DISTRIBUTED ENERGY MANAGEMENT IN SMART GRID

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DISTRIBUTED ENERGY MANAGEMENT IN SMART GRID

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by

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Under the guidance of

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CERTIFICATE OF APPROVAL

Date: __/__/______

Certified that the thesis entitled **Distributed Energy Management in Smart Grid** submitted by **Ayan Mondal** to the Indian Institute of Technology, Kharagpur, for the award of the degree Master of Science has been accepted by the external examiners and that the student has successfully defended the thesis in the viva-voce examination held today.

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DECLARATION

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Ayan Mondal

Dedicated to
My parents and Sister

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Abstract

To achieve high reliability in power systems, the traditional electrical grids need to be designed as modernized electrical systems, termed as 'Smart Grid'. A smart grid is visualized to be a cyber-physical system, which is instrumented by sustainable models of energy production, distribution, and usage. In a smart grid with duplex communication infrastructure, the large scale traditional electrical grid is divided into micro-grids. In the presence of several micro-grids, it is desirable to allow each micro-grid or a group of micro-grids to service a small geographical area or a group of customers based on their demands in a distributed manner, so as to relax the load on the main grid.

Considering that the consumers, i.e., customers and plug-in hybrid electric vehicles (PHEVs), are connected with multiple micro-grids, a dynamic smart grid architecture needs to be designed to incorporate the relationship between energy generation and energy demand. Moreover, the dynamic smart grid architecture needs to ensure high energy consumption of the consumers and high profit of the micro-grids. Additionally, distributed energy management systems need to be designed for the customers and PHEVs, individually.

In this work, we design a dynamic smart grid architecture – coalition formation and data aggregator unit (DAU) selection. By forming coalition dynamically, high quality of energy service is guaranteed. On the other hand, by selecting DAU dynamically, low delay in energy service is ensured, while distributing the communication overhead properly to the available DAUs within a coalition. Additionally, a home energy management system is proposed, in which the customers are equipped with storage devices. Finally, we study different energy management systems for PHEVs – cloud-free and cloud-based. In cloud-free energy management systems, wherein the communication takes place between multiple micro-grids, each PHEV selects its service provider and decides the amount of energy to be consumed, while relying on the real-time communication infrastructure. On the other hand, in cloud-based energy management systems, the PHEVs communicate with the energy cloud service provider (ECSP) and consume energy from the available micro-grids based on the real-time communication with the ECSP.

Keywords: Distributed Energy Management, Game Theory, Coalition, Data Agregator Unit, Storage Devices, Energy Cloud Service Provider, Plug-in Hybrid Electric Vehicle, Micro-grid, Smart Grid

Contents

List of Figures

List of Tables

List of Algorithms

List of Symbols and Abbreviations

List of Symbols

$\mathcal{M}$	Set of micro-grids
$\mathcal{N}^c$	Set of customers
$\tilde{\mathcal{N}^c}_m$	Set of customers connected with micro-grid m
G_m	Predicted amount of energy to be generated by micro-grid m
x_n^c	Minimum amount of required energy by each customer n
$x_n^{c\,*}$	Optimum amount of required energy by each customer n
S_m	Energy supply satisfaction factor of micro-grid m
p_m	Predicted price per unit energy decided by micro-grid m
p_m^*	Optimum price per unit energy decided by micro-grid m
$\mathcal{U}_n^m(\cdot)$	Utility function of customer n connected with micro-grid m in DCF
$\mathcal{B}_m(\cdot)$	Utility function of micro-grid m in DCF
$\mathcal{S}$	Set of smart meters
$\mathcal{D}$	Set of DAUs
$\mathcal{S}^d(\cdot)$	Set of smart meters connected with DAU d
$\mathbf{C}_d$	Number of channels with each DAU d
μ	Channel capacity per single channel
$\mathbf{C}_d^{total}$	Total channel capacity of each DAU d

$\eta_d(\cdot)$	Current population share of each DAU d
$\tilde{\eta}_d(\cdot)$	New population share of each DAU d
$\mathcal{U}_s(\cdot)$	Utility function of each smart meter s in DARTS
$\mathscr{B}_d(\cdot)$	Utility function of each DAU d in DARTS
s_n^c	Requested energy for storage of customer n
e_n^c	Requested energy including s_n^c of customer n
$(E_{max})_n$	Maximum storage capacity of customer n
$(E_{res})_n$	Residual stored energy of customer n
$\psi_n(\cdot)$	Utility function of customer n
P_m	Price vector of micro-grid m
$\varphi_m(\cdot)$	Utility function of micro-grid m for Initialization Phase
$\phi_m(\cdot)$	Utility function of micro-grid m for Finalization Phase
g_m	Amount of energy to be generated by micro-grid m
c_m	Energy generation cost per unit energy of micro-grid m
$\mathcal{N}^p$	Set of available PHEVs in a coalition
$\mathcal{N}_m^p$	Set of PHEVs connected with micro-grid m
$\tilde{d}_n^p$	Current requested energy by PHEV n
d_n^p	Previously requested energy by PHEV n
E_n^{max}	Maximum storage capacity of PHEV n
E_n^{res}	Residual stored energy of PHEV n
$\mathbb{U}_n^m(\cdot)$	Utility function of customer n associated with micro-grid m in ENTRANT
p_m	Price per unit energy decided by micro-grid m
$\mathbb{B}_m(\cdot)$	Utility function of micro-grid m in ENTRANT
G_m	Amount of energy generated by micro-grid m
c_m	Energy generation cost per unit energy of micro-grid m
d_n^p	Current amount of energy requested by PHEV n

$\hat{d}_n^p$	New amount of energy requested by PHEV n
p_n^p	Price per unit energy to be paid by PHEV n
$\vec{\nu}_n^p(\cdot)$	Velocity vector of PHEV n
$\mathcal{E}_n^{max}$	Maximum battery capacity of PHEV n
$\mathcal{E}_n^{res}$	Residual battery capacity of PHEV n
$\mathscr{P}_n(\cdot)$	Concave pricing function of ECSP for PHEV n
c^{avg}	Average energy generation cost per unit energy
c_m	Energy generation cost per unit energy of micro-grid m
$\mathcal{D}^p(\cdot)$	Total amount of energy requested to ECSP
$\mathcal{P}(\cdot)$	Price per unit energy decided by ECSP
$\phi_n^p(\cdot)$	Utility function of PHEV n in VELD
$\varphi(\cdot)$	Utility function of ECSP in VELD

List of Abbreviations

Chapter 1

Introduction

Due to the growing concerns for energy conservation and environment, and for achieving improved quality of service (QoS) in energy distribution, traditional electrical grids are modernized as '*smart grid*' [1–3]. A smart grid is conceptualized to be a cyber-physical system that can augment the efficiency, reliability, and robustness of a power grid by integrating advanced mechanisms such as use of advanced metering infrastructure (AMI), automatic meter reading (AMR), energy management system (EMS), distributed energy system (DES) [2], intelligent electronic devices (IEDs), and plug-in hybrid electrical vehicles (PHEVs) [4]. In the existing power systems, energy is delivered to the customers, unidirectionally, by a main-grid over the low-voltage distribution networks over centralized systems. On the other hand, a smart grid is envisioned to be supported by duplex communication infrastructure, and the large scale traditional electrical grid is divided into the micro-grids having bi-directional electricity exchange facility with the other micro-grids, the substation, and the main grid. Hence, a smart grid is a power network composed of intelligent nodes that can communicate, interact, and operate autonomously in order to deliver energy to the customers, efficiently.

In the presence of several micro-grids, it is desirable to allow each micro-grid or group of micro-grids to service a small geographical area or group of customers based on their demands in a distributed manner, so as to relax the load on the main grid. On the contrary, in the presence of several micro-grids, it is desirable to allow the customers to choose appropriate micro-grids to ensure proper distribution of energy with a lower price. However, there exists no such scheme in the literature that suggest ways in which customers get the option to choose their appropriate micro-grid or service provider.

Therefore, an energy management system, which integrates the choices of both the customers and the micro-grids, requires to ensure quality of energy service of each micro-grid, as well as the overall smart grid infrastructure. Hence, one of the important features in a smart grid is the demand-side energy distribution, which gives the opportunity for flexible energy demand according to the requirements of the customers. Therefore, the distributed energy management schemes designed for smart grids should be designed for the micro-grids and the customers, to ensure better quality of service (QoS) in energy distribution, and utilization of generated energy by the micro-grids.

The rest of this Chapter is organized as follows.

1.1 Scope of the Work

In smart grid, as each micro-grid serves a small geographical area, and generation of energy is mostly dependent on the renewable-energy resources, a micro-grid may have higher energy load, though the generated energy is lower than that demanded. In such a situation, one micro-grid requests other micro-grids to fulfill the former's energy requirements. Due to the effect of fixed selection of micro-grid, energy loss through transmission line is higher. This fixed selection of micro-grid by each customer creates few problems for successful operation of home energy management in smart grid. These problems are discussed in the backdrop of the existing literature. The problem of data aggregator unit selection to reduce overhead and delay in communication is overlooked in the existing literature.

Home energy management in smart grid is one of the important issues for energy management in a distributed manner. Unlike the traditional energy management systems, each customer may be equipped with storage devices. Hence, the customer can use the stored energy in on-peak hours and in the blackout situations.

Some of the existing pieces of literature considered the presence of electric vehicle in the smart grid. However, the choice of multiple micro-grids is not considered. Therefore, as mentioned earlier, due to the presence of multiple micro-grids for the Plug-in Hybrid Electric Vehicles (PHEVs), and the mobility of the PHEVs, the energy management in mobile smart grid becomes more complicated, and creates a few problems needed to be addressed. On the other hand, in the existing literature, no work considers the CSP as energy service provider, i.e., ECSP. Thus, a virtual energy cloud infrastructure and the corresponding energy management system needs to be proposed.

The *objectives* of the work are as follows:

1. Design of a dynamic coalition formation scheme, such that the consumers can choose the energy service provider with higher quality of energy service.

2. Design of a dynamic DAU selection scheme in order reduce delay in service, and communication overhead.

3. Design of a home energy management scheme with storage, such that the customers can use their stored energy to reduce energy load to the micro-grids in on-peak hours.

4. Design of an energy management scheme for the PHEVs, such that they can consume energy to charge their battery efficiently.

5. Design an energy management scheme for the energy cloud service provider (ECSP) to provide Energy-as-a-Service (EaaS).

1.2 Contributions

The major contribution of this work are listed as follows:

- We propose a dynamic coalition formation scheme for providing high Quality of Energy Service (QoS). In this scheme, the customers form coalition dynamically, while satisfying the proper distribution of the energy load within the available micro-grids.
- A dynamic data aggregator unit (DAU) selection scheme is proposed. The customers choose an appropriate DAU to communicate with the meter data management system (MDMS) in order to reduce delay in real-time communication.
- We propose a distributed energy management system, in which the available customers within a coalition are equipped with storage devices, and consume energy from any of the available micro-grids within a coalition.
- We propose a distributed energy management scheme, using which PHEVs form a game theory-based energy trading network while acting non-cooperatively.
- We design a virtual energy management scheme for the energy cloud service provider (ECSP), which provides energy as a service to the connected PHEVs within a coalition.

1.3 Organization of the Thesis

The rest of the thesis are organized as follows:

- **Chapter 2 – Literature Survey**: The related works on smart grid architecture and energy management schemes in smart grid are surveyed in this chapter.
- **Chapter 3 – Dynamic Smart Grid Architecture**: An architecture, which is dynamic in nature, and is capable of providing high Quality of Energy Service

(QoS) while maintaining a lower information delay in real-time communication, is presented in this chapter.

- **Chapter 4 – Distributed Home Energy Management System with Storage in Smart Grid**: In this chapter, the design of a distributed home energy management scheme with storage is presented. We consider that each customer is equipped with storage devices while having the provision to consume from any of the available multiple micro-grids in the coalition.

- **Chapter 5 – Distributed Energy Management System in Mobile Smart Grid**: The design of distributed energy management schemes for Plug-in Hybrid Electric Vehicles (PHEVs) is presented in this chapter considering that each PHEV is connected with multiple micro-grids available in the coalition.

- **Chapter 6 – Conclusion**: This chapter contains the summery of the thesis, while citing few research directions.

Chapter 2

Related Work

In this chapter, we survey the related literature on smart grid architecture and energy management schemes in detail. In existing body of literature consists of various type of coalition formation scheme. Similarly, we have also surveyed different energy management schemes by analyzing prospects and problems.

The rest of the chapter are organized as follows. Section 2.1 presents the related smart grid architecture proposed in the literature. In Section 2.2, we studied the related literature on energy management schemes in smart grid. Finally, Section 2.3 concludes the chapter.

2.1 Smart Grid Architecture

We divide the exiting literature on smart grid architecture into two section – *coalition formation* and *communication network formation*. In the smart grid, coalition formation is followed by the geographical location of the micro-grids. Multiple micro-grids form coalition, while ensuring the energy exchange capability among themselves. Saad *et al.* [1] proposed a method for coalition formation, in which a coalition consists of multiple micro-grids. In such a design, the customer has no choice to change a coalition. One grid having excess energy can transfer that amount of energy to another grid, which is energy deficient. In another work, Saad *et al.* [2] considered that each micro-grid $i \in M$ exchanges the amount of power Q_i with the main grid using the main substation, in the absence of storage and cooperation [2]. The transfer of power is accompanied by power loss over the distribution lines inside the micro-grid network. The authors studied the coalition formation problem using cooperative game theory. Wei *et al.* [3] studied the problem of allowing multiple micro-grids for decreasing the power loss optimally. They considered cooperative game theory to study the problem of coalition formation between multiple micro-grids. They assumed that the micro-grids can leave or join any coalition to increase their payoffs, and each micro-grid can exchange energy with other micro-grids within a coalition. Kantarci *et al.* [5] formulated the cost-aware smart micro-grid network (CoSMoNet) scheme using integral linear programing to form virtual cluster between micro-grids. They assumed that energy transaction can be done only within the same virtual cluster. Luan *et al.* [6] studied a cooperative power consumption scheme for customers. They calculated the modified Pareto optimal solution considering the social welfare of the network. They assumed a transferable utility for forming the coalition. Therefore, each customer exchanges information with the other customers.

Some of the existing literature considering the communication architecture are discussed as follows.Misra *et al.* [7] proposed a distributed dynamic pricing mechanism (D2P) for charging PHEVs. They used two different pricing schemes, namely home pricing scheme and roaming pricing scheme. Niyato and Wang [8] formulated a scheme for cooperative transmission of meter data to the utility provider. In their proposed scheme, after receiving data from the DAU, the MDMS estimates the supply-demand curve, and optimizes the real-time price to maximize the utility of the micro-grid. Ahmed *et al.* [9] studied the communication architecture using cooperation between smart relays to support energy trading in smart grid. Such and Hill [10] proposed that efficient and economic operation of an electric energy distribution system can be improved with the implementation of wind generation and storage devices. They did not focus on any communication architecture that helps to send information to the customers from the micro-grid, and the information from the micro-grid to the customers.

2.2 Energy Management

In most of the existing pieces of literature on smart grid, e.g. [10–13], home energy management is considered to be ideal, i.e., having perfect information. Ibars *et al.* [11] proposed a distributed load management scheme. They assumed that the customers know their energy usages and can schedule their consumption priority according to the new pricing policy. The customers make their own bid by broadcasting their energy demand vector, when a new customer is included in the network. Weaver and Krein [12] formulated a non-cooperative game approach for controlling both loads and energy sources in a small-scale power set $\aleph = L \cup S$, where L represents the set of loads, and S is the set of power sources. The strategy of each player depends on his/her/its type. The objective functions of the load and the source are application dependent.

Such and Hill [10] proposed that efficient and economic operation of an electric energy distribution system can be improved with the implementation of wind generation and storage devices. In such a scenario, they observed that, if in a certain geographical area, there are some storage devices and some wind generation, which are controllable by the micro-grid, the micro-grid decides whether or not to use each of these. The rate of variation of wind power is also controlled to have smooth energy supply to the customers. Bakker *et al.* [13] proposed a distributed load management scheme with dynamic pricing strategy, and have modeled as it a network congestion game. Nash equilibrium is presented in order to have an optimal solution.

Molderink *et al.* [14] proposed an algorithm by using the energy in the off-peak, and the on-peak hours, with a virtual power plant, for energy management. Additionally, they showed that renewable energy sources are useful to achieve cost effective and environment-friendly energy supply to the end users. Sanseverino *et al.* [15] proposed an algorithm for load shifting and storage device management. The authors proposed that during peak-hour, heavy loads should be turned off, and vice-versa. They compared the control mechanism with real storage devices to show the impact of the load shifting scheme on the smart grid. Vytelingum *et al.* [16, 17] proposed an algorithm, in which the customers choose their strategies based on their advanced knowledge about the market. The authors discussed about storage devices and benefits from micro-storage implementation.

Fang *et al.* [18] proposed different energy management schemes. In this work, new opportunities for improved residential energy management and bill reduction are studied without considering the impact of stored energy on the customers. Kantarci and Mouftah [19] proposed a time-to-use (TOU) aware-energy management scheme. In this scheme, a customer consumes energy according to the time, whether it is an on-peak hour or an off-peak hour. If it is an on-peak hour, the customer waits for being served. Otherwise, the customer demands the required energy without waiting, if the delay is greater than the maximum allowable delay which is a local variable to the customer.

Scheduling with priority, in smart grid, can be visualized with the schematic diagram shown in Figure 2.1. It is shown that, if we do not use any scheduling scheme, then the approach is based on first come first serve. So, there is no effect of defining priority of the request. Using any scheduling scheme, it can be overcome. With scheduling with priority [20–22], in smart grid, the requests are scheduled according to their priority and served on the basis of the scheduled structure. We summarize in Table 2.1 some of the prominent existing works on energy management using scheduling and data communication in smart grid.

Zhou *et al.* [23] proposed a quality of experience (QoE)-driven power scheduling framework in context of smart grid. They identified that the Quality-of-Service (QoS)-based power optimization technique could be applied in the case of a single or static model. Analyzing the fluctuation of power load and the transmission delay, they pro-

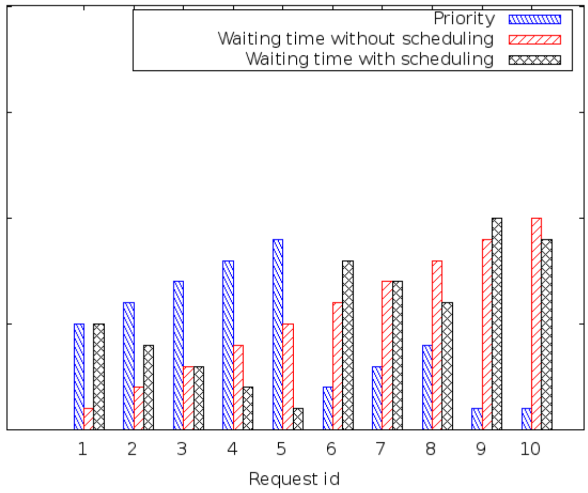


Figure 2.1: Scheduling with Priority

posed a scheduling scheme considering the admission control and QoE exception [23]. They proposed a mathematical model for power scheduling by optimizing the following mathematical equation [23],

$$\sum_{i=1}^{N} (Q_i(C_i) - p_i.c_i) \tag{2.1}$$

In Equation (1), Q_i is the QoE model function, $Q_i(C_i)$ is the power consumption, and p_i is the power price for appliance $i \in N$.

In [24], Chen *et al.* proposed a Real-time Pricing (RTP)-based power scheduling scheme underpinned in the demand response for residual power usage. They used the Stackelberg game, in which the Energy Management Controller (EMC) is the follower of the game, and the utility service provider is the leader. The aim of EMC is to minimize the cost of power usage of the customers, and the aim of the service provider is to set the retail price (p), so that the peak load reduces, and the service providers are profited.

He *et al.* [25] studied a demand-based model with support for real-time pricing to manage opportunistic energy usage by optimizing (maximizing) the overall expected profit. They considered two cases in their model.

- For the non-persistent case, they divided their scheduling problem into two levels.

- For the persistent case, they scheduled the customers as a multi-timescale Markov Decision Process (MDP).

Bu *et al.* [26] suggested a distributed stochastic scheduling scheme as a Partially-observable Markov Decision Process (POMDP) with dynamic power demands. They used the Hidden Markov Models to model renewable energy resources. A value iteration algorithm was proposed by the authors to solve the problem.

Saber and Venayagamoorthy [27] proposed an optimization algorithm to schedule resources under uncertainty with renewable and plug-in hybrid electric vehicles (PHEVs). Using their algorithm, they minimize the expected cost and forecasted load used in Unit Commitment (UC). They used the particle swarm optimization (PSO) technique to generate a successful schedule. Erol-Kantarcia and Mouftah pointed out that the unbalanced charging of PHEVs causes failure of distribution unit. Consequently, the smart grid schedules the PHEVs with efficient charging mechanism [28].

Jiang and Fei [30] explored the potential of managing the charging pattern. They used a decentralized algorithm based on Lagrangian decomposition. In their proposed solution, they used the Normalized Normal Constraint (NNC) method to get a Pareto-optimal solution set for the multi-objective problem. The objectives considered are:

1. To allocate the charging station with adequate and timely resources.

2. To provide satisfying parking services with low monetary cost to the PHEV owners.

Xiong *et al.* [31] proposed a scheduling scheme for information appliances connected over Home Area Network (HAN) and getting real-time pricing using smart meters. They proposed an algorithm that results in reduced peak demand for home. The author assumes that the utility provider distributes power as soon as it receives the energy request from a customer. The customer schedules their appliances according to their priority. If the utility service provider gets a power demand request with low priority at the on-peak hour, then the utility provider schedules the work at the off-peak hour.

