account voltage and current constraints. All actions are implemented by designing appropriate prices at the price-based DR and by sending a DR event to LTAs at the incentive-based DR. The novelty of assessing the DR requirement at each LV feeder is the consideration of not only the total required DR, but also the available DR and the voltage sensitivity at each LV feeder. The amount of required DR is not distributed equally among feeders but the utilisation of flexible demand sources in the network are maximised.

The role of SA is more prominent in price-based DR where the activation of DR by HAs depends on the set tariffs. A four and a two piece-wise linear functions are proposed for SAs to set the RTP or DA-RTP signals. In both schemes, the price coefficients are determined by the participation rate. This novel parameter is calculated, from the information received by LTA or DRPA, as the ratio of the percentage of required DR to available DR.

The physical layer was modelled based on a modified IEEE 69 test system with 8 MV and 48 LV feeders, to demonstrate the advantages of the proposed framework. The chosen network was selected by considering the adequacy of the size of network to accommodate massive demand aggregations and to be the closest possible to the GB standard. The overall network objectives are achieved by solving a power flow that is based on consumer load profile characteristics, taking into account different personal (social, technical, educational and financial incentives) as well as external (time, day and seasonal) factors.

The load profiles of households and the extracted information from the dataset are created by a characterisation-based clustering technique. The data related to only weekdays and for one summer month is investigated. Consumers having missing values for more than one day were removed from the analysis to ensure the quality and accuracy of clustering results. 6 clusters are obtained from the clustering simulation and for each of them the price elasticity of demand as well as their attitudes towards DR participation is determined. Based on these clusters, 1824 synthetic load profiles are created, keeping the consistency of the population in each cluster. The created load profiles are distributed in the test network randomly.

Three case studies are introduced for each objective at LV, MV and MV/LV load management. The probability of start-time of wet appliances is estimated and the results are shown for each cluster of customers. Accordingly, the preferable window of each cluster of households to shift/delay each controllable appliance is determined. The default start time of each appliance in each household is considered based on a random selection among preferable window times. The initial simulation results for the potential of load shifting and load shedding from HAs are presented for the first two and the last case studies respectively.

The simulation results of the DR-MAS-based ADNM are provided and discussed in chapter 5. A summary of all scenarios considered for each case study is shown in table 5-5. The first two case studies applied price-based DR whereas the last one used incentive-based DR.

**Table 5-5:** Summary of case studies and scenarios investigated

| | | Scenarios | | | | | |
|---|---|---|---|---|---|---|---|
| | | Price-based | | | | Incentive-based | |
| Case Study | Network Level | Fixed | ToU | DA-RTP | RTP | EDR | LCDR |
| 1 | LV | * | * | * | * | | |
| 2 | MV | * | | | * | | |
| 3 | MV/LV | | | | | * | * |

Four scenarios are presented for the first case study and these are fixed, ToU, DA-RTP and RTP. In all case studies, the fixed tariff is considered as the reference benchmark. Each scenario implements a different tariff type to enable the comparison among different price-based DR. An analytical evaluation of the simulation results shows that overall, RTP provide greater DR compared to other scenarios. The PAPR, peak demand and standard deviation were reduced by 9.27%, 4.59% and 60.19% as compare to the fixed tariff. An interesting observation is the achievement of more flattened load profiles in dynamic tariffs particularly in RTP. The possibility of a new peak demand is a disadvantage of the ToU and DA-RTP. Alternatively, this can affect the voltage profile magnitudes and results in exceeding the allowable boundary, especially in ToU.

From an economic perspective, HAs achieved maximum savings of 18.81% on total payment and 13.13% on minimum payment in DA-RTP scenario. The second most significant cost saving, up to 12.08%, is achieved under RTP. Since a difference of 26% is observed between the actual and pre-defined tariffs in DA-RTP, the satisfaction of all agents at the network is only possible by RTP.

In a further investigation, the impact of RTP in long-term is studied by introducing a new satisfaction factor for consumers based on the total bill saving. The simulation is performed for one-month and for the whole network (48 LV feeders). The outcome showed an overall improvement on the voltage profile of the network. For better performance of RTP, the available DR at each LV feeder as well as its effectiveness on the operation of MV network should be taken in to account. This is then addressed in designing RTP in SA for case study 2.

Two scenarios are considered in case study 2: before and after implementing RTP. The simulation results showed the capability and effectiveness of the proposed DR framework in controlling the power flow equations in MV feeders. The active power of the network was maintained within the acceptable limits by reducing available flexible demands considering the most influential LV buses. As an example, for feeder 7 at timeslot 37, the required DR was calculated to be 69.44% of the total available flexible demands. The DR implementation resulted in load reduction of 69.30% which indicates the feasibility of this framework. One advantage of the proposed framework is its scalability where the integration of new loads, generations and agents will not affect the simplicity and computational process of the DR algorithms. This allows integrating both centralised and decentralised DR control mechanism as demonstrated in case study 3.

Two different DR schemes are introduced and implemented in case study 3: LCDR and EDR. In the former, agents work in one specific community in order to achieve the community's goal. HAs are motivated by receiving incentives per kW power reduction or by participating in community-reward schemes where the winner shares the reward among DR participants. Based on the type of responsiveness load, 3 scenarios are considered together with the reference one. In the first two scenarios, HAs take action by maximising their local generation and by load shedding. In the third one, the LTA maximises the utilisation of extra available local generation. The performance results for one local community indicated a significant rise in the independency to the power grid. The results show 25.68%, 67.8% and 26.3% load reduction for scenario 1, 2 and 3 respectively. As expected, scenario 2 which integrated PV provided the maximum DR. The simulations are also performed for various factors including participation rate, PV penetration as well as financial motivation. The results show that these factors have an incremental linear relation with percentage load reduction.

The EDR scheme is based on load shedding where the DR participation is on a contract. One advantage of the proposed methodology is that the DCL is allocated to consumers according to their DR potential. Hence, fewer participants may need to be involved during DR events. Consumers in both LCDR and EDR can chose their participation and the quantity of DR provision in real time. This maximises the satisfaction level of households while maintaining the network constraints within acceptable limits.

The results demonstrate that the proposed DR-MAS ADNM framework has the capability to integrate and implement various DR mechanisms for MV/LV network. The advantages of this platform including scalability and configurability are validated through various case studies. It can provide an environment where all DR stakeholders can interact with each other and collaborate in order to manage the power flow across the network while also considering their own interests.

## 6.2 Future Work

The research aim and objectives defined for this thesis are satisfied through the presented works. Yet, this work can be extended and improved in various areas to include future investigations and developments. The probable future research directions are presented in the following.

- ***Scaling-up the Framework:*** The proposed framework in this research assumed a unique DRPA and SA for all HAs within the network. In practice, each household can chose a different electricity supplier and based on the physical location, might be allocated to a different DSO. The proposed framework and DR control algorithms can be extended in order to assess various DRPAs and SAs in the network. In this respect, the design of price for each HA will be set with its specific SAs. As a result, the HAs within a LV feeder, may have distinctive tariffs.

- ***Accommodation of New Loads:*** The impact of considering additional loads such as EVs and HPs is another future work. The high power consumption of these new load sources can provide a great potential of demand flexibility. The DR control mechanism at HAs needs to be modified for adopting with the new demands. The charging time of EVs can be interrupted and distributed over several periods. Hence, a numbers of optimal charging slots can be incorporated in the HAs daily load scheduling. Similarly, since the HP's operating status is dependent to the weather condition, the adjustment of the thermostat can be updated by weather forecasting techniques.

- ***Developing Agents' Methodologies:*** The DR algorithm at HAs can be developed in order to include the local generation in the optimisation of load scheduling. In this way, the shiftable loads can be delayed to the time of maximum generation. The maximum usage will be then matched by the maximum local generation. Moreover, the feedback of reaction of the HAs on changing the price in the dynamic pricing tariffs can also be considered. This benefits both energy suppliers and network operators to mitigate the network constraints.