Table 2.1: Summary of power scheduling approaches in smart grid

Application	Proposed Solution Approache	Future Extension
QoE-driven power scheduling [23]	QoE-based mathematical model	QoE-based mathematical model with real time pricing
Demand response power scheduling [24]	Stackelberg game theory with real-time pricing (RTP)	Game formation with other aspects into account
Opportunistic energy scheduling [25]	Demand model under real-time pricing (RTP)	Modified demand based scheduling
Distributed stochastic scheduling [26]	Partially-observable Markov Decision Process (POMDP)	Scheduling of appliances with privacy issues
Schedule resources under uncertainty [27], [29], [28]	Particle swarm optimization (PSO)	Real-time pricing model without bounding it to a linear function.
Potential of managing the charging pattern [30]	Normalized Normal Constraint (NNC) method	Scheduling of appliances without having prior knowledge to the charging pattern
Scheduling scheme over Home Area Network (HAN) [31]	Reduced peak demand	Proper scheduling of home appliances with less communication delay.
Energy Consumption Scheduling (ECS) [32]	Game theory with Nash equilibrium	Scheduling with pricing model without linear bound

Thus, the utility service provider can maintain a balance of energy between energy distribution in the on-peak hour and the off-peak hour.

Mohsenian-Rad *et al.* [32] proposed a game-theoretic approach to reduce the peak-to-average electricity usage ratio (PAR), by finding an optimal consumption schedule.

The authors considered that the energy consumption scheduling (ECS) units are placed in the smart meters for demand side management. They showed that the unique Nash equilibrium of the energy consumption game can be played between the subscribers. The authors proved that using ECS devices, PAR can be reduced upto 38.1%, and the total energy cost can be reduced upto 37.8% of the actual cost [32].

As we saw, proper power scheduling with minimum data communication in smart grid is an another important issue in power management. Different approaches are proposed for power scheduling. However, there are some drawbacks of these approaches, some of which are mentioned below.

- Zhou *et al.* [23] propose a mathematical model for power scheduling. In the formulation of the mathematical equation, the authors do not consider the real-time pricing model. So, optimally scheduled output may not be the one practically desired.

- In Ref. [24], the authors propose the Stackelberg game. The followers in the game, i.e., the customers, try to minimize the cost of power usage. The customers have other aspects to schedule their appliances such as — uninterrupted power distribution of power, minimum delay, and their satisfaction factor. In smart grid, the customer joins a coalition based on his/her requirements. So, there must be a flexibility of choice to customers as to which coalition the customer will join to fulfill his/her power requirements.

- Xiong *et al.* [31] assumed that there are no delay constraint in the scheduling scheme. But, in reality, there must be some delay in processing the raw customer data, arrange according to the priority of the requests, and transmit electricity to the customer. If the complexity of the approach for scheduling is high, then the delay will be higher.

- In Ref. [32], the authors assume that the daily load of a community of customers is proportional to the daily cost for the utility, with a constant independent of load scheduling. It entails that the price provided by the utility service providers in bounded by a linear function of the daily load of the customer. This is a strong hypothesis which may not be followed by the utility providers.

- Caron and Kesidis [33] assume that if an appliance is scheduled once, it cannot be rescheduled or interrupted by the customers. Hence, if any request from a customer with higher priority arises late to the utility provider, that higher priority job would not be scheduled to serve before the lower priority job that was scheduled previously. The authors also assume that a customer has the knowledge of all the other customers. In that case, the privacy of the customer is not maintained.

2.3 Concluding Remarks

In this chapter, we present the state-of-the-art in architectures and energy management for smart grid. The existing schemes on smart grid architecture proposed in the literature are fixed in nature. Additionally, the customers are connected with a fixed micro-grid, i.e., service provider, while we consider that each customer has options to consume energy from the multiple micro-grids, available in the coalition. However, the formation of coalition dynamically based on the choice of customers is not considered in the existing literature, which leads to high quality of energy service. On the other hand, the customers are connected with a single data aggregator unit (DAU). Moreover, by choosing the DAU dynamically, the customers can reduce the delay in energy service significantly. However, the choice of selecting the DAU dynamically by the customers is not considered in the exiting literature. These problems motivate us to design schemes for dynamic smart grid architecture such as – dynamic coalition formation and dynamic DAU selection scheme.

Energy management schemes in the existing literature did not consider the storage facilities at the customer, where as the stored energy can be used by the customer to relax load on the main grid in the on-peak hour situation or in the blackout situations. In addition to that, the energy management for the PHEVs is not studied in the existing literature considering that each PHEV is connected with multiple micro-grids available in the coalition. Additionally, the energy service to the PHEVs while forming virtual energy network for the energy cloud service provider (ECSP) is also not considered in the existing literature. These problems motivate us to design schemes for energy management considering that the consumers, i.e., customers and PHEVs are connected with multiple micro-grids. Additionally, we design a virtual energy management scheme for the PHEVs while considering that the ECSP provides energy as a service (EaaS).

Chapter 3

Dynamic Smart Grid Architecture

In this Chapter, we present an architecture for distributed energy management. Initially, we form the coalitions dynamically to connect the consumers, i.e., the customers and the plug-in hybrid electric vehicles (PHEVs), with the multiple micro-grids available within a small geographical area. Hence, we propose a scheme for formation the coalitions dynamically, i.e., *Dynamic Coalition Formation* (*DCF*) scheme. Thereafter, we propose another scheme to select the data aggregator unit dynamically, i.e., *Dynamic Data Aggregator Unit Selection* (*DARTS*) scheme. The proposed scheme, DARTS, reduces the communication delay in energy management.

This chapter is organized as follows. The design of DCF is proposed in Section 3.1. Section 3.2 discusses the performance evaluation of DCF scheme with respect to the benchmark scheme. We, then, present DARTS in Section 3.3. In Section 3.4, the performance evaluation of DARTS scheme is discussed. Finally, Section 3.5 concludes this Chapter.

3.1 Dynamic Coalition Formation (DCF) Scheme

3.1.1 System Model

In Figure 3.1, the schematic view of a typical smart grid is shown. Let us consider a power system consisting of S substations. Every substation $k \in S$ consists of M_k number of macro-grids and there are $(N_j)_k$ micro-grids under each macro-grid $j \in M$. Hence, N number of coalitions will be formed. Assuming that each coalition $i \in N$ has an area a_i,

$$(\sum_{i \in N_j} a_i)_j = \alpha_j \tag{3.1}$$

where, N_j is the total number of coalitions under the j^{th} macro-grid and the j^{th} macro-grid has a total area of α_j.

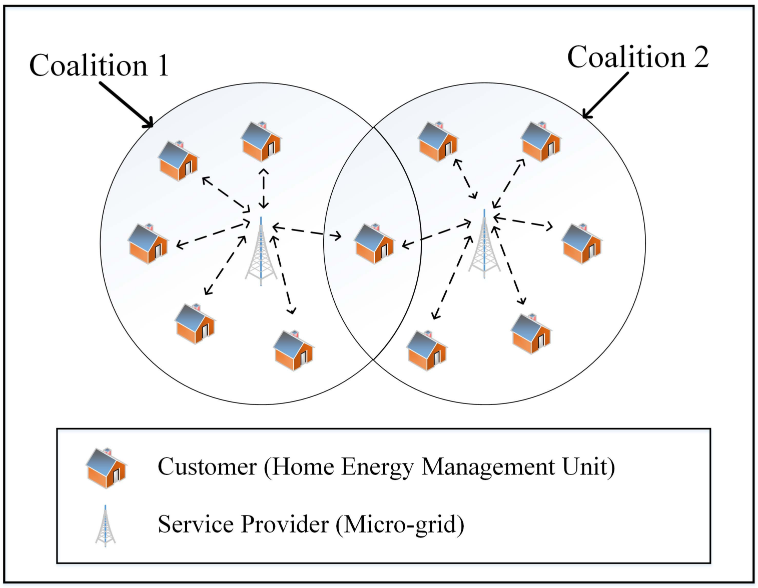


Figure 3.1: Schematic Diagram of Smart Grid

We have another equation for macro-grids,

$$(\sum_{j \in M} \alpha_j)_k = A_k \tag{3.2}$$

where, M_k is the total number of macro-grids under the k^{th} substation and the total area of the k^{th} substation is A_k.

We also assume that the i^{th} micro-grid has a generation capacity of G_i at a certain time t. This generated energy, G_i, can be sold to the $\mathcal{N}$ number of customers that are within the i^{th} coalition, thereby allowing them to meet their demand. The micro-grid will set an appropriate price p (per unit energy) for selling the generated energy to optimize its power economy revenue.

Each customer $n \in \mathcal{N}$, where $\mathcal{N}$ is the set of all the customers, will request a certain amount of energy x_n from the micro-grid, so as to meet its energy requirements. This demand of energy may vary temporally based on different parameters such as the energy storage capacity, the price p per unit of energy and the nature of usage of energy. Since the net energy generation capacity for the i^{th} micro-grid is fixed, the demand of customers must satisfy

$$(\sum x_n)_i \leq G_i \tag{3.3}$$

where $\forall i \in N$ and $\forall n \in \mathcal{N}$.

To successfully complete energy trading, the customers and the micro-grid interact with one another and agree on whether a customer joins a coalition or not. Here, the micro-grid tries to utilize the generated energy properly and increase its power economy revenue. On the other hand, the customer tries to fulfill its total energy requirement efficiently and economically.

3.1.2 Proposed Dynamic Optimized Coalition Formation Method

3.1.2.1 Game formulation

To formally study the interaction between the grids and the customers, we use MDP [34] to design a multi-level decision making process, as shown in Figure 3.2, for forming the coalition in a dynamic way. In Figure 3.2 it is shown how the customer and the micro-grid play games with one another. We consider the customer as Player 1, and the micro-grid as Player 2. Based on the decision of Player 1, the Player 2 chooses its strategy and so on. This game is defined by its strategic form, $\tau = [(\mathcal{N} \cup G), (X_n)_{n \in \mathcal{N}}, (U_n)_{n \in \mathcal{N}}, p]$, having the following components:

i) The customers in $\mathcal{N}$ act as players in the game and respond to the inclusion request by the grids.

ii) The strategy of each customer $n \in \mathcal{N}$, which corresponds to the amount of energy $x_n \in X_n$ from the micro-grid satisfying the constraint $\sum_{n \in \mathcal{N}} x_n \leq G$.

iii) The utility function U_n of each customer n that captures the benefit of consuming demanded energy x_n.

iv) The price p is the per unit of energy charged by grids.

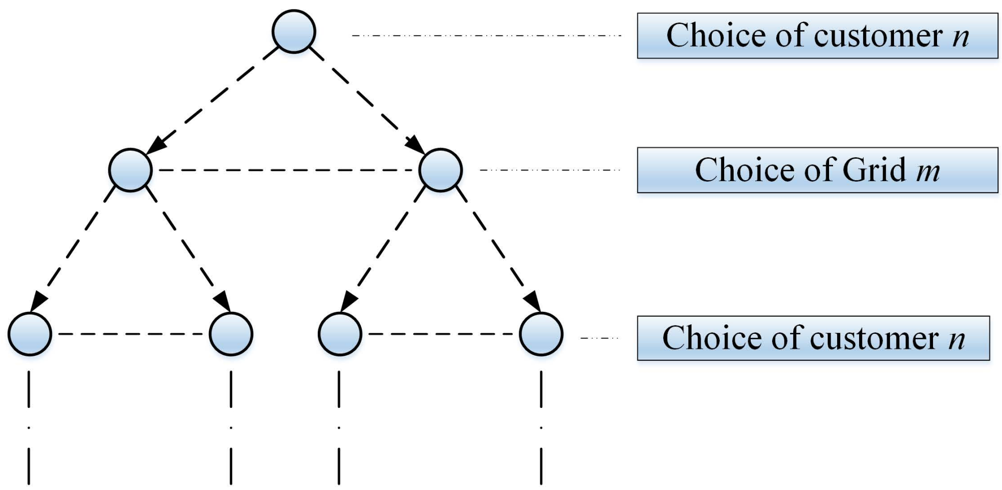


Figure 3.2: Multi-level Decision Making Process

Utility function of a coalition: For every coalition $n \in \mathcal{N}$, we define a utility function $U_n(x_n, x_{-n}, G_i, s_i, a_i, d_n, p)$, which represents the level of will of a customer to join a coalition. Here, G_i is the total amount of energy generated by the micro-grid $i \in N$, and s_i is the satisfaction parameter of the i^{th} micro-grid, which is the measure of satisfaction the micro-grid can achieve by selling energy relative to the generated energy.

For example, Micro-Grid 1 (G_1) and MIcro-Grid 2 (G_2) generate the same amount of energy at a certain point of time, but G_1 is able to sell more energy than G_2. We can infer that the satisfaction of G_1 is more than the satisfaction of G_2 (i.e, $s_2 < s_1$). Therefore, the properties that utility of a customer must satisfy are as follows:

1. The utility function of the customers are considered to be non-increasing, as each customer is interested in consuming more energy. Mathematically,

$$\frac{\delta U_n(x_n, x_{-n}, G_i, s_i, a_i, d_n, p)}{\delta x_n} \leq 0 \tag{3.4}$$

2. The marginal benefit of a customer is considered to be a decreasing function, as the satisfaction-level of micro-grid gets saturated as more energy is sold to the customer. Mathematically,

$$\frac{\delta^2 U_n(x_n, x_{-n}, G_i, s_i, a_i, d_n, p)}{\delta x_n^2} < 0 \tag{3.5}$$

3. Assuming that each micro-grid generates the same amount of energy, a larger value of $\sum_{n \in \mathcal{N}} x_n$ will lead to higher satisfaction. So, we have,

$$\frac{\delta U_n(x_n, x_{-n}, G_i, s_i, a_i, d_n, p)}{\delta s_i} < 0 \tag{3.6}$$

Therefore, in this work, we consider the following specific utility:

$$U_n(x_n, x_{-n}, G_i, s_i, a_i, p) = G_i x_n + p x_n - \frac{1}{2} s_i x_n^2 \tag{3.7}$$

where $x_n \in [0, G - \sum_{q=1, q \neq n}^{\mathcal{N}} x_q]$ and $x_{-n} = [x_1, x_2, \cdots, x_{n-1}, x_{n+1}, \cdots, x_N]$.

3.1.2.2 Existence of Nash Equilibrium Solution

In this section, we determine the generalized Nash equilibrium for dynamic coalition formation game in the proposed scheme, DCF, using the variational inequality condition, as discussed in Theorem 1.

Theorem 1. *Given a fixed price p by the micro-grid $m \in \mathcal{M}$, there exists a generalized Nash equilibrium (GNE), as there exists a variational equilibrium for the utility function $U_n(\cdot)$, for each customer $n \in \mathcal{N}(\cdot)$, and the condition for generalized Nash equilibrium is as follows:*

$$U_n\left(x_n^*, \boldsymbol{x}_{-n}^*, G_i, s_i, a_i, p^*\right) \geq U_n\left(x_n, \boldsymbol{x}_{-n}^*, G_i, s_i, a_i, p^*\right) \tag{3.8}$$

Proof. We know that the utility function of each customer n, i.e., $U_n(\cdot)$, needs to be maximized in order to reach the generalized Nash equilibrium. Hence, applying the Karush-Kuhn-Tucker condition [35], we try to find out the variational equilibrium solution. Hence, we get:

$$\nabla_n U_n(\cdot) = 0 \tag{3.9}$$

Therefore, considering the overall utility function of the macro-grid, we can rewrite Equation (3.9) as follows:

$$\nabla \sum_{n \in \mathcal{N}(\cdot)} U_n(\cdot) = 0 \tag{3.10}$$

By performing the Jacobian transformation of the matrix derived by first-order derivative on Equation (3.10), we get a non-positive diagonal matrix. Hence, there exists a variational equilibrium for the proposed scheme, DCF. Therefore, we conclude that the proposed scheme, DCF, holds a generalized Nash equilibrium solution. □

3.1.2.3 Algorithm

In order to reach the equilibrium in energy distribution from the micro-grid to the customer, the customer and the micro-grid must take their strategy choices with a small communication overhead between one another to form the coalition. In this work, we propose two different algorithms. The customers and the grids individually follow different algorithms. The customer follows its own algorithm to get uninterrupted power supply with less cost per unit, whereas the micro-grid follows its own algorithm to increase its revenue, and tries to utilize the generated energy properly. By executing the two algorithm sequentially, we infer how dynamically coalition will be formed. First, the micro-grid broadcasts its payoff function to customers and the priority of including any customer to form the new coalition will be based on the radial distance of that customer from the micro-grid. After knowing the payoff function of each micro-grid, those micro-grids, which want to include a particular customer $n \in N$, the customer n will decide whether to accept the proposal of joining the coalition or to decline the proposal based on the consumption of its utility function, U_n.

Algorithm for Micro-Grids: Each micro-grid $i \in N$ calculates its excess energy by evaluating the function $E(i) = G_i - \sum_{q=1,q\neq n}^{\mathcal{N}} x_q$. A micro-grid broadcasts its payoff function having the amount of excess energy, E, and the cost per unit, p. After getting these values, the customer $n \in \mathcal{N}$ makes a decision based on its utility function. In case a customer is unwilling to join the coalition, then the micro-grid receives that information and modifies its previously assigned cost per unit p, to maximize its revenue. Thereafter, it broadcasts that message. This process continues until the micro-grid makes the proper utilization of its generated energy and gets the maximum revenue by selling the generated energy to the customer. Mathematically,

$$U_i^{g*}(G, \sum_{n=1}^{\mathcal{N}} x_n + x_{new}, p*) \geqslant U_i^{g}(G, \sum_{n=1}^{\mathcal{N}} x_n, p) \tag{3.11}$$

In Equation (11), U_i^g is the utility function of the i^{th} micro-grid, $p*$ is the modified cost per unit energy, and p is the cost per unit energy prior to the modification.

Algorithm 3.1: DCF algorithm for Micro-grid

Input: Amount of generated energy G_i by micro-grid $i \in N$
Output: Request customer $n \in \mathcal{N}$ to join its coalition

while $G_i > \sum_{n \in \mathcal{N}} x_n$ **do**
    evaluate $\sum_{n=1}^{\mathcal{N}} x_n$
    if $(G_i - \sum_{n=1}^{\mathcal{N}} x_n) > 0$ **then**
        evaluate satisfaction factor s_i, where $s_i = \frac{\sum_{n=1}^{\mathcal{N}} x_n}{G_i}$
        request a new customer, $j \notin \mathcal{N}$ to join its coalition
    else
        energy generated by micro-grid i, G_i, is properly utilized; system is stable, so formed coalition is fixed
    end
end

Algorithm for Customers: Each customer has two choices. One of its options is to join the coalition of the requested micro-grid, i. Another option is that it will not join that coalition and will remain in the same coalition l, where $l \in N$, and $l \neq i$). Before making this choice, the customer calculates its utility function $U_n(x_n, x_{-n}, G_i, s_i, a_i, p) = G_i x_n + p x_n - \frac{1}{2} s_i x_n^2$, and chooses the micro-grid having a better utility factor at that time instant t, to ensure an uninterrupted power supply in an efficient way. Mathematically,

$$\begin{aligned} &U_n^*(x_n, (x_{-n})_i, G_i, s_i, a_i, (d_n)_i, p*) \geqslant \\ &\quad U_n(x_n, (x_{-n})_j, G_j, s_j, a_j, (d_n)_j, p) \end{aligned} \tag{3.12}$$

where, U_n^* is the modified utility function of customer n.

Algorithm 3.2: DCF algorithm for Customer

Input: Amount of energy, x_n, required for customer $n \in \mathcal{N}$
Output: Energy requirement of customer $n \in \mathcal{N}$ is fulfilled
while $U_n^* \geq U_n$ **do**
  evaluate utility function U_n according to Equation (10)
  if $(U_n^*(x_n, (x_{-n})_i, G_i, s_i, a_i, (d_n)_i, p*) \geqslant U_n(x_n, (x_{-n})_j, G_j, s_j, a_j, (d_n)_j, p))$ **then**
    join i^{th} coalition, $i \in N$
  else
    remain in the same coalition
  end
end

3.2 Results and Discussions

We considered randomly generated positions of the grids and the customers using the MATLAB simulation platform. Based on the distance between a customer and a micro-grid, a matrix is generated. From that matrix, the customer decides to join the coalitions of the micro-grid which has the minimum distance from the customer. In this work, we have considered that the payoff value of all the grids is unity. As the payoff of the grids changes with time, according to that payoff, a customer calculates its utility factor. If the customer gets a higher utility factor for one of the grids, the customer decides to join the coalition of that micro-grid. Thus, we have modified the coalition dynamically and studied its effect on different parameters.

Table 3.1: Simulation Parameters: DCF

Parameter	Value
Number of micro-grids	50
Number of customers	100
Initial payoff of micro-grids	1
Minimum requested energy	90 kWh
Maximum requested energy	100 kWh
Minimum generated energy	50 MWh
Maximum generated energy	65 MWh

3.2.1 Change in Coalition

In Figure 3.3, dynamic coalition formation is shown. We have taken two different scenarios. In *Coalition 1* a customer $n \in \mathcal{N}$ chooses a coalition of micro-grid $i \in N$ as a service provider. But at a certain point of time, the customer i joins the coalition of micro-grid $j \in N$, where $i \neq j$, as micro-grid j provides better consistent energy supply with less cost per unit. Mathematically,

$$U_i^g(G_i, \sum_{k=1}^{\mathcal{N}_i} x_k) \leq U_j^g(G_j, \sum_{k=1}^{\mathcal{N}_j} x_k) \tag{3.13}$$

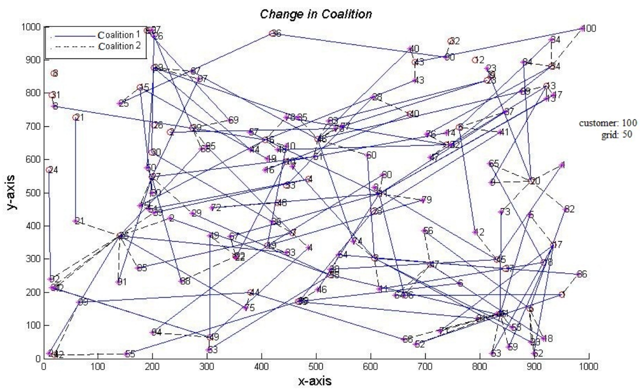


Figure 3.3: Dynamically formed coalition

In Figure 3.1, we have such a scenario, where one customer, x_4, has the option to choose two different coalitions. However, depending on its utility function, U_4, it decides to join Coalition 1 over Coalition 2.

Using simulation, we observe that the coalition is formed dynamically for high quality of energy service, as shown in Figure 3.3.

3.2.2 Utilization of Energy

In Figure 3.4, the satisfaction factor, s_i, of the i^{th} micro-grid, where $i \in N$, is chosen randomly. Based on the parameter s_i, the customer n generates its utility function,

U_n. Accordingly the customer chooses its service providing micro-grid $k \in N$. It may happen that $i \neq k$. Figure 3.4 shows how the customers change their service providing micro-grid and get better facilities.

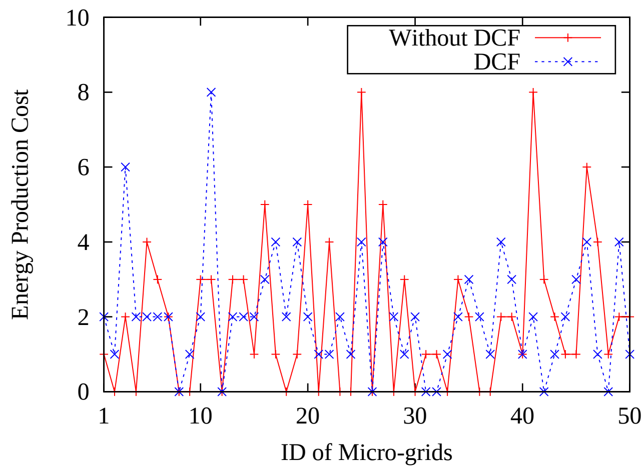


Figure 3.4: Utilization of Energy

In Figure 3.4, the average energy distribution cost per unit for all the grids is less in Coalition 2 than Coalition 1. By varying the number of grids and the number of customers, we have shown in Figure 3.5 that the energy production cost of grids change. In both the Figures, the grids will have much higher revenue and satisfaction parameter.

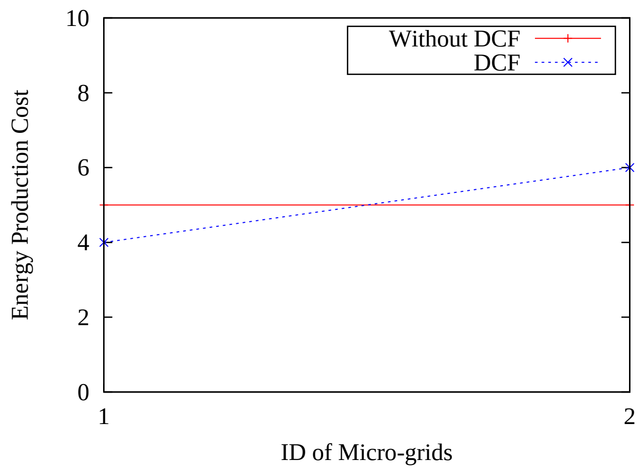


Figure 3.5: Utilization of Energy

Due to random deployment, the grids and the customers are not uniformly distributed. The abrupt change in energy production cost and quality of energy service is due to the randomness of the grids and the customers in Figures 3.4 and 3.6.

3.2.3 Quality of Energy Service

Figure 3.6 shows how the Quality of Service (QoS) for the customers can be improved by using this dynamic coalition formation scheme. In Figure 3.6, the reliability and the amount of energy distributed to the customers is obtained to be much more higher in the dynamically formed coalition, Coalition 2, than Coalition 1. So, it can be inferred that the QoS of Coalition 2 is much higher than the QoS of Coalition 1 in Figure 3.6.

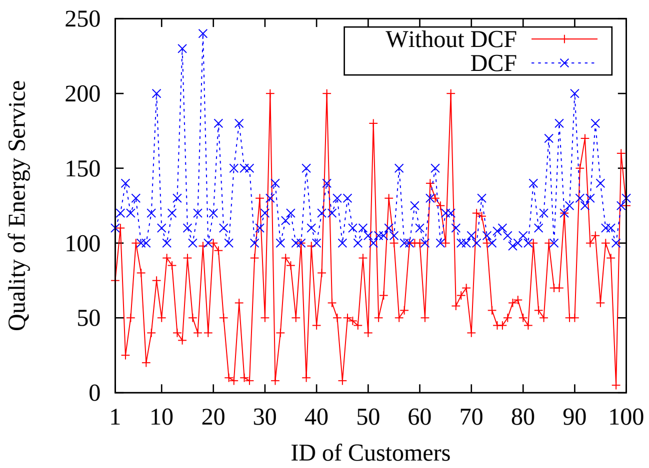


Figure 3.6: Quality of Service

In Figure 3.7, we showed how the QoS changes with the change in the number of customers, and the number of grids. The QoS in Coalition 2 is much better than the QoS in Coalition 1.

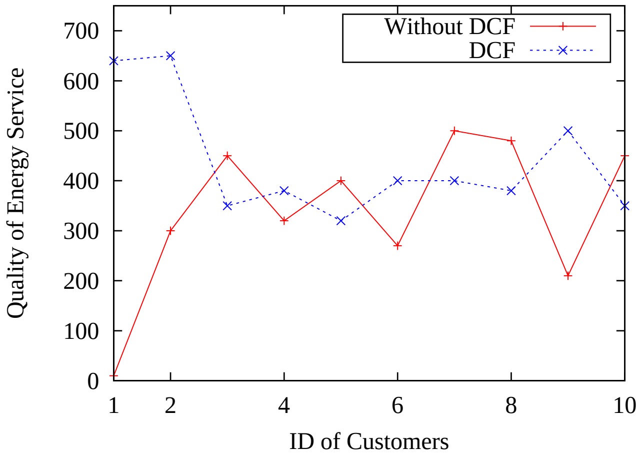


Figure 3.7: Quality of Service

3.3 Dynamic Data Aggregator Unit Selection (DARTS) Scheme

3.3.1 System Model

We consider a energy distribution system of coalition [36] consisting of single micro-grid and multiple customers. Each customer is equipped with a *smart meter*. The smart meter collects the information of the energy consumption profile of the appliances at the customer-end using home area network (HAN), and sends the information to the *data aggregator unit* (DAU) using neighborhood area network (NAN). The DAU sends the aggregated information to the *meter data management system* (MDMS) using wide area network (WAN). The schematic diagram of smart micro-grid communication architecture is shown in Figure 3.8. We consider that each DAU has multiple dedicated channels, and the channel capacity is the same for all the channels.

Each smart meter $s \in \mathcal{S}$, where $\mathcal{S}$ is the set of smart meters connected to the micro-grid, i.e., the MDMS, within a coalition, chooses a DAU dynamically to send the energy consumption information of the customers to the MDMS. We consider that there are $|\mathcal{D}|$ number of DAUs, where $\mathcal{D}$ is the set of available DAUs in a coalition. We assume that each DAU $d \in \mathcal{D}$ has $\mathbf{C}_d$ number of channels. The number of channels is fixed for each DAU $d \in \mathcal{D}$. Mathematically,

$$\mathbf{C}_1 \triangleq \mathbf{C}_2 \triangleq \cdots \triangleq \mathbf{C}_d \triangleq \cdots \triangleq \mathbf{C}_{|\mathcal{D}|} \triangleq \mathbf{C} \tag{3.14}$$

We define the total channel capacity of each DAU $d \in \mathcal{D}$, i.e., $\mathbf{C}_d^{total}$, as follows:

$$\mathbf{C}_d^{total} = \mu \mathbf{C}_d, \quad \forall d \in \mathcal{D} \tag{3.15}$$

where μ is the channel capacity per single channel. We assume that, at time slot $t \in T$, where T is the set of time slots in a day, each DAU $d \in \mathcal{D}$ uses a linear pricing model. The price coefficient, $p_d(t)$, i.e., price to be paid for connection by each smart meter to a DAU $d \in \mathcal{D}$, is a linear function of the ratio of the number of smart meters connected to DAU d, i.e., $\mathcal{S}^d(t) \subseteq \mathcal{S}$, and the available smart meters in the coalition, $\mathcal{S}$.

$$p_d(t) = f\left(\frac{\mathcal{S}^d(t)}{\mathcal{S}}\right), \quad \forall d \in \mathcal{D} \tag{3.16}$$

With the increase in the number of smart meters connected to each DAU d, i.e., $\mathcal{S}^d(t)$, the price coefficient, $p_d(t)$, increases. On the other hand, with the increase in $\mathcal{S}^d(t)$, the delay in communication between DAU d and the MDMS, i.e., τ_d also becomes higher due to the increase of queue length of the messages. Hence, each smart meter $s \in \mathcal{S}^d(t)$ has to wait for longer duration of time to get the energy service from the micro-grid or the energy service-provider. We consider that using the proposed framework of DAU selection, the network congestion and the service delay in smart grid decrease. In this scenario, the pricing coefficient, $p_d(\cdot)$, plays a major role in dynamic data aggregator unit selection. The price paid by the smart meter s, i.e., $p^s(t)$, for the communication service can be different for using different DAUs to communicate with the MDMS.

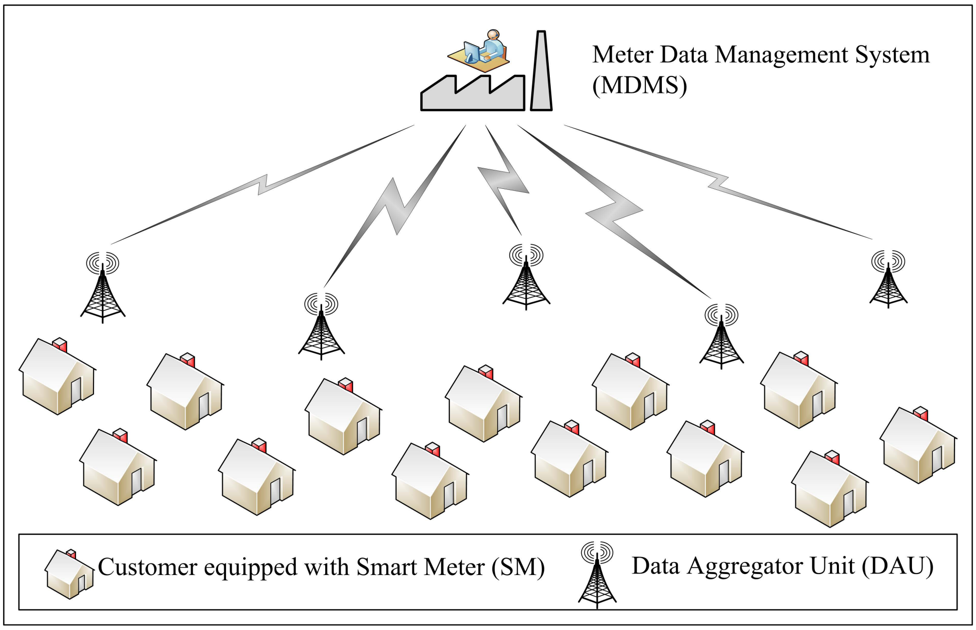


Figure 3.8: Schematic diagram of smart grid communication architecture

Communication between the micro-grid and the Customers: We assume that the smart meters communicate with the data aggregator units (DAUs) using IEEE 802.11b protocol, which is a Wi-Fi wireless network communication technology used for neighborhood area network (NAN). To complete energy trading successfully, each smart meter $s \in \mathcal{S}$ placed at the customer-end sends a *request message* to the MDMS through the selected DAU, which acts as a router in the smart grid communication architecture. The request message format is shown in Figure 3.9. Based on the requested

ReqMsgType	CustomerID	ReqEnergy	FinalSelectFlag
1 byte	4 byte	2 byte	1 byte

Figure 3.9: *Request* message by a smart meter

amount energy to the micro-grid, the MDMS decides the price per unit energy, and sends an *acknowledgment message* to the smart meters through the DAUs with information about the price per unit energy. The acknowledgment message format is shown in Figure 3.10.

AckMsgType	MDMS_ID	Price	AckFlag
1 byte	4 byte	2 byte	1 byte

Figure 3.10: *Acknowledgment* message by a MDMS

3.3.2 Proposed Dynamic Data Aggregator Unit Selection Game

3.3.2.1 Game Formulation

To study the interaction between the DAUs and the smart meters for selecting the DAUs dynamically, we use a dynamic evolutionary game theoretic approach. Here, the set of DAUs $\mathcal{D}$, acting as players, forwards the energy request messages of the smart meters $\mathcal{S}$ at the customer-end to the MDMS, i.e., the micro-grid. Each smart meter $s \in \mathcal{S}$ acts as another player, needs to choose an appropriate DAU, dynamically, to reduce the delay in energy service of the micro-grid, and to utilize the available channel capacity in the smart grid. The *population share* of each DAU $d \in \mathcal{D}$, i.e., $\eta_d(t)$, using the proposed *dynamic data aggregator unit selection* (DARTS) scheme is defined in Definition 1.

Definition 1. *In the proposed DARTS scheme, the population share of each DAU $d \in \mathcal{D}$, is defined by the ratio of the number of smart meters connected with the DAU d, i.e., $|\mathcal{S}^d(t)|$, and the total number of smart meters in the coalition, i.e., $|\mathcal{S}|$. Mathematically,*

$$\eta_d(t) = \frac{|\mathcal{S}^d(t)|}{|\mathcal{S}|}, \quad \forall d \in \mathcal{D} \tag{3.17}$$

The elements in the *population share vector*, $\vec{\boldsymbol{\eta}}(t)$, defined in Definition 2, act as the total population in the proposed DARTS game, and define a foundation to obtain the equilibrium solution for the game of evolution, i.e., dynamic evolutionary game.

Definition 2. *In the proposed DARTS game, the population share vector, $\vec{\boldsymbol{\eta}}(t)$, is defined the vector with $|\mathcal{D}|$ number of elements of population share in a coalition. Mathematically,*

$$\vec{\boldsymbol{\eta}}(t) = \Big[\eta_1(t), \eta_2(t), \cdots, \eta_d(t), \cdots, \eta_{|\mathcal{D}|}(t)\Big]^T \tag{3.18}$$

In particular, given the channel capacity of each DAU $d \in \mathcal{D}$, the smart meters $\mathcal{S}$ compete to share the available channel capacity of the selected DAU d. We use a dynamic evolutionary game, as the proposed approach can capture the dynamics of the chosen DAUs, i.e., strategies chosen by smart meters $\mathcal{S}$, based on the available information and rational bounds on the smart meters $\mathcal{S}$. Hence, each smart meter $s \in \mathcal{S}$ slowly evolves by changing the population share of each DAU $d \in \mathcal{D}$, $\eta_d(t)$, if the smart meter s observes that its payoff is less than the average payoff of all the smart meters $\mathcal{S}$ in the coalition. In the proposed scheme, DARTS, the evolutionary equilibrium is considered as the optimum solution, which confirms that all the smart meters receive similar payoffs in the coalition. The strategic form of the proposed DARTS scheme, i.e., $\boldsymbol{\theta}$, is defined as follows:

$$\boldsymbol{\theta} = \langle (\mathcal{S} \cup \mathcal{D}), [p^s(\cdot), \mathcal{U}_s(\cdot)]_{s\in\mathcal{S}}, [\eta_d(\cdot), p_d(\cdot), \mathscr{B}_d(\cdot)]_{d\in\mathcal{D}} \rangle \tag{3.19}$$

The components of the strategic form $\boldsymbol{\theta}$ are as follows:

1. Each smart meter $s \in \mathcal{S}$ chooses a DAU $d \in \mathcal{D}$, dynamically, to be connected with MDMS, and to send the energy consumption request messages from the customer-end to the micro-grid.

2. The price to be paid by each smart meter $s \in \mathcal{S}$, $p^s(\cdot)$, is evaluated using the following equations:

$$\begin{aligned} p^s(\cdot) &= p_d(\cdot), \qquad\qquad \text{if } s \in \mathcal{S}^d(\cdot) \\ &= \alpha_s \frac{|\mathcal{S}^d(\cdot)|}{|\mathcal{S}|} = \alpha_s \eta_d(\cdot) \end{aligned} \tag{3.20}$$

   where $\alpha_s \geq 1$, and α_s is a constant for smart meter $s \in \mathcal{S}$.

3. The set of smart meters choosing the DAU $d \in \mathcal{D}$, i.e., $\mathcal{S}^d(\cdot)$, contributes population share, $\eta_d(\cdot)$, in the total population of the proposed DARTS scheme.

4. Each DAU $d \in \mathcal{D}$ decides the price coefficient, $p_d(\cdot)$, based on the population share of the DAU d in the dynamic data aggregator selection game.

5. The payoff of a smart meter $s \in \mathcal{S}$ is determined by its net utility, $\mathcal{U}_s(\cdot)$. On the other hand, the payoff of a DAU $d \in \mathcal{D}$, i.e., $\mathscr{B}_d(\cdot)$, is determined by the average utility of the connected smart meter, $\mathcal{S}^d(t) \subseteq \mathcal{S}$, at time instant $t \in T$.

Utility function of a smart meter: For each smart meter $s \in \mathcal{S}$, we define the utility function $\mathcal{U}_s(\cdot)$ as a *concave function*, which signifies the quantified satisfaction of smart meter s on channel capacity consumption. For choosing a particular DAU d, the net utility of each smart meter s is expressed as the difference between the revenue function of the smart meter s, i.e., $\mathcal{R}_s(\cdot)$, and the cost function of the smart meter s, i.e., $\mathcal{C}_s(\cdot)$. Mathematically,

$$\mathcal{U}_s(\cdot) = \mathcal{R}_s(\cdot) - \mathcal{C}_s(\cdot), \quad s \in \mathcal{S} \tag{3.21}$$

Using dynamic evolutionary game, each smart meter s tries to maximize its satisfaction factor by choosing the DAU d having higher payoff of the utility function $\mathscr{B}_d(\cdot)$. Consider that a smart meter, i.e., $s \in \mathcal{S}$, selects the DAU $d \in \mathcal{D}$, and another smart meter, i.e., $\tilde{s} \in \mathcal{S}$, where $\tilde{s} \neq s$, selects another DAU $\tilde{d} \in \mathcal{D}$ for sending the energy information to the MDMS. Hence, if the payoff of the DAU d is higher than the payoff of the DAU $\tilde{d}$, i.e., $\mathscr{B}_d(\cdot) > \mathscr{B}_{\tilde{d}}(\cdot)$, the smart meter s has higher satisfaction factor than the smart meter $\tilde{s}$, i.e., $\mathcal{U}_s(\cdot) > \mathcal{U}_{\tilde{s}}(\cdot)$. Therefore, the properties that utility of a smart meter s, i.e., $\mathcal{U}_s(\cdot)$, must satisfy are as follows:

1. The utility function of each smart meter $s \in \mathcal{S}$, i.e., $\mathcal{U}_s(\cdot)$, is considered to be a non-increasing function, as each smart meter s tries to maximize its satisfaction factor. We consider that population share changes from $\eta_d(\cdot)$ to $\tilde{\eta}_d(\cdot)$, where $\eta_d(\cdot)$ and $\tilde{\eta}_d(\cdot)$ are the current population share and new population share of the DAU

d, respectively. Mathematically,

$$\frac{\delta \mathcal{U}_s(\cdot)}{\delta \tilde{\eta}_d(\cdot)} \geq 0 \tag{3.22}$$

2. The marginal payoff of the utility function of each smart meter s, $\mathcal{U}_s(\cdot)$, is considered to be a decreasing function, as at marginal condition, if a smart meter chooses to select a different DAU, the payoff of the utility function decreases with change in population share of the DAUs $\mathcal{D}$. Mathematically,

$$\frac{\delta^2 \mathcal{U}_s(\cdot)}{\delta [\tilde{\eta}_d(\cdot)]^2} < 0 \tag{3.23}$$

3. The cost function of each smart meter s, i.e., $\mathcal{C}_s(\cdot)$, yields higher value with the increase price coefficient of the DAU d, $p_d(\cdot)$. With the increase in price coefficient of DAU d, $p_d(\cdot)$, the price to be paid by the each smart meter s also increases, as shown in Equation (3.20). Therefore,

$$\frac{\delta \mathcal{C}_s(\cdot)}{\delta p^s(\cdot)} \geq 0, \text{ and } \frac{\delta \mathcal{U}_s(\cdot)}{\delta p^s(\cdot)} < 0 \tag{3.24}$$

We consider that the revenue function of smart meter s, i.e., $\mathcal{R}_s(\cdot)$, as a concave function. Therefore, we define the revenue function of smart meter s, i.e., $\mathcal{R}_s(\cdot)$, as follows:

$$\mathcal{R}_s(\cdot) = |\mathcal{S}| \tan^{-1}\left(e^{\frac{\dot{\eta}_d(\cdot)}{\eta_d(\cdot)}}\right) \tag{3.25}$$

where $\dot{\eta}_d(\cdot)$ is defined as the change in population share of the DAU $d \in \mathcal{D}$. Mathematically,

$$\dot{\eta}_d(\cdot) = \tilde{\eta}_d(\cdot) - \eta_d(\cdot), \quad \forall d \in \mathcal{D} \tag{3.26}$$

The cost function of each smart meter $s \in \mathcal{S}$, i.e., $\mathcal{C}_s(\cdot)$, is defined as follows:

$$\mathcal{C}_s(\cdot) = p^s(\cdot)|\mathcal{S}^d(\cdot)|, \quad \forall s \in \mathcal{S}^d(\cdot) \tag{3.27}$$