# Appendix A

Table A.1. Active and Reactive Power of the Modified IEEE-69 Bus Network

| Bus No. | P (kW) | Q (kW) | Bus No. | P (kW) | Q (kW) | Bus No. | P (kW) | Q (kW) |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 24 | 28 | 20 | 47 | 0 | 0 |
| 2 | 0 | 0 | 25 | 0 | 0 | 48 | 79 | 56.4 |
| 3 | 0 | 0 | 26 | 14 | 10 | 49 | 384.7 | 274.5 |
| 4 | 0 | 0 | 27 | 14 | 10 | 50 | 384.7 | 274.5 |
| 5 | 0 | 0 | 28 | 26 | 18.6 | 51 | 40.5 | 28.3 |
| 6 | 2.6 | 2.2 | 29 | 26 | 18.6 | 52 | 3.6 | 2.7 |
| 7 | 40.4 | 30 | 30 | 0 | 0 | 53 | 4.35 | 3.5 |
| 8 | 75 | 54 | 31 | 0 | 0 | 54 | 26.4 | 19 |
| 9 | 30 | 22 | 32 | 0 | 0 | 55 | 24 | 17.2 |
| 10 | 28 | 19 | 33 | 14 | 10 | 56 | 0 | 0 |
| 11 | 145 | 104 | 34 | 19.5 | 14 | 57 | 0 | 0 |
| 12 | 145 | 104 | 35 | 6 | 4 | 58 | 0 | 0 |
| 13 | 8 | 5.5 | 36 | 26 | 18.55 | 59 | 100 | 72 |
| 14 | 8 | 5.5 | 37 | 26 | 18.55 | 60 | 0 | 0 |
| 15 | 0 | 0 | 38 | 0 | 0 | 61 | 1244 | 888 |
| 16 | 45.5 | 30 | 39 | 24 | 17 | 62 | 32 | 23 |
| 17 | 60 | 35 | 40 | 24 | 17 | 63 | 0 | 0 |
| 18 | 60 | 35 | 41 | 1.2 | 1 | 64 | 227 | 162 |
| 19 | 0 | 0 | 42 | 0 | 0 | 65 | 59 | 42 |
| 20 | 1 | 0.6 | 43 | 6 | 4.3 | 66 | 18 | 13 |
| 21 | 114 | 81 | 44 | 0 | 0 | 67 | 18 | 13 |
| 22 | 5.3 | 3.5 | 45 | 39.22 | 26.3 | 68 | 28 | 20 |
| 23 | 0 | 0 | 46 | 39.22 | 26.3 | 69 | 28 | 20 |

Table A.2. Line Parameters of the LV feeder in the modified IEEE 69-bus test network

| LINE | | R (Ω) | X (Ω) | LINE | | R (Ω) | X (Ω) |
|---|---|---|---|---|---|---|---|
| From bus | To bus | | | From bus | To bus | | |
| 1 | 2 | 0.0415 | 0.0145 | 6 | 11 | 0.2607 | 0.026 |
| 2 | 3 | 0.0424 | 0.0189 | 6 | 10 | 1.3605 | 0.1357 |
| 3 | 4 | 0.0444 | 0.0198 | 4 | 13 | 0.14 | 0.014 |
| 4 | 5 | 0.0369 | 0.0165 | 3 | 19 | 0.7763 | 0.0744 |
| 5 | 6 | 0.052 | 0.0232 | 2 | 14 | 0.5977 | 0.0596 |
| 6 | 7 | 0.0524 | 0.0234 | 1 | 16 | 0.1423 | 0.0496 |
| 7 | 9 | 0.0005 | 0.0002 | 16 | 17 | 0.0837 | 0.0292 |
| 7 | 8 | 0.2002 | 0.0199 | 17 | 18 | 0.3123 | 0.0311 |
| 7 | 11 | 1.734 | 0.1729 | 1 | 15 | 0.0163 | 0.0062 |