Hence, we get the utility function of each smart meter $s \in \mathcal{S}$, $\mathcal{U}_s(\cdot)$, as follows:

$$\begin{aligned} \mathcal{U}_s(\cdot) &= \mathcal{R}_s(\cdot) - \mathcal{C}_s(\cdot) \\ &= |\mathcal{S}| \tan^{-1}\left(e^{\frac{\tilde{\eta}_d(\cdot)-\eta_d(\cdot)}{\eta_d(\cdot)}}\right) - p^s(\cdot)|\mathcal{S}^d(\cdot)| \end{aligned} \tag{3.28}$$

Lemma 1. *The value of population share of each DAU $d \in \mathcal{D}$, i.e., $\tilde{\eta}_d(\cdot)$, follows the property defined as follows:*

$$0 < \tilde{\eta}_d(\cdot) \leq 1 \tag{3.29}$$

Proof. We consider the population share of each DAU d, $\tilde{\eta}_d(\cdot)$, as shown in Equation (3.17). We know that $\mathcal{S}^d(\cdot) \subseteq \mathcal{S}$. Therefore, we conclude:

$$\begin{aligned} |\mathcal{S}^d(\cdot)| &\leq |\mathcal{S}| \\ \text{or,} \quad \tilde{\eta}_d(\cdot) &\leq 1 \end{aligned} \tag{3.30}$$

On the other hand, we consider that a subset of the available smart meters $\mathcal{S}$ chooses each DAU $d \in \mathcal{D}$, i.e., $\mathcal{S}^d(\cdot) \neq \{\phi\}$. Hence, we conclude:

$$\begin{aligned} |\mathcal{S}^d(\cdot)| &> 0 \\ \text{or,} \quad \tilde{\eta}_d(\cdot) &> 0 \end{aligned} \tag{3.31}$$

Therefore, the value of population share of each DAU $d \in \mathcal{D}$, i.e., $\tilde{\eta}_d(\cdot)$, satisfies the condition: $0 < \tilde{\eta}_d(\cdot) \leq 1$. □

Utility function of a DAU: For each DAU $d \in \mathcal{D}$, the utility function, $\mathscr{B}_d(\cdot)$, signifies the utilization factor of the available channel capacity of the DAU d. Here, we consider that the payoff of the utility function, $\mathscr{B}_d(\cdot)$, is transferable, i.e., the *transferable utility* defined in Definition 3, among the DAUs $\mathcal{D}$ in the coalition. With the increase in the number of smart meters connected with the DAU d, i.e., $|\mathcal{S}^d(\cdot)|$, the payoff of the utility function $\mathscr{B}_d(\cdot)$ increases, as the DAU d earns higher revenue using a limited channel capacity, and the utilization factor of the available channel capacity is also higher. Mathematically,

$$\frac{\delta \mathscr{B}_d(\cdot)}{\delta |\mathcal{S}^d(\cdot)|} > 0 \tag{3.32}$$

Therefore, we define the utility function of a DAU $d \in \mathcal{D}$, $\mathscr{B}_d(\cdot)$, as follows:

$$\mathscr{B}_d(\cdot) = \sum_{s \in \mathcal{S}^d(\cdot)} \frac{|\mathcal{S}^d(\cdot)|}{|\mathcal{S}|} \mathcal{U}_s(\cdot) = \sum_{s \in \mathcal{S}^d(\cdot)} \tilde{\eta}_d(\cdot) \mathcal{U}_s(\cdot) \tag{3.33}$$

Considering the transferable utility, defined in Definition 3, we evaluate the payoff of the average utility function of available DAUs $\mathcal{D}$, i.e., $\bar{\mathscr{B}}(\cdot)$, in the coalition. We define the average utility function of the coalition, $\bar{\mathscr{B}}(\cdot)$, as follows:

$$\bar{\mathscr{B}}(\cdot) = \sum_{d \in \mathcal{D}} \tilde{\eta}_d(\cdot) \mathscr{B}_d(\cdot) \tag{3.34}$$

Definition 3. *The transferable utility is considered to be the average payoff of the utility function of the players available within a coalition. Using transferable utility, we consider the overall payoff of the utility functions of the available players in a coalition, in spite of considering the individual payoff of each player, individually.*

In the proposed scheme, DARTS, we consider the payoff of the average utility function of the coalition, $\bar{\mathscr{B}}(\cdot)$, while not considering the individual payoff of the utility function of each DAU $d \in \mathcal{D}$, i.e., $\mathscr{B}_d(\cdot)$.

Replicator dynamics of dynamic data aggregator unit selection scheme: Using dynamic evolutionary game theoretic approach, each DAU $d \in \mathcal{D}$ forms a population share, i.e., a *replicator* defined in Definition 4.

Definition 4. *A replicator acts as a player in the evolutionary game, is able to reproduce itself through the process of mutation and evolution, i.e., evolution. A replicator with higher payoff is able to reproduce itself quicker than any replicator with lower payoff.*

We model the reproduction procedure in evolutionary game using a ordinary differential equation, defined as *replicator dynamics*. We define the replicator dynamics of DARTS as follows:

$$\frac{\delta \eta_d(\cdot)}{\delta t} = \lambda \eta_d(\cdot) \left[\mathscr{B}_d(\cdot) - \bar{\mathscr{B}}(\cdot) \right] \tag{3.35}$$

where λ is a constant, controls the speed of the smart meters $\mathcal{S}$ in observing and adopting the DAU selection and $\lambda > 0$, and $\eta_d(\cdot)$ is the current population share of the DAU $d \in \mathcal{D}$.

In the proposed scheme, DARTS, using dynamic evolutionary game, the evolutionary equilibrium is evaluated by a set of fixed values of the replicator dynamics, i.e., Pareto optimal solution of the dynamic evolutionary game. Based on the replicator dynamics, we conclude that the evolutionary equilibrium solutions are stable in nature. Therefore, to reach the stable evolutionary equilibrium solution, each smart meter $s \in \mathcal{S}$ choose strategy, i.e., evolves, over time depending on the replicator dynamics. At evolutionary equilibrium, the payoff of each smart meter s, i.e., individual players in the population, is equal to the average payoff of the smart meters. Therefore, after reaching the stable evolutionary equilibrium point, each smart meter $s \in \mathcal{S}$ does not change its strategy, i.e., dynamically chosen DAU $d \in \mathcal{D}$, to evolve further.

3.3.2.2 Existence of Evolutionary Equilibrium Solution

We determine the existence of evolutionary equilibrium solution in the proposed scheme, DARTS, by considering the properties of dynamic evolutionary game theory [37], as shown in Theorem 2.

Theorem 2. *Given the fixed size of the population, i.e., the number of smart meters, $\mathcal{S}$, there exists a stable solution for evolutionary equilibrium. Therefore, at a stable equilibrium solution point the proposed DARTS scheme must satisfy the following constraint:*

$$\frac{\delta \eta_d(\cdot)}{\delta t} = 0, \quad \forall d \in \mathcal{D} \tag{3.36}$$

Proof. We know that each DAU $d \in \mathcal{D}$ must satisfy the constraint given in Equation 3.36. Therefore,

$$\lambda \eta_d(\cdot) \left[\mathscr{B}_d(\cdot) - \bar{\mathscr{B}}(\cdot) \right] = 0, \quad \forall d \in \mathcal{D} \tag{3.37}$$

We define λ to be a constant, and $\lambda > 0$. We also consider that the population share of each DAU d is always greater than zero, i.e., $\eta_d(\cdot) > 0$. Hence, we get,

$$\mathscr{B}_d(\cdot) - \bar{\mathscr{B}}(\cdot) = 0, \quad \forall d \in \mathcal{D} \tag{3.38}$$

Therefore, we rewrite Equation (3.38) as follows:

$$\mathscr{B}_d(\cdot) = \bar{\mathscr{B}}(\cdot) = \sum_{d \in \mathcal{D}} \tilde{\eta}_d(\cdot) \mathscr{B}_d(\cdot) \tag{3.39}$$

Hence, we get,

$$\mathscr{B}_d(\cdot) = \frac{\tilde{\eta}_1(\cdot)\mathscr{B}_1(\cdot) + \cdots + \tilde{\eta}_{d-1}(\cdot)\mathscr{B}_{d-1}(\cdot) + \tilde{\eta}_{d+1}(\cdot)\mathscr{B}_{d+1}(\cdot) + \cdots + \tilde{\eta}_{|\mathcal{D}|}(\cdot)\mathscr{B}_{|\mathcal{D}|}(\cdot)}{1 - \tilde{\eta}_d(\cdot)} \tag{3.40}$$

Hence,

$$\mathscr{B}_d(\cdot) - \mathscr{B}_k(\cdot) = \tilde{\eta}_k(\cdot)\mathscr{B}_k(\cdot) - \tilde{\eta}_d(\cdot)\mathscr{B}_d(\cdot) \tag{3.41}$$

where $d \neq k$, and $d, k \in \mathcal{D}$. Using dynamic evolutionary game theory, we know that $\mathscr{B}_d(\cdot) = \mathscr{B}_k(\cdot)$, where $d \neq k$. Therefore, from Equation (3.41), we get,

$$\tilde{\eta}_k(\cdot) = \tilde{\eta}_d(\cdot) \tag{3.42}$$

where $d \neq k$, and $d, k \in \mathcal{D}$. Equation (3.42) provides the evolutionary equilibrium solution which signifies that the population share of each DAU d is the same in the DARTS scheme. Equation (3.42) can be rewritten as follows:

$$\tilde{\eta}_1(\cdot) = \tilde{\eta}_2(\cdot) = \cdots = \tilde{\eta}_d(\cdot) = \cdots = \tilde{\eta}_{|\mathcal{D}|}(\cdot) \tag{3.43}$$

□

3.3.2.3 Algorithms

In order to reach the stable solution point of the proposed dynamic evolutionary game, each smart meter $s \in \mathcal{S}$ needs to choose appropriate DAU $d \in \mathcal{D}$, dynamically. Due to this dynamic nature of the proposed DARTS scheme, the population share of each DAU $d \in \mathcal{D}$, i.e., $\tilde{\eta}_d(\cdot)$, changes or evolves gradually. Hence, the population share of each DAU $d \in \mathcal{D}$ changes from $\eta_d(\cdot)$ to $\tilde{\eta}_d(\cdot)$, where $\eta_d(\cdot)$ and $\tilde{\eta}_d(\cdot)$ are the current value and the new value of the population share of the DAU d, respectively. In the proposed scheme, DARTS, each smart meter $s \in \mathcal{S}$ and each DAU $d \in \mathcal{D}$ needs to execute Algorithms 3.3 and 3.4, respectively.

3.4 Performance Evaluation

3.4.1 Simulation Parameters

For performance evaluation, we consider a randomly generated position of the smart meters and the DAUs on a MATLAB simulation platform, as shown in Table 3.2. In

Algorithm 3.3: DARTS Algorithm for smart meter

Inputs : α_s: Constant factor in price function
$\mathscr{B}_d(\cdot)$: Utility function of the chosen DAU d
$\bar{\mathscr{B}}(\cdot)$: Average utility function of the coalition
λ: Constant for controlling the speed of change in population share
$\mathcal{S}$: Set of smart meters in the coalition

Outputs: d^{select}: Dynamically selected DAU d
$\mathcal{U}_s(\cdot)$: Utility function of smart meter $s \in \mathcal{S}$

if $\mathscr{B}_d(\cdot) \neq \bar{\mathscr{B}}(\cdot)$ **then**
  $\tilde{\eta}_d(\cdot) = \eta_d(\cdot) + \lambda\eta_d(\cdot)\left[\mathscr{B}_d(\cdot) - \bar{\mathscr{B}}(\cdot)\right]$
  if $rand() < \frac{\mathscr{B}_d(\cdot) - \bar{\mathscr{B}}(\cdot)}{\mathscr{B}_d(\cdot)}$ **then**
    // $rand()$ `function generates a random value between` 0 `and` 1
    Choose another DAU $k \in \mathcal{D}$ // `where` $k \neq d$
  else
    Choose the DAU $d \in \mathcal{D}$ again
  end
  Calculate $\mathcal{U}_s(\cdot)$ using Equation (3.28)
else
  // `Evolutionary equilibrium state reached`
  Choose the DAU $d \in \mathcal{D}$ again
end
return

this work, we assumed that each smart meter chooses a DAU, randomly, to be connected with the MDMS.

3.4.2 Benchmark

The performance of the proposed scheme, DARTS, for dynamic data aggregator unit selection by the smart meters is evaluated by comparing with an another scheme, i.e., fixed selection of data aggregator unit without any game theoretic approach (WDARTS). We refer to these different data aggregator selection policies as DARTS, and WDARTS, through the rest of the chapter. We show that the Proposed DARTS scheme performs better than WDARTS scheme.

Algorithm 3.4: DARTS Algorithm for DAU

Inputs : $\tilde{\eta}_k(\cdot)$: Population share of DAU $k \in \mathcal{D}$
$\mathscr{B}_k(\cdot)$: Utility function of the chosen DAU k
$\mathcal{S}^d(\cdot)$: Set of smart meters chose DAU d
$\mathcal{S}$: Set of available smart meters in the coalition
$\mathcal{U}_s(\cdot)$: Utility function of smart meter $s \in \mathcal{S}$

Output: $\mathscr{B}_d(\cdot)$: Utility function of the chosen DAU d
$\bar{\mathscr{B}}(\cdot)$: Average utility function of the coalition

1 $\mathscr{B}_d(\cdot) = \sum_{s \in \mathcal{S}^d(\cdot)} \tilde{\eta}_d(\cdot)\mathcal{U}_s(\cdot)$ `// Calculate` $\mathscr{B}_d(\cdot)$

2 $\bar{\mathscr{B}}(\cdot) = \sum_{d \in \mathcal{D}} \tilde{\eta}_d(\cdot)\mathscr{B}_d(\cdot)$ `// Calculate` $\bar{\mathscr{B}}(\cdot)$

3 **return**

Table 3.2: Simulation Parameters: DARTS

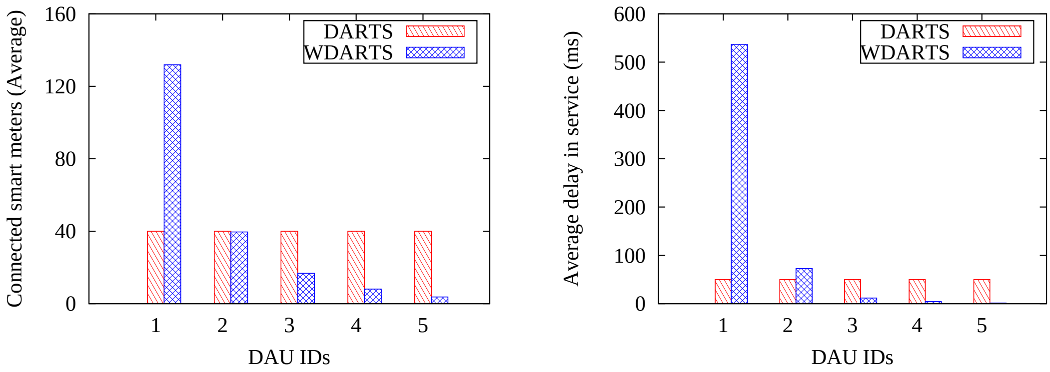
Parameter	Value
Simulation area	10 km×10 km
Number of MDMS	1
Number of DAUs	5
Number of smart meters	200
Number of channels per DAU	50
Evolution speed control factor (λ)	>0
Constant for price function (α_s)	1

3.4.3 Performance Metrics

- *Connected smart meter per DAU*: The smart meters select the data aggregator units (DAUs), dynamically, to send the energy consumption information to the MDMS. By selecting DAUs dynamically, the message load to the each DAU is distributed.

- *Delay in service per DAU*: We define the delay in service using the time difference between the time at which the message is submitted to the selected DAU by the smart meters and the time when the DAU gets the corresponding acknowledgment message from the MDMS.

- *Population share of DAUs*: Using the evolutionary game proposed in DARTS,



(a) Connected smart meters

(b) Delay in service

Figure 3.11: Performance of each DAU

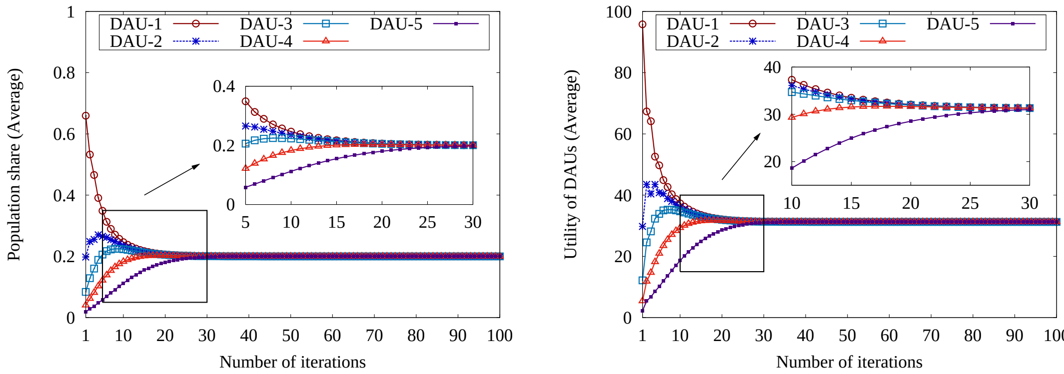
the population share of each DAU is defined with the ratio of the smart meters connected with the DAU and the total available smart meters in the coalition.

- *Payoff of the utility function of DAUs*: Based on the payoff of the utility function of each DAU, and the average payoff of the available DAUs in the coalition, each smart meter chooses its strategy, i.e., selects an appropriate DAU, dynamically.

3.4.4 Results and Discussions

For the sake of simulation, we consider that the data rate using IEEE 802.11b protocol is 2 $Mbit/s$. Figure 3.11(a) shows the number of smart meters connected with each DAU. From Figure 3.11(a), we conclude that using the proposed scheme, DARTS, the communication load on each DAU is distributed properly. On the other hand, using fixed selection of DAU, i.e., WDARTS scheme, the communication load is higher for some of the available DAUs, and the communication load is low for some DAUs. Therefore, we infer that communication load is properly distributed, and is improved by 69.23% using DARTS, than using WDARTS.

As the communication load is distributed using proposed DARTS scheme, the service delay is almost same for all the available DAUs as shown in Figure 3.11(b). Delay in



(a) Population share of different DAUs

(b) Utility of different DAUs

Figure 3.12: Evolution in strategy of each DAU

service reduces by 82.3% for the available DAUs using DARTS, than using fixed selection of DAUs scheme, i.e., WDARTS.

Figure 3.12(a) shows that the initial population share of the DAUs are selected randomly. However, within a few iterations, i.e., 20-25 iterations, the population share of each DAU reaches the evolutionary equilibrium state, and remains stable. Therefore, from Figure 3.12(a), we conclude that the smart meter selects the appropriate DAU dynamically, and also satisfies the evolutionary equilibrium condition.

Figure 4.11 shows that the payoff of utility function of each DAU satisfies the evolutionary equilibrium points. The proposed DARTS scheme reaches the evolutionary equilibrium within a finite iteration, as show in Figure 4.11.

3.5 Concluding Remarks

In this chapter, two schemes considering dynamic behavior of the smart grid are presented.

In this chapter, we formulated a MDP-based approach to study the problem of optimum energy distribution between the customers of the micro-grids. Based on this optimization method, we showed how the coalitions can be formed, and energy can be properly utilized while ensuring high quality of energy service. The simulation results show that the proposed approach yields improved results.

On the other hand, a dynamic evolutionary game theoretic approach is used to study the problem of dynamic data aggregator unit selection, DARTS, by the smart meters in smart grid. Based on the proposed approach, i.e., DARTS, we showed how each smart meter can evolve its strategy, i.e., select an appropriate DAU, in order to reach the evolutionary equilibrium state. The simulation results show using our proposed approach, how the communication load over each DAU can be distributed, and delay in energy service yields improved results.

Chapter 4

Distributed Home Energy Management System with Storage in Smart Grid

In this chapter, we study an aspect of storage devices in home energy management system, by considering that the customers are equipped with storage devices. Each customer tries to consume high amount of energy to charge his/her storage devices. Hence, we propose a *home energy management scheme with storage* (*HoMeS*). Using the proposed scheme, the customers consume higher amount of energy while paying less. On the other hand, the profit of the micro-grids is also ensured while maximizing the utilization factor of the generated amount of energy.

This chapter consists of four sections. The design of HoMeS scheme is proposed in Section 4.1. Section 4.2 depicts game formulation and algorithms of the proposed scheme, HoMeS. Section 4.3 discusses the performances evaluation of the HoMeS scheme with respect to benchmark schemes. Finally, Section 4.4 concludes this chapter.

4.1 System model

We consider a energy distribution system consisting of multiple micro-grids and multiple customers. The schematic diagram of an energy management system is given in Figure 4.1. In this, the micro-grids are connected to the main grid through the substations. Each customer has a smart meter and a communication unit. Based on the communication, the customer decides the amount of energy needed to meet its energy requirement knowing the price per unit energy decided by the micro-grid. We consider a group of customers connected to a single micro-grid. The total charging period in a day is divided into multiple time slots, T. In each time slot $t \leq T$, where T is the number of the time slots in a day, each micro-grid, $m \in \mathcal{M}$, where $\mathcal{M}$ the set of micro-grids, where $\mathcal{M} = \{1, 2, \cdots, M\}$, has to decide the amount of energy to be generated G_m^t for selling to the connected customers to meet their energy demand and maximizing their own revenue. The total energy generated in time slot t and the total energy generated by each micro-grid $m \in \mathcal{M}$ in a day are denoted as G^t and G_m respectively. Mathematically,

$$G^t = \sum_{m=1}^{m \in M} G_m^t \tag{4.1}$$

$$G_m = \sum_{t=1}^{T} G_m^t \tag{4.2}$$

A group of micro-grids $\mathcal{W} \subseteq \mathcal{M}$ form a coalition Co_w, where $w \in (0, \frac{|\mathcal{M}|}{|\mathcal{W}|}]$, and serve a small geographical area, $\mathcal{A}_w$, consisting of a group of customers $\mathcal{C}_w \subseteq \mathcal{N}$, where $\mathcal{N}$ is the set of N number of customers, and $\mathcal{C}_w$ is the set of customers under coalition Co_w. Within a coalition, the micro-grids can exchange energy between themselves. Let us consider that in a coalition Co_w with $\mathcal{W}$ micro-grids, the micro-grid $i \in \mathcal{W}$ has a surplus of power, and the micro-grid $j \in \mathcal{W}$, where $j \neq i$, has a need of energy to fulfill the demand. Hence, the micro-grid $i \in \mathcal{W}$ has excess energy of Q_i unit and the micro-grid $j \in \mathcal{W}$ has a need of Q_j amount of energy. The micro-grid j has an opportunity to

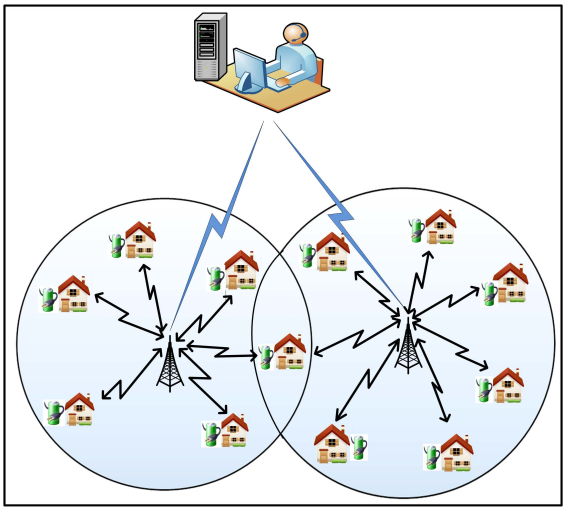


Figure 4.1: Schematic Diagram of Home Energy Management System with Storage

acquire energy from the micro-grid i, if it satisfies the following condition:

$$\sum_{i=1}^{i\in\mathcal{W}} Q_i \geq \sum_{j=1,j\neq i}^{j\in\mathcal{W}} Q_j \tag{4.3}$$

Each customer $n \in \mathcal{N}$ requests a certain amount of energy e_n from its service provider, i.e., the corresponding micro-grid, to fulfill its energy requirement, i.e., the energy requirement for the appliances of the customer n, and energy requirement for storage. We assume that for customer n, the energy requirement for the appliances is a_n, and the requested energy for storage is x_n. Therefore,

$$e_n = a_n + x_n, \qquad \forall n \in \mathcal{N} \tag{4.4}$$

The demand of energy, e_n, of a customer n may vary in different time slots, as the energy requirement of a customer n is based on different parameters such as the maximum storage capacity, E_{max}; the amount of remaining stored energy, E_{res}; the price per unit energy p decided by the service provider; the energy required for daily appliances, a_n; and the energy required for storage, x_n. We assume that the energy requirement for daily appliances, a_n, is known to the micro-grids on a day-ahead basis, and the micro-grid has to supply a_n amount of required energy. Therefore, in a coalition Co_w having $\mathcal{W}$ micro-grids, the total amount of energy has to be generated is at least $\sum_{n=1}^{n\in\mathcal{C}_w} a_n$ amount of energy. Mathematically,

$$\arg\min \sum_{m=1}^{m\in\mathcal{W}} G_m \geq \sum_{n=1}^{n\in\mathcal{C}_w} a_n \tag{4.5}$$

$$\sum_{m=1}^{m\in\mathcal{W}} G_m \geq \sum_{n=1}^{n\in\mathcal{C}_w} e_n \tag{4.6}$$

Hence, the net available energy for storage $\mathcal{S}_w$ in a coalition Co_w having $\mathcal{W}$ micro-grids is given by:

$$\mathcal{S}_w = \left(\sum_{m=1}^{m\in\mathcal{W}} G_m - \sum_{n=1}^{n\in\mathcal{C}_w} a_n \right) \tag{4.7}$$

Since the net available energy $\mathcal{S}_w$ is fixed for the customers, the demands for storage of a customer n, i.e., x_n, has to satisfy the following condition:

$$\sum_{n=1}^{n\in\mathcal{C}_w} x_n \leq \mathcal{S}_w \tag{4.8}$$

Based on the total energy requirement of the appliances in a coalition Co_w, i.e., $\sum_{n=1}^{n\in\mathcal{C}_w} a_n$, the micro-grids need to decide among themselves the minimum amount of energy G_{min} required to be generated, and the minimum price per unit energy, p_{min}, to optimize the overall revenue of the micro-grids. To provide the minimum energy requirement of each customer n, i.e., a_n, each micro-grid decides the price p with the cooperation of other micro-grids, i.e., the minimum price per unit energy p_{min}. Each micro-grid $m \in \mathcal{W}$ tries to sell the excess amount of generated energy with a higher price p per unit energy to maximize its revenue. Hence, an optimal price, which is neither too high nor too low, needs to be chosen by each micro-grid, to maximize its profit.

To complete energy trading successfully, proper interaction among the central energy management unit (CEMU), the micro-grids, and the customers is needed. We divide the interactions into two stages — *initialization phase with cooperation* (IPC), and *finalization phase with non-cooperation* (FPN). In IPC, each micro-grid m exchanges information with the CEMU to decide the minimum energy to be generated G_{min}, and the minimum price per unit energy p_{min}. In FPN, each customer n in a coalition Co_w needs to decide the amount of energy to be requested to the micro-grid m, and the micro-grid $m \in \mathcal{W}$ needs to decide the price per unit energy p, where $p \geq p_{min}$. However, the price per unit energy p also depends on the total energy required by a customer n, i.e., e_n, and the number of customers under micro-grid m, i.e., $|\mathcal{C}_m|$. If the amount of energy acquire for appliances, i.e., a_n, is higher, the excess energy for storage, $\mathcal{S}_w$, will be reduced.

The energy requested by each customer has to fulfill the constrains given in Equations (4.5), and (4.6). It is also to be noted that the price decided by a micro-grid is also dependent on the amount of requested energy. Thus, the main challenges faced to develop the approach that can capture the two stages decision making processes are as follows:

1. Modeling the decision making processes, the interactions between the micro-grids and the CEMU, and the micro-grids and the customers in the network, subject to the constrains in Equations (4.5) and (4.6).

2. Developing an algorithm for the micro-grids to decide the minimum energy to be generated by each micro-grid G_{min}, and the minimum price per unit energy p_{min}, by having interaction with the CEMU.

3. Developing another algorithm for the micro-grids to decide the amount of energy to be generated, and the actual price per unit energy p.

4. Each customer n needs to decide the total amount of energy e_n based on the optimally decided amount of energy for storage x_n to maximize its storage satisfaction level.

Communication between the Customer and Micro-Grid: We assume that the communication networking model between the micro-grids and the customers is wireless mesh network (WMN). We use the IEEE 802.11b protocol for the communication between the micro-grids and the customers. In the *Initialization Phase*, each customer sends a message with the information of minimum energy requirement for the appliances, as shown in Figure 4.2.

Type (Energy)	EnergyRequested (MWh)	CustomerID
1 Byte	2 Byte	2 Byte

Figure 4.2: Initial request message from customer

Type (Price)	Price (USD)	ExcessEnergy (MWh)	GridID
1 Byte	2 Byte	2 Byte	2 Byte

Figure 4.3: Reply message from micro-grid

In the *Finalization Phase*, each micro-grid replies with the decided price per unit energy to the customers. The reply message format is shown in Figure 4.3. After receiving the reply message from the micro-grids, each customer decides how much energy s/he needs to consume, including the required energy for storage, and sends a request packet again to the micro-grids. The message format is shown in Figure 4.4. This message exchange continues until the customer decides an optimal value of requested energy, and the micro-grid gets the optimal price per unit energy.

Type (Energy)	Energy (MWh)	SelectionFlag	CustomerID
1 Byte	2 Byte	1 Byte	2 Byte

Figure 4.4: Request message from customer

4.2 Proposed Home Energy Management with Storage Game

4.2.1 Game formulation

To study the interactions between the micro-grids and the customers, as mentioned earlier, we use a multiple leader multiple follower Stackelberg game. Multiple leader multiple follower Stackelberg game is a multi-stage and multi-level game, where a group of players, i.e., the followers, take decision based on the decision of the leaders, using a non-cooperative game, and the leaders make decision among themselves using a cooperative game. In this paper, we consider the micro-grids as the leaders, and the customers as the followers. Hence, in the *Initialization Phase*, the micro-grids need to decide the amount of minimum energy to be generated G_{min}, and the minimum price per unit energy p_{min}, using a cooperative game theoretic approach. In the *Finalization Phase*, the customers need to decide the amount of energy to be requested e_n, including the optimum amount of energy for storage x_n, and the micro-grids need to decide the price per unit energy, p, using a non-cooperative game theoretic approach. The overall game is defined by using the strategic form,

$$\Upsilon = \{(\mathcal{N} \cup \mathcal{M}), (X_n)_{n\in\mathcal{N}}, (A_n)_{n\in\mathcal{N}}, (E_n)_{n\in\mathcal{N}}, (\psi_n)_{n\in\mathcal{N}}, (G_m)_{m\in\mathcal{M}}, (P_m)_{m\in\mathcal{M}}, (\varphi_m))_{m\in\mathcal{M}}, (p_m)_{m\in\mathcal{M}}, (\phi_m)_{m\in\mathcal{M}}, G_{min}, p_{min}\} \quad (4.9)$$

The components in the strategic form Υ are as follows:

1. Each customer $n \in \mathcal{N}$ acts as a follower in the game, and needs to decide the optimum energy demand e_n, based on the optimum price decided by the micro-grid.

2. The strategy of each customer $n \in \mathcal{N}$ is to decide the total amount of energy e_n from the micro-grid, while satisfying the constraints given in the Equations (4.5), (4.6), and (4.8).

3. Each customer $n \in \mathcal{N}$ optimizes the amount of energy to be stored, while satisfying the constraint:

$$\mathcal{S} \geq \sum_{n=1}^{n \in \mathcal{N}} x_n$$

where $\mathcal{S}$ is the total amount of excess energy that can be acquired by the customers for stored energy. Mathematically,

$$\mathcal{S} = \sum_{w=1}^{w=\left\lfloor \frac{|\mathcal{M}|}{|\mathcal{W}|} \right\rfloor} \mathcal{S}_w \tag{4.10}$$

4. The utility function ψ_n of a customer $n \in \mathcal{N}$ is used to maximize the payoff value by capturing the benefit of the total consumed energy e_n, which includes the consumed energy by the appliances a_n, and the requested amount of energy for storage x_n.

5. The utility function $\varphi_m(p_m)$ of a micro-grid $m \in \mathcal{M}$ is used to maximize the payoff value of micro-grid m using the information of total consumed energy from micro-grid m.

6. The price p_m denotes the price per unit energy decided by the micro-grid $m \in \mathcal{M}$.

7. The utility function ϕ_m of a micro-grid $m \in \mathcal{W}$, where $\mathcal{W} \subseteq \mathcal{M}$, captures the minimum profit by selling the energy to fulfill the minimum energy requirement by the customers $\mathcal{C}_w$ in a coalition Co_w.

8. The energy G_{min} denotes the minimum energy needed to be generated by each micro-grid $m \in \mathcal{M}$.

The game formulation of the *Initialization* and the *Finalization Phases* of the multi leader multi follower Stackelberg game are discussed in Sections 4.2.1.1, and 4.2.1.2, respectively.

4.2.1.1 Game formulation for the Initialization Phase

a) *Utility function of a micro-grid for Initialization Phase*: In the Initialization Phase, each micro-grid $m \in \mathcal{W}$, that acts as a leader, decides the minimum amount of energy to be generated G_{min}, and the minimum price per unit energy P_{min}, based on the minimum amount of requested energy by the customers, i.e., a_n, where $\forall n \in \mathcal{C}_w$. The vector showing the amount of energy A_n, requested by each customer $n \in \mathcal{C}_w$, is the maximum expected energy vector to be needed for the appliances, and is forecasted on a day-ahead basis. Mathematically,

$$A_n = \{a_n^1, a_n^2, \cdots, a_n^t, \cdots, a_n^T\},\ G_{min} = \{g_{min}^1, g_{min}^2, \cdots, g_{min}^t, \cdots, g_{min}^T\}, \text{ and}$$
$$P_{min} = \{p_{min}^1, p_{min}^2, \cdots, p_{min}^t, \cdots, p_{min}^T\} \quad (4.11)$$

where T is the number of time slots in a day, a_n^t, g_n^t, p_n^t are the minimum expected energy of a customer $n \in \mathcal{C}_w$ for time slot t, the minimum energy to be generated for time slot t, and the minimum price per unit energy for time slot t, respectively, where $t = \{0, 1, \cdots, T\}$.

Initially, in a coalition Co_w, each customer $n \in \mathcal{C}_w$ calculates its expected amount of energy vector A_n and broadcasts to the micro-grids $\mathcal{W}$. The micro-grid $m \in \mathcal{W}$ decides to generate g_m amount of energy to maximize its utility function $\phi_m(g_m, \mathbf{g}_{-m})$, while the price per unit energy p would be fixed for all the micro-grids in a coalition. Mathematically,

$$\arg\max_{g_m} \phi_m(g_m, \mathbf{g}_{-m}), \qquad \forall m \in \mathcal{W} \quad (4.12)$$

Equation (4.12) must satisfy the constraint:

$$\sum_{m \in \mathcal{W}} g_m^t \geq \sum_{n \in \mathcal{C}_w} a_n^t \quad (4.13)$$

where $\mathbf{g}_{-m} = \{g_1, g_2, \cdots, g_{m-1}, g_{m+1}, \cdots, g_{|\mathcal{W}|}\}$, and $t = \{1, 2, \cdots, T\}$. Hence, the properties that the utility function must satisfy are as follows:

1. The utility function of a micro-grid m, ϕ_m, is considered as a non-increasing function. With the increase in energy demand, the total revenue of a micro-grid m increases. Mathematically,

$$\frac{\delta \phi_m(g_m, \mathbf{g}_{-m})}{\delta g_m} \leq 0, \qquad \forall m \in \mathcal{W} \text{ and } \forall n \in \mathcal{C}_w \tag{4.14}$$

2. If the total generated energy by a micro-grid m equals the total requested energy by a group of customers, i.e., $\sum_{n=1}^{n \in \mathcal{C}_w} a_n$, the utility function is considered to be in the marginal position. In this situation, the utility function of the micro-grids are considered to be non-increasing function. Mathematically,

$$\frac{\delta^2 \phi_m(g_m, \mathbf{g}_{-m})}{\delta {g_m}^2} < 0, \qquad \forall m \in \mathcal{W} \tag{4.15}$$

3. With the increase in the total amount of energy demand by the customers, $\sum_n a_n$, the payoff of the utility function ϕ_m increases. Mathematically,

$$\frac{\delta \phi_m(g_m, \mathbf{g}_{-m})}{\delta a_n} > 0, \qquad \forall m \in \mathcal{W}, \text{ and } \forall n \in \mathcal{C}_w \tag{4.16}$$

4. With a fixed amount of energy request, i.e., $\sum_n a_n$, if the price per unit energy p increases, the payoff of the utility function ϕ_m also increases. Mathematically,

$$\frac{\delta \phi_m(g_m, \mathbf{g}_{-m})}{\delta p} > 0, \qquad \forall m \in \mathcal{M} \tag{4.17}$$

The utility function ϕ_m denotes the maximum profit of micro-grid m that it can have by selling the minimum amount of energy. Therefore, the utility function ϕ_m becomes,

$$\phi_m(g_m, \mathbf{g}_{-m}) = p g_m - c_m g_m \tag{4.18}$$

where, c_m is the generation cost per unit energy for micro-grid $m \in \mathcal{M}$, g_m is the generated energy by the micro-grid m. The total energy that needs to be generated by the micro-grids $\mathcal{W}$ in a coalition, $\mathcal{G}$, is defined as,

$$\mathcal{G}_{\mathcal{W}} = \sum_{m=1}^{m \in \mathcal{W}} g_m \tag{4.19}$$

b) *Existence of Generalized Nash Equilibrium for the Initialization Phase*: In any optimization approach, there should be an optimal or Pareto-optimal solution. Therefore, we need to investigate the existence of generalized Nash equilibrium for the Initialization Phase. In this Phase, we find out the equilibrium point under the assumptions — in a coalition, (i) each micro-grid has the same generation cost per unit energy c, and (ii) the minimum price per unit energy p_{min}, would be fixed for all the micro-grids.

Definition 5. *While the total demand of energy for all the customers is fixed, with the increase in supply of the total amount of energy, the price per unit energy reduces. So, the price function varies inversely with the demand function. We formulate an inverse demand function $\mathcal{P}(\mathcal{G}_{\mathcal{W}})$ as follows:*

$$\mathcal{P}(\mathcal{G}_{\mathcal{W}}) = A - \mathcal{G}_{\mathcal{W}} \tag{4.20}$$

where A is a constant, and $\mathcal{G}_{\mathcal{W}}$ is the total generated energy by $\mathcal{W}$ micro-grids in the coalition Co_w. $\mathcal{G}_{\mathcal{W}}$ must satisfy the following condition:

$$\mathcal{G}_{\mathcal{W}} \geq \sum_{n=1}^{n \in \mathcal{C}_w} a_n \tag{4.21}$$

The utility function ϕ_m reaches a generalize Nash equilibrium (GNE), if and only if it satisfies the following inequality:

$$\phi_m({g_m}^*, \mathbf{g}^*_{-m}) \geq \phi_m(g_m, \mathbf{g}^*_{-m}) \tag{4.22}$$

Theorem 3. *If the generation cost per unit energy for each micro-grid is the same, the amount of energy to be generated by each micro-grid $m \in \mathcal{W}$, i.e., g_m will be same, if and only if the following inequality holds,*

$$\phi_m(g^*_m, \boldsymbol{g}^*_{-m}) \geq \phi_m(g_m, \boldsymbol{g}^*_{-m})$$

Proof. For the micro-grids $m \in \mathcal{W}$, the generation cost per unit energy c_m remains the same, i.e., $c_m = c$, $\forall m \in \mathcal{W}$, where c is a constant. The optimal energy supply of the the micro-grid m, i.e., the best response of micro-grid m, is defined as follows:

$$g^*_m(c_m) = \arg\max_{g_m}((A - \mathcal{G}_{\mathcal{W}}) - c_m)g_m \tag{4.23}$$

We rewrite the function by replacing c_m by c. As stated before, the generation cost per unit energy c_m is the same. Therefore,

$$g^*_m(c) = \arg\max_{g_m}((A - \mathcal{G}_{\mathcal{W}}) - c)g_m \tag{4.24}$$

Hence,

$$\begin{aligned} & g^*_1(c) = \arg\max\nolimits_{g_1}[(A - \mathcal{G}_{\mathcal{W}}) - c]g_1 \\ \Rightarrow \quad & g^*_1(c) = \arg\max\nolimits_{g_1}\left[\left(A - g_1 - g^*_2 - \sum_{m=3}^{m\in\mathcal{W}} g^*_m\right) - c\right]g_1 \end{aligned} \tag{4.25}$$

Similarly,

$$g^*_2(c) = \arg\max_{g_2}\left[\left(A - g^*_1 - g_2 - \sum_{m=3}^{m\in\mathcal{W}} g^*_m\right) - c\right]g_2 \tag{4.26}$$

The optimal value of g_1, i.e., g^*_1, can be obtained from the necessary condition, as follows:

$$\left.\frac{\delta g_1(c)}{\delta g_1}\right|_{g_1=g_1^*} = 0$$

$$A - 2g_1^* - g_2^* - \sum_{m=3}^{m\in\mathcal{W}} g_m^* - c = 0$$

$$g_1^* = \frac{A - g_2^* - \sum\limits_{m=3}^{m\in\mathcal{W}} g_m^* - c}{2} \tag{4.27}$$

Similarly, we get the optimum value of g_2 as follows:

$$g_2^* = \frac{A - g_1^* - \sum\limits_{m=3}^{m\in\mathcal{W}} g_m^* - c}{2} \tag{4.28}$$

By solving Equations (4.27), and (4.28), we get,

$$g_1^* = g_2^* = A - c \tag{4.29}$$

From Equation (4.29), we infer that,

$$g_1^* = g_2^* = \cdots = g_m^* = \cdots = g_{|\mathcal{W}|}^*$$

Hence, within a coalition, each micro-grid $m \in \mathcal{W}$ generates the same minimum amount of energy to satisfy the inequality for GNE, i.e., $\phi_m(g_m^*, \mathbf{g}_{-m}^*) \geq \phi_m(g_m, \mathbf{g}_{-m}^*)$. □