Table A.3. Line Parameters of the MV feeders in the modified IEEE-69 Bus Network

| LINE | | R (Ω) | X (Ω) | LINE | | R (Ω) | X (Ω) | LINE | | R (Ω) | X (Ω) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **From bus** | **To bus** | | | **From bus** | **To bus** | | | **From bus** | **To bus** | | |
| 1 | 2 | 0.0005 | 0.0012 | 24 | 25 | 0.7488 | 0.2475 | 47 | 48 | 0.0851 | 0.2083 |
| 2 | 3 | 0.0005 | 0.0012 | 25 | 26 | 0.3089 | 0.1021 | 48 | 49 | 0.2898 | 0.7091 |
| 3 | 4 | 0.0015 | 0.0036 | 26 | 27 | 0.1732 | 0.0572 | 49 | 50 | 0.0822 | 0.2011 |
| 4 | 5 | 0.0251 | 0.0294 | 3 | 28 | 0.0044 | 0.0108 | 8 | 51 | 0.0928 | 0.0473 |
| 5 | 6 | 0.366 | 0.1864 | 28 | 29 | 0.064 | 0.1565 | 51 | 52 | 0.3319 | 0.1114 |
| 6 | 7 | 0.3811 | 0.1941 | 29 | 30 | 0.3978 | 0.1315 | 9 | 53 | 0.174 | 0.0886 |
| 7 | 8 | 0.0922 | 0.0470 | 30 | 31 | 0.0702 | 0.0232 | 53 | 54 | 0.203 | 0.1034 |
| 8 | 9 | 0.0493 | 0.0251 | 31 | 32 | 0.351 | 0.1160 | 54 | 55 | 0.2842 | 0.1447 |
| 9 | 10 | 0.819 | 0.2707 | 32 | 33 | 0.839 | 0.2816 | 55 | 56 | 0.2813 | 0.1433 |
| 10 | 11 | 0.1872 | 0.0619 | 33 | 34 | 1.708 | 0.5646 | 56 | 57 | 1.59 | 0.5337 |
| 11 | 12 | 0.7114 | 0.2351 | 34 | 35 | 1.474 | 0.4873 | 57 | 58 | 0.7837 | 0.263 |
| 12 | 13 | 1.03 | 0.3400 | 3 | 36 | 0.0044 | 0.0108 | 58 | 59 | 0.3042 | 0.1006 |
| 13 | 14 | 1.044 | 0.3450 | 36 | 37 | 0.064 | 0.1565 | 59 | 60 | 0.3861 | 0.1172 |
| 14 | 15 | 1.058 | 0.3496 | 37 | 38 | 0.1053 | 0.1230 | 60 | 61 | 0.5075 | 0.2585 |
| 15 | 16 | 0.1966 | 0.0650 | 38 | 39 | 0.0304 | 0.0355 | 61 | 62 | 0.0974 | 0.0496 |
| 16 | 17 | 0.3744 | 0.1238 | 39 | 40 | 0.0018 | 0.0021 | 62 | 63 | 0.145 | 0.0738 |
| 17 | 18 | 0.0047 | 0.0016 | 40 | 41 | 0.7283 | 0.8509 | 63 | 64 | 0.7105 | 0.3619 |
| 18 | 19 | 0.3276 | 0.1083 | 41 | 42 | 0.31 | 0.3623 | 64 | 65 | 1.041 | 0.5302 |
| 19 | 20 | 0.2106 | 0.0696 | 42 | 43 | 0.041 | 0.0478 | 11 | 66 | 0.2012 | 0.0611 |
| 20 | 21 | 0.3416 | 0.1129 | 43 | 44 | 0.0092 | 0.0116 | 66 | 67 | 0.0047 | 0.0014 |
| 21 | 22 | 0.014 | 0.0046 | 44 | 45 | 0.1089 | 0.1373 | 12 | 68 | 0.7394 | 0.2444 |
| 22 | 23 | 0.1591 | 0.0526 | 45 | 46 | 0.0009 | 0.0012 | 68 | 69 | 0.0047 | 0.0016 |
| 23 | 24 | 0.3463 | 0.1145 | 4 | 47 | 0.0034 | 0.0084 | | | | |

# Appendix B

Table B.1. RC Values for different trials implemented in the dataset

| TOU tariff | day | peak | Night |
|---|---|---|---|
| **Tariff A** | 1.29 | 0.90 | 1.50 |
| **Tariff B** | 1.33 | 0.69 | 1.64 |
| **Tariff C** | 1.38 | 0.56 | 1.80 |
| **Tariff D** | 1.44 | 0.47 | 2.00 |
| **Tariff W** | 1.80 | 1.29 | 0.47 |

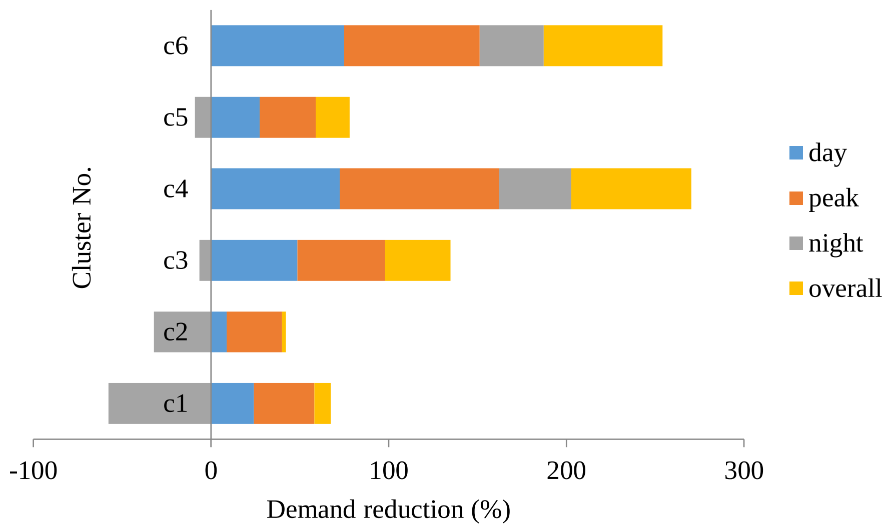



Figure B.1. Percentage of demand reduction in different time periods

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