4.2.1.2 Game Formulation for the Finalization Phase

The interaction between the micro-grids and the customers in a coalition is evaluated using the second part of the multiple leader multiple follower Stackelberg game, where each micro-grid $m \in \mathcal{W} \subseteq \mathcal{M}$ acts as the leader, and the customers $n \in \mathcal{C}_w$ act as the followers. Initially, each leader, i.e., micro-grid m, generates energy using renewable energy resources. The micro-grid m needs to generate energy using non-renewable energy resources, if the micro-grid does not satisfy the following inequality:

$$(G_{RE})_m \geq G_{min} \tag{4.30}$$

where $(G_{RE})_m$ is the amount of energy generated using renewable energy resources by micro-grid m. Therefore, we can define the amount of energy generated using non-renewable energy resources, $(G_{NE})_m$ by a micro-grid m is as follows:

$$(G_{NE})_{m_{min}} = \begin{cases} 0 & \text{if } (G_{RE})_m \geq G_{min} \\ G_{min} - (G_{RE})_m & \text{if } (G_{RE})_m < G_{min} \end{cases} \tag{4.31}$$

a) *Utility function of a customer*: For each customer $n \in \mathcal{C}_w$ in the coalition Co_w, we formulate the utility function $\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m)$ to introduce the amount of energy requested to fulfill the requirement of the customers. In the utility function ψ_n, the maximum energy storage capacity of the customer n is denoted by $(E_{max})_n$, the stored energy of a customer n is denoted by $(E_{res})_n$, the total amount of energy requested by the customer n is denoted by e_n, and $\mathbf{e}_{-n}$ denotes the total amount of energy requested by the other customers in the coalition, except customer n. Mathematically, we define $\mathbf{e}_{-n}$ as follows:

$$\mathbf{e}_{-n} = \{e_1, e_2, e_3, \cdots, e_{n-1}, e_{n+1}, \cdots, e_{|\mathcal{C}_w|}\}$$

where $|\mathcal{C}_w|$ is the number of customers in a coalition Co_w having the micro-grids $\mathcal{W} \subseteq \mathcal{M}$. Each customer n intends to increase its residual energy $(E_{res})_n$, as that can be used by her/him at the on-peak hour of the day, and also in a blackout or islanding situation. So, having a fixed amount of maximum energy storage capacity $(E_{max})_n$, the customer n requests higher e_n due to higher amount of energy needed for storage x_n. The amount of energy requested for storage will be affected by the decided price per unit energy, p_m, by micro-grid m. Thus the property of the utility function ψ_n of a customer $n \in \mathcal{C}_w$

must satisfy the following conditions,

1. The utility function ψ_n of the customer $n \in \mathcal{N}$ is considered as a non-increasing function, as each customer wants to acquire more amount of energy e_n to maximize its residual energy, $(E_{res})_n$. Mathematically,

$$\frac{\delta\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m)}{\delta e_n} \leq 0 \tag{4.32}$$

2. The limiting value of the utility function ψ_n of a customer n is considered to be a non-increasing function, as the residual energy $(E_{res})_n$ increases the amount of requested energy e_n. Mathematically,

$$\frac{\delta^2\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m)}{\delta {e_n}^2} < 0 \tag{4.33}$$

3. If the amount of maximum energy storage capacity $(E_{max})_n$ is higher, the energy requirement of the customer n will be higher. So, the utility function ψ_n varies proportionally with $(E_{max})_n$. Mathematically,

$$\frac{\delta\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m)}{\delta (E_{max})_n} > 0 \tag{4.34}$$

4. If the amount of stored energy $(E_{res})_n$ decreases, the the energy requirement of the customer n increases. The utility function ψ_n has an inversely-proportional relationship with the amount of residual energy $(E_{res})_n$. Mathematically,

$$\frac{\delta\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m)}{\delta (E_{res})_n} < 0 \tag{4.35}$$

5. The amount of requested energy, e_n, is affected by the price per unit energy, p_m, decided by the micro-grid m. With the higher value of price, the payoff of the

utility function ψ_n of a customer n decreases. Mathematically,

$$\frac{\delta\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m)}{\delta p_m} < 0 \tag{4.36}$$

Therefore, the utility function ψ_n is formulated as follows:

$$\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m) = (E_{max})_n e_n - \frac{1}{2}\alpha\frac{(E_{res})_n}{(E_{max})_n}{e_n}^2 - \beta\frac{p_m}{p_{min}}\mathcal{S}_w e_n \tag{4.37}$$

$\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m)$ must satisfy the following constrains,

1. e_n is defined in Equation (4.4)
2. The amount of requested energy for the appliances a_n by the customer n satisfies:

$$a_n \in \left[0, \sum_{m=1}^{m\in\mathcal{W}} g_m - \sum_{q=1,q\neq n}^{q\in\mathcal{C}_w} a_q\right] \tag{4.38}$$

3. The amount of requested energy for the storage a_n by the customer n also satisfies:

$$x_n \in \left[0, \sum_{m=1}^{m\in\mathcal{W}} g_m - \sum_{r=1}^{r\in\mathcal{C}_w} a_r - \sum_{q=1,q\neq n}^{q\in\mathcal{C}_w} x_q\right] \tag{4.39}$$

and

$$\sum_{n}^{n\in\mathcal{C}_w} x_n \leq \mathcal{S}_w \tag{4.40}$$

4. α and β are constants, and have a fixed value within a coalition. These constants also satisfy the following inequality,

$$\alpha,\, \beta > 0 \tag{4.41}$$

b) *Utility function of a micro-grid*: Each micro-grid $m \in \mathcal{W}$ gets a revenue of $p_m e_n$ by selling e_n amount of energy with p_m price per unit energy. Each micro-grid m tries to maximize its revenue by selling maximum amount of energy with higher price per unit energy. Mathematically,

$$\varphi_m(e_n(p_m), p_m) = p_m \sum_n e_n \tag{4.42}$$

where p_m is the fixed price per unit energy for micro-grid $m \in \mathcal{W}$. However, each micro-grid knows that if the value of p_m is lower, the amount of energy requested by the customers is higher, and vice-versa, in either case it may get less revenue. So, the micro-grid m needs to choose an optimize value of p_m to maximize its revenue. Mathematically,

$$\arg\max \varphi_m(e_n(p_m), p_m) = \max_{p_m} \sum_m \sum_n p_m e_n \tag{4.43}$$

where $m \in \mathcal{W}$, $\mathcal{W} \subseteq \mathcal{M}$, and $p_m \geq p_{min}$.

The requested energy e_n of each customer n is not only dependent on the price per unit energy decided by the micro-grid, and the amount of required energy to fulfill its maximum storage capacity, i.e., $((E_{max})_n - (E_{res})_n)$, but also the requested energy by the other customers, except customer n. Therefore, this scenario leads to a non-cooperative game that deals with sharing a common product having a fixed constraint for all. We will prove in Subsection 4.2.1.2 that there exists generalized Nash equilibrium (GNE).

Definition 6. *The set of strategies* $(\{e_n^*\}_{n\in\mathcal{N}}, \{p_m^*\}_{m\in\mathcal{M}})$ *are considered as the generalized Nash equilibrium solutions, if those satisfy the following inequality:*

$$\psi_n(e_n^*, \boldsymbol{e}_{-n}^*, (E_{max})_n, (E_{res})_n, p_m^*) \geq \psi_n(e_n, \boldsymbol{e}_{-n}^*, (E_{max})_n, (E_{res})_n, p_m^*) \tag{4.44}$$

and

$$\varphi_m(e_n^*(p_m^*), p_m^*) \geq \varphi_m(e_n^*(p_m), p_m) \tag{4.45}$$

where e_n^* *is the optimum energy requested by the customer* n*, and* p_m^* *is the optimum price per unit energy decided by the micro-grid* m*. Each customer* n *cannot maximize the payoff of the utility function* ψ_n *by changing the value of* e_n *from the value of* e_n^**.*

Similarly, each micro-grid m cannot maximize the payoff of the utility function φ_m by choosing a higher price p_m than the price p_m^*.

c) *Existence of Generalized Nash Equilibrium for the Finalization Phase*: In this section, we determines the existence of GNE by showing that it satisfies the properties of *variation inequality* (VI), as it is used to get the optimum concave solution under some constraints of inequality.

Theorem 4. *Given a fixed price p_m by the micro-grid $m \in \mathcal{M}$, there exists a generalized Nash equilibrium (GNE), as there exists a variational equilibrium for the utility function $\psi_n(e_n^*, \boldsymbol{e}_{-n}^*, (E_{max})_n, (E_{res})_n, p_m^*)$.*

Proof. In the Finalization Phase, the utility function $\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m)$ needs to be maximized. The utility function $\psi_{k,k\neq n}(e_k, \mathbf{e}_{-k}, (E_{max})_k, (E_{res})_k, p_m)$, where $k \in \mathcal{C}_w$, also needs to be maximized.

$$\psi_{k,k\neq n}(e_k, \mathbf{e}_{-k}, (E_{max})_k, (E_{res})_k, p_m) = (E_{max})_k e_k - \frac{1}{2}\alpha \frac{(E_{res})_k}{(E_{max})_k} {e_k}^2 - \beta \frac{p_m}{p_{min}} \mathcal{S}_w e_k \tag{4.46}$$

From Equations (4.37) and (4.46), we get,

$$\begin{gathered}\psi\big(e_1, e_2, \cdots, e_n, \cdots, e_{|\mathcal{C}_w|}; (E_{max})_1, (E_{max})_2, \cdots, (E_{max})_n, \cdots, (E_{max})_{|\mathcal{C}_w|}; (E_{res})_1, (E_{res})_2, \cdots, \\ (E_{res})_n, \cdots, (E_{res})_{|\mathcal{C}_w|}; p_m\big) = \\ \sum_n (E_{max})_n e_n - \frac{1}{2}\alpha \sum_n \frac{(E_{res})_n}{(E_{max})_n} {e_n}^2 - \beta \frac{p_m}{p_{min}} \mathcal{S}_w \sum_n e_n \end{gathered} \tag{4.47}$$

Using the method of Lagrangian multiplier, the *Karush-Kuhn-Tucker* (KKT) condition of the customer n for the generalized Nash equilibrium problem becomes:

$$\nabla_{e_n}\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m) - \nabla_{e_n}\left(\sum_n x_n - \mathcal{S}_w\right)\mu_n = 0, \tag{4.48}$$

$$\left(\sum_n x_n - \mathcal{S}_w\right)\mu_n = 0, \tag{4.49}$$

$$\text{and} \qquad \mu_n \geq 0 \tag{4.50}$$

where μ_n is the Lagrangian multiplier for the customer n.

By using the property of variational inequality (VI), we get VI($\mathbf{B}, \mathbf{X}$) as the solution of the variational equilibrium, where $\mathbf{X}$ is the set of optimum points for x, and $\mathbf{B} = \nabla_{e_n}\psi_n(e_n, \mathbf{e}_{-n}, (E_{max})_n, (E_{res})_n, p_m)$. We get the Jacobian matrix of $\mathbf{B}$ as follows,

$$\begin{aligned} \mathbf{J_B} &= \nabla_{\mathbf{e}}\mathbf{B} \\ &= \begin{bmatrix} (E_{max})_1 - \alpha\frac{(E_{res})_1}{(E_{max})_1}e_1 - \beta\frac{p_m}{p_{min}}\mathcal{S}_w \\ (E_{max})_2 - \alpha\frac{(E_{res})_2}{(E_{max})_2}e_2 - \beta\frac{p_m}{p_{min}}\mathcal{S}_w \\ \vdots \\ (E_{max})_n - \alpha\frac{(E_{res})_n}{(E_{max})_n}e_n - \beta\frac{p_m}{p_{min}}\mathcal{S}_w \\ \vdots \\ (E_{max})_{|\mathcal{C}_w|} - \alpha\frac{(E_{res})_{|\mathcal{C}_w|}}{(E_{max})_{|\mathcal{C}_w|}}e_{|\mathcal{C}_w|} - \beta\frac{p_m}{p_{min}}\mathcal{S}_w \end{bmatrix} \end{aligned} \tag{4.51}$$

The Hessian matrix of $\mathbf{B}$ is the Jacobian matrix of $\nabla_{\mathbf{e}}\mathbf{B}$. Mathematically,

$$\mathbf{H_B} = \mathbf{J}(\nabla_{\mathbf{e}}\mathbf{B}) \tag{4.52}$$

Therefore, $\mathbf{H_B}$ is as follows,

$$\mathbf{H_B} = \begin{bmatrix} -\alpha\frac{(E_{res})_1}{(E_{max})_1} & 0 & \cdots & 0 \\ 0 & -\alpha\frac{(E_{res})_2}{(E_{max})_2} & \cdots & 0 \\ . & . & \cdots & . \\ . & . & \cdots & . \\ . & . & \cdots & . \\ 0 & 0 & \cdots & -\alpha\frac{(E_{res})_{|\mathcal{C}_w|}}{(E_{max})_{|\mathcal{C}_w|}} \end{bmatrix} \tag{4.53}$$

As the Hessian matrix $\mathbf{H_B}$ is a diagonal matrix, we infer that vector $\mathbf{e}$ has a unique solution, where $\mathbf{e} = \{e_1, e_2, \cdots, e_{|\mathcal{C}_w|}\}$, and the variational equilibrium exists. Therefore, for a fixed price, there exists a generalized Nash equilibrium (GNE). □

4.2.2 Proposed Solution Approach

From Section 4.2.1, we get that GNE exists for the multiple leader multiple follower Stackelberg game theoretic approach used in HoMeS. In this section, we compute the optimum solutions of the unknown variables.

a) *Solution approach for the Initialization Phase*: In the Initialization Phase, the minimum amount of energy to be generated by each micro-grid m, i.e., $\arg\min(g_m)$, and the minimum price per unit energy, i.e., $\arg\min(p_m)$, are decided, where the generation cost per unit energy c is fixed for the micro-grids $m \in \mathcal{M}$.

Definition 7. *In a coalition, the price per unit energy, p_{min} is the same as the generation cost per unit energy c. Mathematically,*

$$p_{min} = c\ , \quad c > 0 \tag{4.54}$$

If in a micro-grid $m \in \mathcal{M}$, the price per unit energy, p, is the same as the generation cost per unit energy c, i.e., p_{min}, then the profit of the micro-grid m equals zero.

Lemma 2. *In a coalition, each micro-grid needs to generate the same minimum amount* *of energy to fulfill customers' energy demand.*

Proof. From Theorem 3 and Equation (4.19), we get,

$$g_1^* = \frac{g_2^* + g_3^* + g_4^* + \cdots + g_{|\mathcal{W}|}^*}{|\mathcal{W}| - 1} \tag{4.55}$$

We rewrite Equation (4.55) as follows:

$$g_1^* = \frac{g_1^* + g_2^* + g_3^* + \cdots + g_{|\mathcal{W}|}^*}{|\mathcal{W}|}$$

Hence,

$$g_1^* = \frac{\sum\limits_{m=1}^{m \in \mathcal{W}} g_m^*}{|\mathcal{W}|} \tag{4.56}$$

Therefore, the minimum energy to be generated by each micro-grid m, $m \in \mathcal{W}$, is given by,

$$\arg\min(g_m) = g_m^* = \frac{\sum\limits_{k=1}^{k \in \mathcal{W}} g_k^*}{|\mathcal{W}|}, \qquad \forall m \in \mathcal{W} \subseteq \mathcal{M} \tag{4.57}$$

□

b) *Solution approach for the Finalization Phase*: In this section, the value of the optimum amount of energy requested by each customer n, i.e., e_n^*, given the fixed price per unit energy p_m, and the value of optimum price, i.e., p_m^*, for the given optimum amount of energy e_n^*, is computed.

For each customer n, solving the *Karush-Kuhn-Tucker* (KKT) condition for the GNE problem defined in Equation (4.48), we get:

$$(E_{max})_n - \alpha \frac{(E_{res})_n}{(E_{max})_n} e_n - \beta \frac{p_m}{p_{min}} \mathcal{S}_w - \mu_n = 0 \tag{4.58}$$

From Equation (4.50), we get $\mu_n \geq 0$. Therefore,

$$(E_{max})_n - \alpha \frac{(E_{res})_n}{(E_{max})_n} e_n - \beta \frac{p_m}{p_{min}} \mathcal{S}_w \geq 0 \tag{4.59}$$

Solving Equation (4.59), we get,

$$e_n \leq \frac{(E_{max})_n}{\alpha (E_{res})_n} \left[(E_{max})_n - \beta \frac{p_m}{p_{min}} \mathcal{S}_w \right] \tag{4.60}$$

and

$$p_m \leq \frac{p_{min}}{\beta \mathcal{S}_w} \left[(E_{max})_n - \alpha \frac{(E_{res})_n}{(E_{max})_n} e_n \right] \tag{4.61}$$

So, the optimal values of e_n and p_m, i.e., e_n^* and p_m^*, respectively, are as follows:

$$e_n^* = \frac{(E_{max})_n}{\alpha (E_{res})_n} \left[(E_{max})_n - \beta \frac{p_m^*}{p_{min}} \mathcal{S}_w \right] \tag{4.62}$$

$$p_m^* = \frac{p_{min}}{\beta \mathcal{S}_w} \left[(E_{max})_n - \alpha \frac{(E_{res})_n}{(E_{max})_n} e_n^* \right] \tag{4.63}$$

and

$$\mu_n = (E_{max})_n - \alpha \frac{(E_{res})_n}{(E_{max})_n} e_n^* - \beta \frac{p_m^*}{p_{min}} \mathcal{S}_w \tag{4.64}$$

4.2.3 Proposed Algorithms

In order to reach the equilibrium in home energy management system, the micro-grids and the customers take their respective strategies, while incurring a marginal communication overhead. In this paper, we propose two different algorithms — the *initialization phase with cooperation* (IPC) algorithm, and the *finalization phase with non-cooperation* (FPN) algorithm. In the IPC algorithm, the customers provide their energy consumption profile for appliances on a day-ahead basis. After getting the information of total minimum energy consumption of the customers in a coalition, the micro-grids communicate within themselves to finalize the minimum value of the energy to be generated, G_{min}, and the minimum cost per unit energy, p_{min}. In the FPN algorithm, the customers communicate with the corresponding micro-grids within the coalition, and decide the amount of actual energy to be consumed, e_n. After getting the actual consumption profile of the customers, each micro-grid $m \in \mathcal{M}$ decides the actual price per unit energy, p_m for micro-grid m, on a real-time basis.

4.2.3.1 Initialization Phase with Cooperation Algorithm

Initially, each customer $n \in \mathcal{N}$ broadcasts a vector representing his/her energy consumption profile for the appliances, i.e., A_n. The micro-grids receive all the information and distribute the energy profile in a linear fashion over all the time-slots in a day. Based on that information, the micro-grids decide the amount of energy to be generated by each micro-grid to fulfill the minimum requirement of the customers in a coalition, as discussed in Algorithm 4.1. The micro-grids also make an agreement within themselves to decide the minimum price per unit energy.

4.2.3.2 Finalization Phase with Non-cooperation Algorithm

In the Finalization Phase, the customers and the micro-grids within a coalition execute two different algorithms — Algorithm 4.2 and Algorithm 4.3, respectively. In a coalition, the customers decide the amount of energy to be requested, including the amount of energy for storage, based on the optimum price decided by the micro-grids. The micro-grids need to decide the actual price per unit energy, p_m, where $p_m \geq (p_m)_{min}$.

4.3 Performance Evaluation

4.3.1 Simulation Settings

For performance evolution, we considered randomly generated values for the micro-grids and the customers, as shown in Table 4.1, on a MATLAB simulation platform. The

Algorithm 4.1: IPC algorithm for each micro-grid

Input : Each customer n broadcasts the energy consumption vector for appliances, A_n.

Outputs: The minimum energy to be generated by each micro-grid m, i.e., G_{min}. The minimum price per unit energy decided by each micro-grid m, p_m, in a coalition.

while $\sum_{m=1}^{m \in \mathcal{W}} g_m < \sum_{n=1}^{n \in \mathcal{C}_w} a_n$ **do**
  if $\phi_m(g_m^*, \boldsymbol{g}_{-m}^*) \ngeq \phi_m(g_m, \boldsymbol{g}_{-m}^*)$ **then**
    Optimized value of g_m, i.e., g_m^* is found
  else
    Evaluate the amount of energy to be generated, $g_m^{modified}$
    Decide the minimum energy to be generated, $g_m = g_m^{modified}$
  end
end
Each micro-grid m decides the minimum price per unit energy, p_m
Calculate minimum profit $= (p_m - c)g_m$, where c is the generation cost per unit energy
while $(p_m - c) < 0$ **do**
  Decide higher value of p_m, $p_m^{modified}$, which is the minimum price per unit energy generated by the micro-grid m
  The minimum price per unit energy, $p_m = p_m^{modified}$, is computed
end

micro-grids form a coalition, based on the total energy requirement of the customers, the generation capacity of the micro-grids, and the area covered by the coalition, as discussed in [36].

The customer decides the energy required for the appliances on a day-ahead basis. Accordingly, the micro-grids decide the minimum amount of energy to be generated to fulfill the minimum energy requirement of the customers. Each customer takes the chance of using their storage non-cooperatively, based on real-time communication with the micro-grids, as discussed in [36]. Here, the micro-grids decide to maximize their revenue by maximizing their payoffs. In the Finalization Phase, the micro-grids as well as the customers try to maximize their payoffs by choosing the optimum values for the price per unit energy and the requested energy, respectively.

Algorithm 4.2: FPN algorithm for a customer

Inputs : The optimum price per unit energy, p_m^*.
Total energy for storage $\mathcal{S}_w$, where $w \in \frac{|\mathcal{M}|}{|\mathcal{W}|}$.
Output: Amount of energy to be served e_n^*.

Decide the amount of energy to be requested e_n^* by customer n
while $\psi_n(e_n^*, \boldsymbol{e}_{-n}^*, (E_{max})_n, (E_{res})_n, p_m^*) \ngeq \psi_n(e_n, \boldsymbol{e}_{-n}^*, (E_{max})_n, (E_{res})_n, p_m^*)$ **do**
  $e_n = e_n^*$
  Evaluate the modified value of energy to be requested, $e_n^{modified}$
  $e_n^* = e_n^{modified}$
end

Algorithm 4.3: FPN algorithm for a micro-grid

Input : Amount of energy to be served e_n^*.
Output: The optimum price per unit energy, p_m^*.

Decide the price per unit energy p_m^*, by micro-grid m
while $\varphi_m(e_n^*(p_m^*), p_m^*) \ngeq \varphi_m(e_n^*(p_m), p_m)$ **do**
  $p_m = p_m^*$
  Evaluate the modified value of price per unit energy, $p_m^{modified}$
  $p_m^* = p_m^{modified}$
end

Table 4.1: Simulation Parameters: HoMeS

Parameter	**Value**
Simulation area	20×20 km^2
Number of micro-grids	10
Number of Customers	1000
Minimum requested energy for appliances	90 MWh
Maximum requested energy for appliances	100 MWh
Customer's minimum storage capacity	35 MWh
Customer's maximum storage capacity	65 MWh
Customer's minimum residual stored energy	20 KWh
Minimum renewable energy generated	500 MWh
Maximum renewable energy generated	650 MWh
Generation cost	10-20 USD/MWh

4.3.2 Benchmarks

The performance of the proposed scheme, HoMeS, is evaluated by comparing it with other energy management policies, such as the economics of electric vehicle charging

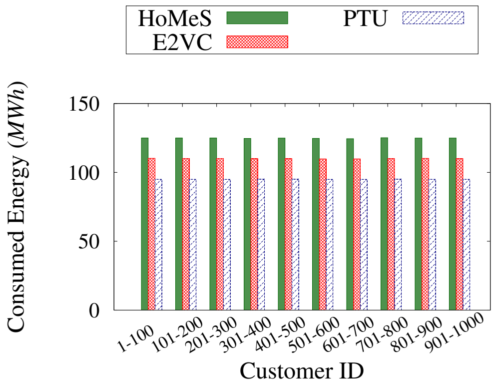


Figure 4.5: Energy consumption of the customers

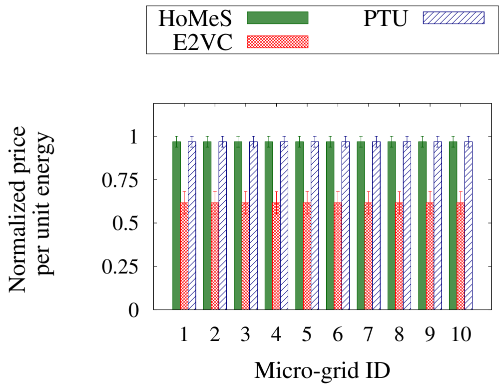


Figure 4.6: Price decided by the micro-grids

(E2VC) [4] approach, and the price taking user (PTU) [38] approach.

We refer to these different energy management policies as HoMeS, E2VC, and PTU, through the rest of the paper. Tushar *et al.* [4] proposed a game theoretic approach with storage. Samadi *et al.* [38] proposed a home energy management system without storage. Though E2VC [4] has been used for energy management system of the PHEVs, its authors did not consider any mobility model for the PHEVs. Thus, we can improve the efficiency in the home energy management system by using our proposed approach, HoMeS, over E2VC and PTU.

4.3.3 Performance Metrics

- *Real-time pricing policy for storage*: The price is decided by the micro-grids based on the real-time communication with the customers, i.e., the information of the consumed energy by the customers, the micro-grids decide the price per unit energy.

- *Utility of the customers*: Each customer tries to maximize the payoff of its utility function that symbolizes the energy consumption with optimal price. A customer tries to maximize its utility by maximizing its energy consumption, while satisfying the inequality given in Equation (4.44).

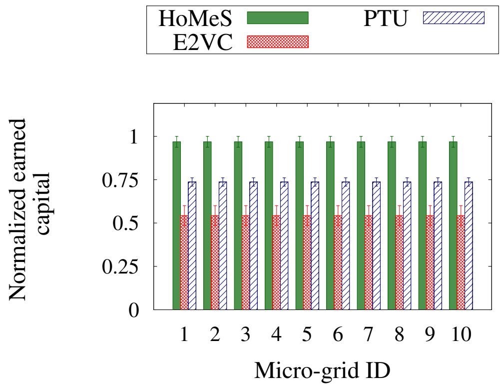


Figure 4.7: Earned Capital of the micro-grids

- *Consumed energy by the customers*: The amount of energy to be consumed for the appliances is decided on a day-ahead basis, whereas the actual energy to be consumed by each customer is decided by the customers in real-time. So, effectively, the energy consumed by the customers is decided by real-time home energy management system, and the lower limit of the consumed energy is decided *a priori*.

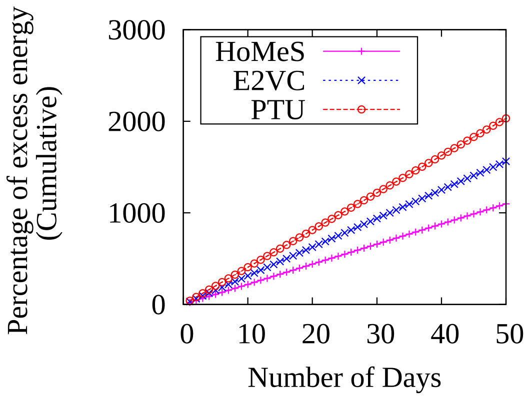


Figure 4.8: Excess energy

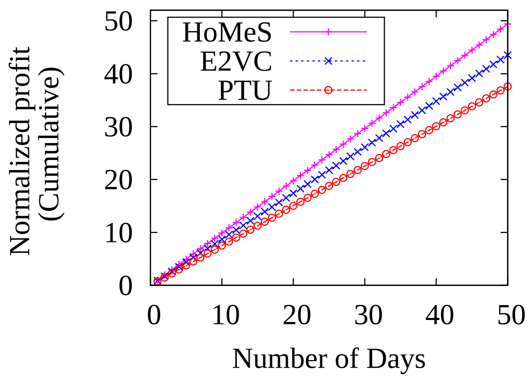


Figure 4.9: Profit over days

4.3.4 Results and Discussions

For the sake of simulation, we assume that each micro-grid calculates the real-time supply and demand in every 10 seconds interval.

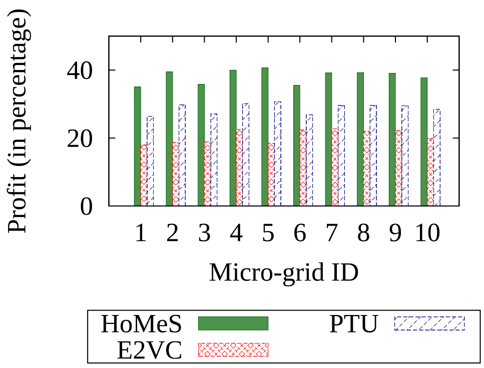


Figure 4.10: Profit of micro-grids

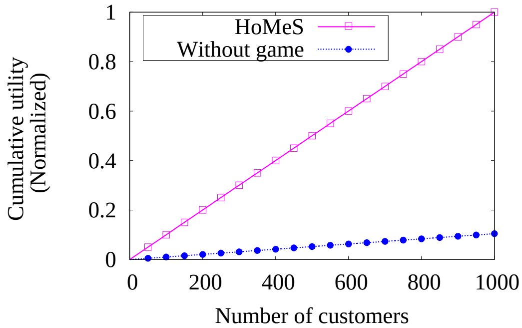


Figure 4.11: Utility of customers

In Figure 4.5, the comparison of consumed energy, e_n, by each customer, n, is the summation of requested energy for the appliances, a_n, and the requested energy for storage, x_n. The energy consumption for the appliances is same for HoMeS, E2VC, and PTU. The customer decide the energy to be requested for storage on a real-time basis. Figure 4.5 shows that the consumed energy our proposed method, i.e., HoMeS, is 30% and 55% higher than E2VC and PTU, respectively. Therefore, the energy generated by the micro-grids is more adequately utilized using HoMeS, than using the other approaches — E2VC and PTU.

In Figure 4.6, the comparison of price per unit energy is shown. The price per unit energy using E2VC is lower than using HoMeS and PTU. However, the capital earned by selling the generated energy by the micro-grids is much higher using HoMeS, than using other approaches — E2VC and PTU, as shown in Figure 4.7. Therefore, each micro-grid, using HoMeS, earns higher than using E2VC and PTU.

Figure 4.8 shows that the percentage of excess energy, generated by the micro-grids, is also lower for HoMeS than E2VC and PTU. Therefore, Figure 4.8 re-establishes the fact that the energy generated by the micro-grids is more adequately utilized using HoMeS than using E2VC and PTU.

Figure 4.9 shows that the overall profit of the micro-grids in a coalition is 15.39% and 30.79% higher using HoMeS, than using E2VC and PTU, respectively. In Figure 4.9, the cumulative profit of the micro-grids is shown. On the other hand, Figure 4.10 shows the profit of each micro-grid, individually. Therefore, each micro-grid, using HoMeS, gets higher profit than using E2VC and PTU, and the overall profit of the coalition formed by the micro-grids is also higher using HoMeS than using other approaches, i.e., E2VC and PTU.

Figure 4.11 shows the utility of the customers, which combines the effect of utilization of energy generated by the micro-grids, energy consumption of the customers with optimum price, and the profit of the micro-grids, varies significantly using HoMeS, which uses the multiple leader multiple follower Stackelberg game theoretic approach, than using a different approach. Therefore, with the increase in the number of customers, the utility of the micro-grids is much higher using HoMeS than using any non-game theoretic approach.

4.4 Concluding Remarks

In this paper, we formulated a multiple leader multiple follower Stackelberg game theoretic approach, named HoMeS, to study the problem of distributed home energy management system with storage facilities. Using the proposed approach, we showed how distributed energy management system for the home appliances in the presence of storage can be done with the optimum value of the energy requested by the customers, and the optimum price decided by each micro-grid. The simulation results show that the proposed approach yields improved results.

Future extension of this work includes understanding how the energy distribution can be improved by exchanging less number of messages, so that the delay in energy supply can be reduced, and the service provided by the micro-grids to the customers can be improved, thereby improving the utilization of the micro-grids.

Chapter 5

Distributed Energy Management System in Mobile Smart Grid

In this chapter, we present two energy management schemes – *Energy Trading Network Topology Control* (*ENTRANT*), a cloud-free scheme, and *Virtual Energy Cloud Topology Control* (*VELD*), a cloud-based scheme. Both these schemes are suitable for plug-in Hybrid Electric Vehicles (PHEVs) in mobile smart grid environment.

This chapter consists of six sections. The design of ENTRANT is presented in Section 5.1. Section 5.2 discusses the performance evaluation of ENTRANT scheme with respect to the benchmark schemes. We, then, present VELD in Section 5.3. In Section 5.4, the performance evaluation of VELD is discussed. Finally, Section 5.5 concludes this chapter.

5.1 Energy Trading Network Topology Control (ENTRANT) Scheme

5.1.1 System Model

We consider an energy trading network in smart grid consisting of multiple micro-grids and several *consumers*. The consumers, i.e., the customers and the plug-in hybrid vehi-

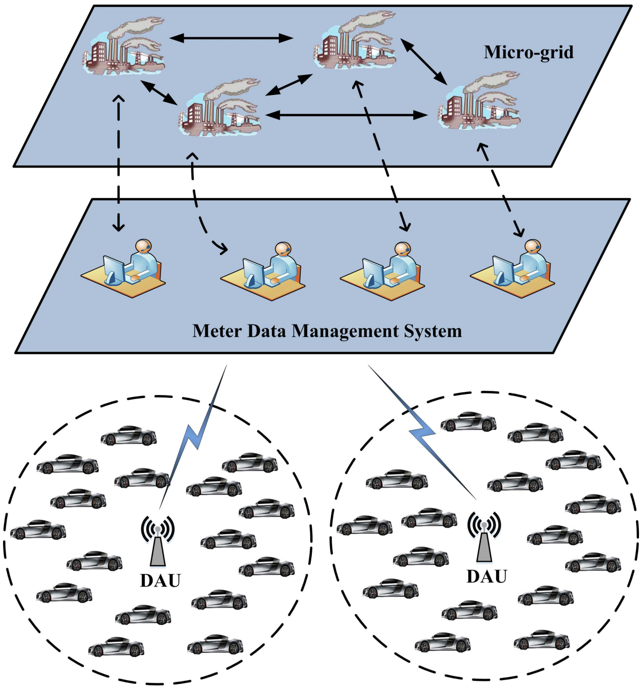


Figure 5.1: Schematic diagram of energy trading network

cles (PHEVs), may request for energy service to any micro-grid from the set of available micro-grids in a coalition [36]. After meeting the energy requirements of the customers connected to the micro-grids, each micro-grid decides to sell the excess amount of generated energy to the PHEVs, which are available in the coalition at that time instant in mobile smart grid. The schematic diagram of the energy trading network for mobile smart grid environment is shown in Figure 5.1. We consider that each micro-grid has a communicating device, i.e., meter data management system (MDMS). With the help of MDMS, each micro-grid sends information to the data aggregation points (DAPs) using wide area network (WAN). Each DAP communicates with the smart meters, which are associated with the consumers, i.e., the customers and the PHEVs, using neighborhood area network (NAN). The appliances at the consumer-end send their energy-consumption informations to the smart meters using home area network (HAN).

We consider that at each time slot $t \in \mathcal{T}$, where $\mathcal{T}$ is the set of time slots in a day, in a coalition, each consumer $n \in \mathcal{N}(t)$, where $\mathcal{N}(t)$ is the set of the consumers at time slot t, consumes $d_n(t)$ amount of energy. At each time slot $t \in \mathcal{T}$, the set of consumers, $\mathcal{N}(t)$, is combination of the set of customers ,$\mathcal{N}^c(t)$, who are static in nature, and the set of PHEVs ,$\mathcal{N}^p(t)$, which are mobile in nature. Mathematically,

$$\mathcal{N}(\cdot) = \mathcal{N}^c(\cdot) \cup \mathcal{N}^p(\cdot) \tag{5.1}$$

We consider that at time slot $t \in \mathcal{T}$, each micro-grid $m \in \mathcal{M}$, where $\mathcal{M}$ is the set of micro-grids in the coalition, generates $\mathcal{G}_m(t)$ amount of energy. After meeting the energy demand of the set of connected customers, $\mathcal{N}^c_m(t)$, i.e., $\mathcal{C}_m(t)$, each micro-grid m has $\mathcal{E}x_m(t)$ amount of excess energy, as shown below:

$$\mathcal{E}x_m(\cdot) = \mathcal{G}_m(\cdot) - \mathcal{C}_m(\cdot) \tag{5.2}$$

where $\mathcal{C}_m(\cdot) = \sum_{n \in \mathcal{N}^c_m(\cdot)} d^c_n(\cdot)$, $\mathcal{N}^c_m(\cdot) \subseteq \mathcal{N}^c(\cdot)$, and $d^{(n)}_c(\cdot)$ is the amount of energy requested by each customer $n \in \mathcal{N}^c_m(\cdot)$. The excess amount of generated energy by each micro-grid m, i.e., $\mathcal{E}x_m(\cdot)$, must satisfy the following constraint:

$$\mathcal{E}x_m(\cdot) \geq 0, \quad \forall m \in \mathcal{M} \tag{5.3}$$

The amount of excess energy generated by each micro-grid $m \in \mathcal{M}$, i.e., $\mathcal{E}x_m(\cdot)$, is used for serving a subset of the available PHEVs, $\mathcal{N}^p(\cdot)$, i.e., $\mathcal{N}^p_m(\cdot)$, in the coalition. Mathematically,

$$\mathcal{N}^p_m(\cdot) \subseteq \mathcal{N}^p(\cdot) \tag{5.4}$$

Each PHEV $n \in \mathcal{N}^p(\cdot)$ has a requirement of d^p_n amount of energy. To fulfill the energy requirement, each PHEV n chooses a micro-grid m having $\mathcal{E}x_m(\cdot)$ amount of generated energy. Therefore, the total amount of energy requested to each micro-grid m by the PHEVs $\mathcal{N}^p_m(\cdot)$, where $\mathcal{N}^p_m(\cdot)$ is the set of PHEVs demanded energy from micro-grid

$m \in \mathcal{M}$ and $\mathcal{N}_m^p(\cdot) \subseteq \mathcal{N}^p(\cdot)$, must satisfy the following constraint:

$$\mathcal{E}x_m(\cdot) \geq \sum_{n=1}^{n \in \mathcal{N}_m^p(\cdot)} d_n^p(\cdot) \tag{5.5}$$

On the other hand, based on the total demanded amount of energy, each micro-grid $m \in \mathcal{M}$ decides the *price coefficient*, $p_m(\cdot)$, i.e., the multiplying factor of the price per unit energy to be paid by the set of connected PHEVs, $\mathcal{N}_m^p(\cdot)$. The price coefficient of each micro-grid m, i.e., $p_m(\cdot)$, is defined in Definition 8.

Definition 8. *The price coefficient of each micro-grid m, i.e., $p_m(\cdot)$, is a function of the ratio of the amount of energy requested to micro-grid m, i.e., $\sum_{n=1}^{n \in \mathcal{N}_m^p(\cdot)} d_n^p(\cdot)$, and the excess amount of generated energy by micro-grid m, i.e., $\mathcal{E}x_m(\cdot)$. Mathematically,*

$$\begin{aligned} p_m(\cdot) &= f\left(\sum_{n=1}^{n \in \mathcal{N}_m^p(\cdot)} \tilde{d}_n^p(\cdot), \mathcal{E}x_m(\cdot)\right) \\ &= \frac{\sum\limits_{n=1}^{n \in \mathcal{N}_m^p(\cdot)} \tilde{d}_n^p(\cdot)}{\mathcal{E}x_m(\cdot)} \end{aligned} \tag{5.6}$$

With the increase in the number of connected PHEVs with micro-grid m, the amount of energy requested to micro-grid m increases. Hence, the price coefficient increases. On the other hand, the quality of energy service provided by the micro-grids decreases with the increase in the amount of requested energy by the PHEVs. The *satisfaction factor* of the micro-grid m, i.e., $s_m(\cdot)$, also increases with the decrease in the remaining amount of generated energy. We define the satisfaction factor of micro-grid $m \in \mathcal{M}$ in Definition 9.

Definition 9. *The satisfaction factor of micro-grid $m \in \mathcal{M}$, $s_m(\cdot)$, is defined by the ratio of remaining amount of excess energy, i.e., $\mathcal{E}x_m^{res}(\cdot)$, and the excess amount of generated energy after fulfilling the energy demand of the customers, $\mathcal{N}_m^c(\cdot)$, i.e., $\mathcal{E}x_m(\cdot)$.*

Mathematically,

$$\begin{aligned} s_m(\cdot) &= \frac{\mathcal{E}x_m^{res}(\cdot)}{\mathcal{E}x_m(\cdot)} \\ &= \frac{\mathcal{E}x_m(\cdot) - \sum\limits_{n=1}^{n\in\mathcal{N}_m^p(\cdot)} d_n^p(\cdot)}{\mathcal{E}x_m(\cdot)} \\ &= 1 - \frac{\sum\limits_{n=1}^{n\in\mathcal{N}_m^p(\cdot)} d_n^p(\cdot)}{\mathcal{E}x_m(\cdot)} \end{aligned} \tag{5.7}$$

Mobility Model for Mobile Smart Grid Environment: We assume that the PHEVs follow the mobility pattern of Gauss-Markov mobility model [7, 39]. According to the mobility model, each PHEV n updates its location periodically, after crossing a threshold distance. The position and the velocity are considered to be correlated with time, i.e., the position of each PHEV n at time instant τ depends on the location and velocity of the PHEV at previous time instant $(\tau-1)$. We consider that the PHEVs move in a two-dimensional plane. Hence, the Gauss-Markov mobility model is represented as [39]:

$$\vec{\upsilon}_n(\tau) = \upsilon_n^x(\tau)\hat{i} + \upsilon_n^y(\tau)\hat{j} \tag{5.8}$$

where $\upsilon_n^x(\cdot)$ and $\upsilon_n^y(\cdot)$ are the velocity components of each PHEV n towards $\mathbf{x}$ and $\mathbf{y}$ direction. We define $\vec{\upsilon}_n(\tau)$ as follows:

$$\vec{\upsilon}_n(\tau) = \alpha\upsilon_n(\tau-1) + (1-\alpha)\mu + \sigma\sqrt{1-\alpha^2}\mathcal{W}(\tau-1) \tag{5.9}$$

where $\vec{\upsilon}_n(\tau)$ denotes the velocity vector of PHEV n at time τ, α is the variance over time, μ signifies the mean of the velocity, σ denotes the standard deviation, and $\mathcal{W}(\cdot)$ is an uncorrelated Gaussian process with zero mean with unit variance and is independent.

Therefore, we define the components of $\vec{\upsilon}_n(\cdot)$, i.e., $\upsilon_n^x(\tau)$ and $\upsilon_n^y(\tau)$ in Equation (5.8), as follows:

$$\upsilon_n^x(\tau) = \alpha \upsilon_n^x(\tau-1) + (1-\alpha)\mu^x + \sigma^x \sqrt{1-\alpha^2}\mathcal{W}^x(\tau-1) \tag{5.10}$$

$$\upsilon_n^y(\tau) = \alpha \upsilon_n^y(\tau-1) + (1-\alpha)\mu^y + \sigma^y \sqrt{1-\alpha^2}\mathcal{W}^y(\tau-1) \tag{5.11}$$

We define the direction of each PHEV n, i.e., $\theta_n(\cdot)$, as follows:

$$\theta_n(\cdot) = \tan^{-1}\left(\frac{\upsilon_n^y(\cdot)}{\upsilon_n^x(\cdot)}\right) \tag{5.12}$$

To design the mobility model, we consider that α is a constant, and $0 \leq \alpha \leq 1$.

Communication Model for Mobile Smart Grid Environment: We assume that the communication topology between the micro-grids and the PHEVs is a wireless mesh network (WMN). We use the IEEE 802.11b protocol for communication between the micro-grids and the PHEVs. Initially, each PHEV $n \in \mathcal{N}^p(\cdot)$ sends a request message having information of the amount of required energy. The request message format of each PHEVs is shown in Figure 5.2(a).

ReqMsgType	PHEV_ID	ReqEnergy	FinalSelectFlag
1 byte	4 byte	2 byte	1 byte

(a) Request message format

AckMsgType	MG_ID	Price	AckFlag
1 byte	4 byte	2 byte	1 byte

(b) Reply message format

Figure 5.2: Message formats using ENTRANT scheme

Based on the total amount of requested energy, each micro-grid decides the price coefficient, $p_m(\cdot)$, and the price per unit energy to be paid by each PHEV. The reply message format of each micro-grid is shown in Figure 5.2(b).

5.1.2 An Energy Trading Network Topology Control Game

5.1.2.1 Why Multi-Leader Multi-Follower Stackelberg Game?

In an energy trading network, each PHEV tries to charge its battery by consuming high amount of energy. On the other hand, each micro-grid tries to maximize its revenue by deciding an optimum price per unit energy. In the proposed scheme, ENTRANT, we considered that each PHEV can communicate with multiple micro-grids. In such a scenario, the PHEVs initiate the energy trading process by broadcasting the amount of energy to be consumed, and the micro-grids follow the process by replying with the information of price per unit energy. Thereby, we use *multi-leader multi-follower Stackelberg game* [40], where the PHEVs act as leaders, and the micro-grids act as followers.

5.1.2.2 Game Formulation

To study the interaction between the PHEVs and the micro-grids in *energy trading network topology control* (ENTRANT), we use a non-cooperative multi-leader multi-follower Stackelberg game theoretic approach [40]. In ENTRANT, each PHEV acts as a leader, and needs to decide the amount of energy to be requested to the selected micro-grid. The micro-grids are the followers, which decide the price per unit energy based on the amount of requested energy by the leaders, i.e., the PHEVs. The components of the proposed scheme, ENTRANT, are as follows:

1. Each PHEV $n \in \mathcal{N}^p(\cdot)$ selects a micro-grid $\tilde{m}$ from the set of available micro-grids,i.e., $\mathcal{M}$, within the communication range.

2. Each PHEV $n \in \mathcal{N}^p(\cdot)$ decides the amount of energy to be requested, i.e., $d_n^p(\cdot)$, to the selected micro-grid $\tilde{m} \in \mathcal{M}$, when each micro-grid m has $\mathcal{E}x_m(\cdot)$ amount of

excess energy after meeting the requirement of the set of connected customers, i.e., $\mathcal{N}^c(\cdot)$.

3. Based on the requested amount of energy by the PHEVs, $\mathcal{N}^p_m(\cdot)$, each micro-grid $m \in \mathcal{M}$ decides the price coefficient $p_m(\cdot)$ using Equation (5.6).

Utility function of a PHEV: In the proposed scheme, ENTRANT, the utility function of each PHEV $n \in \mathcal{N}^p(\cdot)$, i.e., $\mathbb{U}^{\tilde{m}}_n(\cdot)$, represents the satisfaction factor PHEV n by consuming $d^p_n(\cdot)$ amount of energy from micro-grid $\tilde{m}$. The satisfaction factor of each PHEV $n \in \mathcal{N}^p(\cdot)$ is defined in Definition 10.

Definition 10. *The satisfaction factor of each PHEV $n \in \mathcal{N}^p(\cdot)$ is evaluated with the ratio of the amount of energy requested to the selected micro-grid $\tilde{m} \in \mathcal{M}$, i.e., $d^p_n(\cdot)$, and the maximum amount of energy required, i.e., $\max d^p_n(\cdot)$ defined as below:*

$$\max d^p_n(\cdot) = E^{max}_n - E^{res}_n(\cdot) \tag{5.13}$$

where E^{max}_n and $E^{res}_n(\cdot)$ are the maximum battery capacity and the residual energy of each PHEV $n \in \mathcal{N}^p(\cdot)$, respectively.

We define the rules for utility calculation of each PHEV n as follows:

1. The utility function of each PHEV n, $\mathbb{U}^{\tilde{m}}_n(\cdot)$, is considered to be a non-decreasing function. Hence, in each time-slot, with the increase in the amount of consumed energy $d^p_n(\cdot)$, i.e., $\bar{d}^p_n(\cdot) = \tilde{d}^p_n(\cdot) - d^p_n(\cdot)$, the satisfaction factor of each PHEV n becomes higher. Here, $\tilde{d}^p_n(\cdot)$ and $d^p_n(\cdot)$ are the new and the modified recent amount of requested energy by PHEV n to the selected micro-grid $\tilde{m} \in \mathcal{M}$. Mathematically,

$$\frac{\delta \mathbb{U}^{\tilde{m}}_n(\cdot)}{\delta \tilde{d}^p_n(\cdot)} \geq 0 \tag{5.14}$$

2. The marginal utility of each PHEV n is considered to be decreasing, as with increase in consumed energy after reaching equilibrium state, the PHEVs will be over powered or the PHEVs have to pay a huge amount. Mathematically,

$$\frac{\delta^2 \mathbb{U}_n^{\tilde{m}}(\cdot)}{\delta[\tilde{d}_n^p(\cdot)]^2} < 0 \tag{5.15}$$

3. The amount of energy to be consumed reduces with the increase in price coefficient. Therefore, the utility value of $\mathbb{U}_n^{\tilde{m}}(\cdot)$ reduces with the increase in price coefficient of the selected micro-grid $\tilde{m} \in \mathcal{M}$. Mathematically,

$$\frac{\delta \mathbb{U}_n^{\tilde{m}}(\cdot)}{\delta p_{\tilde{m}}(\cdot)} < 0 \tag{5.16}$$

Therefore, for each PHEV $n \in \mathcal{N}^p(\cdot)$, we define the revenue function, $\mathbb{R}_n^p(\cdot)$, and the cost function, $\mathbb{C}_n^p(\cdot)$, in Definitions 11 and 12, respectively. We consider that the utility function, $\mathbb{U}_n^{\tilde{m}}(\cdot)$, of each PHEV n is defined as the difference of revenue function, $\mathbb{R}_n^p(\cdot)$, and the cost function, $\mathbb{C}_n^p(\cdot)$. Mathematically,

$$\mathbb{U}_n^{\tilde{m}}(\cdot) = \mathbb{R}_n^p(\cdot) - \mathbb{C}_n^p(\cdot) \tag{5.17}$$

Definition 11. *The revenue function of each PHEV n, i.e., $\mathbb{R}_n^p(\cdot)$, is considered to be a concave function. Therefore, we define the revenue function, $\mathbb{R}_n^p(\cdot)$, as follows:*

$$\begin{aligned} \mathbb{R}_n^p(\cdot) &= E_n^{max} \tan^{-1}\left(e^{-\frac{\bar{d}_n^p(\cdot)}{\tilde{d}_n^p(\cdot)}}\right) \\ &= E_n^{max} \tan^{-1}\left(e^{-\frac{\tilde{d}_n^p(\cdot) - d_n^p(\cdot)}{\tilde{d}_n^p(\cdot)}}\right) \end{aligned} \tag{5.18}$$

Definition 12. *The cost function of PHEV $n \in \mathcal{N}^p(\cdot)$, i.e., $\mathbb{C}_n^p(\cdot)$, is considered to be a linear function having linear coefficient of the selected micro-grid $\tilde{m}$, i.e., price coefficient* *defined in Equation (5.6). Mathematically,*

$$\begin{aligned}\mathbb{C}_n^p(\cdot) &= p_{\tilde{m}}(\cdot)\tilde{d}_n^p(\cdot) \\ &= f\left(\frac{\sum_{n=1}^{n\in\mathcal{N}_m^p(\cdot)} e_n^p(\cdot)}{\mathcal{E}x_m(\cdot)}\right) e_n^p(\cdot) \\ &= \frac{\sum_{n=1}^{n\in\mathcal{N}_m^p(\cdot)} e_n^p(\cdot)}{\mathcal{E}x_m(\cdot)} e_n^p(\cdot) \qquad (5.19)\end{aligned}$$

Therefore, using Definitions 11 and 12, we redefine the utility function $\mathbb{U}_n^{\tilde{m}}(\cdot)$ as follows:

$$\mathbb{U}_n^{\tilde{m}}(\cdot) = E_n^{max}\tan^{-1}\left(e^{-\frac{\tilde{d}_n^p(\cdot)-d_n^p(\cdot)}{\tilde{d}_n^p(\cdot)}}\right) - p_{\tilde{m}}(\cdot)\tilde{d}_n^p(\cdot) \qquad (5.20)$$

Utility function of a micro-grid: In the proposed scheme, ENTRANT, each micro-grid $m \in \mathcal{M}$ makes profit by selling the excess amount of energy to the set of connected PHEVs, i.e., $\mathcal{N}^p(\cdot)$. Each micro-grid m calculates the price coefficient, $p_m(\cdot)$, based on the amount of requested energy by the PHEVs $\mathcal{N}_m^p(\cdot)$, i.e., $\sum_{n=1}^{n\in\mathcal{N}_m^p(\cdot)} \tilde{d}_n^p(\cdot)$. The utility of each micro-grid $m \in \mathcal{M}$, i.e., $\mathbb{B}_m^p(\cdot)$, represents the profit of each micro-grid m by selling the excess amount of energy. Therefore, we define the utility function, $\mathbb{B}_m^p(\cdot)$, of each micro-grid $m \in \mathcal{M}$ as follows:

$$\mathbb{B}_m^p(\cdot) = [p_m(\cdot) - c_m(\cdot)] \sum_{n=1}^{n\in\mathcal{N}_m^p(\cdot)} \tilde{d}_n^p(\cdot) \qquad (5.21)$$

where $c_m(\cdot)$ is the generation-cost coefficient of each micro-grid $m \in \mathcal{M}$.

In ENTRANT, each PHEV $n \in \mathcal{N}$ and each micro-grid $m \in \mathcal{M}$ try to maximize the payoff of the utility function, individually, following the proposed non-cooperative game theoretic approach.

5.1.2.3 Existence of Generalized Nash Equilibrium Solution

We determine the existence of generalized Nash equilibrium solution using *variational inequality* (VI) [41] as shown in Theorem 5.

Theorem 5. *Given a fixed amount of energy to be consumed by each PHEV, there exists a generalized Nash equilibrium solution, as there exists a variational inequality solution, for each PHEV n and each micro-grid m. Hence, each PHEV selects micro-grid $\tilde{m}$ over micro-grid m and each micro-grid decides the price coefficient, $p_m(\cdot)$, while satisfying the following constraints:*

$$\mathbb{U}_n^{\tilde{m}}(\cdot) \geq \mathbb{U}_n^m(\cdot), \qquad \textit{where } \forall m, \tilde{m} \in \mathcal{M} \tag{5.22}$$

$$\mathbb{B}_m^{p*}(\cdot) \geq \mathbb{B}_m^p(\cdot) \tag{5.23}$$

where $\mathbb{B}_m^{p*}$ is the utility function of micro-grid m at Nash equilibrium point.

Proof. The utility function of each PHEV n, i.e., $\mathbb{U}_n^m(\cdot)$, and the utility function of each micro-grid m, i.e., $\mathbb{B}_m^p(\cdot)$, need to be maximized. Hence, applying Karush-Kuhn-Tucker (KKT) conditions, we get:

$$\begin{gathered}\nabla_n \mathbb{U}_n^m(\cdot) = \nabla_n \lambda_n(\cdot)\left[\mathcal{E}x_m(\cdot) - \sum_{n=1}^{n\in\mathcal{N}_m^p(\cdot)} \tilde{d}_n^p(\cdot)\right], \\ \nabla_n \lambda_n(\cdot)\left[\mathcal{E}x_m(\cdot) - \sum_{n=1}^{n\in\mathcal{N}_m^p(\cdot)} \tilde{d}_n^p(\cdot)\right] = 0, \text{ and } \lambda_n(\cdot) > 0\end{gathered} \tag{5.24}$$

where $\lambda_n(\cdot)$ is the Lagrangian constant. Considering an overall utility function, we get:

$$\boldsymbol{\nabla}\boldsymbol{\mathcal{U}}^m(\cdot) - \boldsymbol{\nabla}\boldsymbol{\lambda}(\cdot)[\mathcal{E}x_m(\cdot) - \sum_{n=1}^{n\in\mathcal{N}_m^p(\cdot)} \tilde{d}_n^p(\cdot)] = 0 \tag{5.25}$$

where $\boldsymbol{\mathcal{U}}^m(\cdot) = \sum \mathbb{U}_n^m(\cdot)$, and $\boldsymbol{\lambda} \triangleq \lambda_1 \triangleq \cdots \triangleq \lambda_{|\mathcal{N}_m^p(\cdot)|}$. Hence, We get the Jacobian matrix of $\boldsymbol{\mathcal{U}}^m(\cdot)$ as follows:

$$\boldsymbol{J\mathcal{U}}^m(\cdot) = \begin{bmatrix} K_1 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & K_n & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & K_{|\mathcal{N}_m^p(\cdot)|} \end{bmatrix} \tag{5.26}$$

where $K_n = \frac{E_n^{max} e_n^p}{[\tilde{d}_n^p]^2 + [\bar{d}_n^p]^2} e^{-\left(\frac{\bar{d}_n^p}{\tilde{d}_n^p}\right)} - p_m(\cdot)$.

$\boldsymbol{J\mathcal{U}}^m(\cdot)$ is a positive diagonal matrix, as we assume that the amount of requested energy for each PHEV n is non-negative. Therefore, we conclude that there exists variational inequality solution, i.e., generalized Nash equilibrium solution. □

5.1.2.4 Algorithms

In order to reach the equilibrium of energy trading networks using the proposed scheme, ENTRANT, the PHEVs and the micro-grids take their respective strategies, while incurring marginal communication overhead. In this work, we propose two different algorithms — (a) for PHEV, and (b) for micro-grid, as shown in Algorithms 5.1 and 5.2, respectively. Each PHEV n decides the amount of energy to be requested to the selected micro-grid using Algorithm 5.1. On the other hand, each micro-grid m calculates the price coefficient based on the amount of energy requested by the connected PHEVs using Algorithm 5.2, and broadcasts the calculated price coefficient, $p_m(\cdot)$.

Algorithm 5.1: ENTRANT Algorithm for PHEV

Inputs : E_n^{max}: Maximum battery capacity of PHEV n
$E_n^{res}(\cdot)$: Residual energy of PHEV n
$d_n^p(\cdot)$: Current value of request energy by PHEV n
$p_m(\cdot)$: price co-efficient of each micro-grid $m \in \mathcal{M}$
Outputs: $\tilde{d}_n^p(\cdot)$: Modified value of request energy by PHEV n
$\tilde{m}$: Selected micro-grid for energy supply

Calculate $\tilde{d}_n^p(\cdot)$ using following equation:
$\tilde{d}_n^p(\cdot) = (1 + \frac{E_n^{res}(\cdot)}{E_n^{max}})d_n^p(\cdot)$
// $\frac{E_n^{res}(\cdot)}{E_n^{max}}$ `is allowable change in energy request`
Calculate $\mathbb{U}_n^m(\cdot)$, where $\forall m \in \mathcal{M}$
if $\max \mathbb{U}_n^m(\tau) > \mathbb{U}_n^{\tilde{m}}(\tau - 1)$ **then**
  if $\mathbb{U}_n^{\tilde{m}}(\cdot) \geq \mathbb{U}_n^m(\cdot)$ **then**
    Request micro-grid $\tilde{m}$ to supply $\tilde{d}_n^p(\cdot)$ amount of energy
  else
    Request micro-grid m to supply $\tilde{d}_n^p(\cdot)$ amount of energy
  end
else
  $\tilde{d}_n^p(\cdot) = d_n^p(\cdot)$
  // `Nash Equilibrium reached`
  Request previously selected micro-grid $\tilde{m}$ to supply $\tilde{d}_n^p(\cdot)$ amount of energy
  // `Here,` $\tilde{m}$ `is the selected micro-grid in the previous iteration`
end
return

5.2 Performance Evaluation

5.2.1 Simulation Parameters

For performance evaluation, we consider randomly generated positions of the micro-grids, and the initial positions of the PHEVs on a MATLAB simulation platform, as shown in Table 5.1. In this work, we assumed that each PHEV follows the Gauss-Markov mobility model. Therefore, we calculated the position of the PHEVs using Equations (5.8), (5.10), and (5.11). We considered randomly generated values for maximum battery capacity of the PHEVs.

In a coalition, each residential customer, i.e., home-users, decides his/her energy

Algorithm 5.2: ENTRANT Algorithm for micro-grid

Inputs : $\tilde{d}_n^p(\cdot)$: Amount of request energy by PHEV n
$c_m(\cdot)$: Generation-cost coefficient of micro-grid m
$\mathcal{E}x_m(\cdot)$: Excess amount of generated energy
Output: $p_m(\cdot)$: Price coefficient of micro-grid m
Calculate $p_m(\cdot)$ using Equation (5.6)
if $\mathbb{B}_m^p(\tau) == \mathbb{B}_m^p(\tau - 1)$ **then**
    `// Nash Equilibrium reached`
end
Broadcast the price coefficient $p_m(\cdot)$
return

Table 5.1: Simulation Parameters: ENTRANT

Parameter	Value
Simulation area	20 km×20 km
Number of micro-grids	4
Number of PHEVs	500
Maximum battery capacity	35-65 MWh
Residual energy of each PHEV	>10 MWh
Excess energy per micro-grid	99 MWh

consumption profile *a priori*. Hence, based on the amount of energy generated by the micro-grids using renewable energy resources, each micro-grid calculates the amount of excess energy generated. For the sake of simulation, we considered that each micro-grid has a fixed amount of excess energy, i.e., 90 MWh [4], and the residual energy at the PHEV-end is generated randomly. Hence, based on the amount of requested energy by the connected PHEVs, each micro-grid decides the price coefficient, and the price to be paid by each customer.

5.2.2 Benchmark

The performance of the proposed scheme, energy trading network topology control (ENTRANT), is evaluated by comparing the results with other energy trading policies, such as the economics of electric vehicle charging (E2VC) [4], the energy trading without any game-theoretic approach (WoENT).

We refer to these different energy trading policies as ENTRANT, E2VC, and WoENT, through the rest of the work. In E2VC [4], the authors proposed a non-cooperative game theoretic approach. Though the authors did not consider the choice of multiple micro-grids for each PHEV available in the coalition. In WoENT, we considered that each PHEV chooses the appropriate micro-grid from the available micro-grids based on the minimum distance to be traveled. Thus, we can improve the satisfaction factor of the PHEVs, and the energy load to each micro-grid using the proposed scheme, ENTRANT, than using other approaches, i.e., E2VC and WoENT.

5.2.3 Performance Metrics

1. *Consumed energy per iteration*: The utilization of excess amount of energy generated can be visualized with the amount of consumed energy per iteration. In each iteration, with the increase in consumed energy by the PHEVs, the satisfaction factor of the micro-grids increases, as higher amount of energy is consumed by the PHEVs.

2. *Energy price per micro-grid*: Each PHEV wants to consume energy with lower price. However, if the energy-load to any micro-grid becomes higher, the price per unit energy of that micro-grid becomes high, while using dynamic pricing strategy. Hence, to utilize the excess amount of generated energy of each micro-grid, we need to distribute the energy request such that the price per unit energy becomes moderated, i.e., neither too high nor too low.

3. *Price paid per PHEV*: Based on the price per unit energy decided by the micro-grids and amount of energy to consumed by each PHEV, each micro-grid decides the amount of billing for each PHEV. However, the price decided by the micro-grids and the amount of energy requested by each PHEV are interdependent. If the amount of energy requested by each micro-grid becomes too high, the price becomes high. As a result, each PHEV needs to re-decide the amount of energy

to consumed and request the selected micro-grid. On the other hand, if the price per unit energy decided by the micro-grid becomes too low, each PHEV requests high amount of energy. Therefore, the price per unit energy becomes high.

4. *Satisfaction factor of PHEVs*: Satisfaction factor of each PHEV is defined as the ratio of the amount of energy consumed, and the total demand of a PHEV. Hence, higher satisfaction factor signifies higher portion of required energy is served by the micro-grid. Each PHEV behaving rationally tries to maximize its satisfaction factor by consuming higher amount of energy.

5. *Quality of energy service*: We consider that higher utility value signifies higher quality of energy service. Therefore, each PHEV tries to get higher quality of energy service by maximizing the payoff of the its utility function.

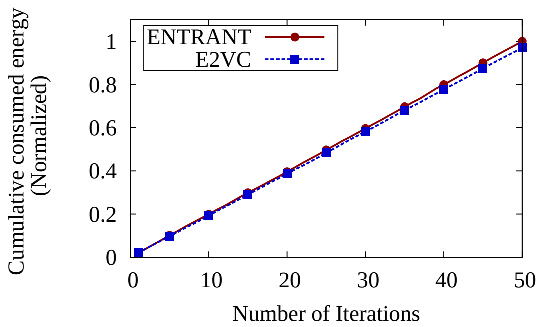


Figure 5.3: Consumed Energy per iteration

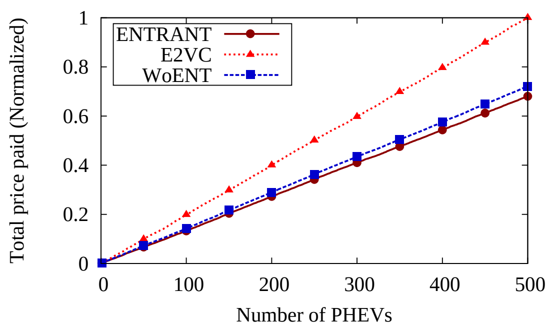


Figure 5.4: Price paid by the PHEVs

5.2.4 Results and Discussions

For simulation purpose, we assume that each micro-grid calculates the real-time supply and demand in every 10 seconds interval. Each micro-grid has 99 MWh excess amount of energy that can be sold to the available PHEVs within the coalition. Hence, each micro-grid makes profit by selling the excess amount of energy. On the other hand, the maximum energy storage capacity of the PHEVs are chosen randomly from a range of

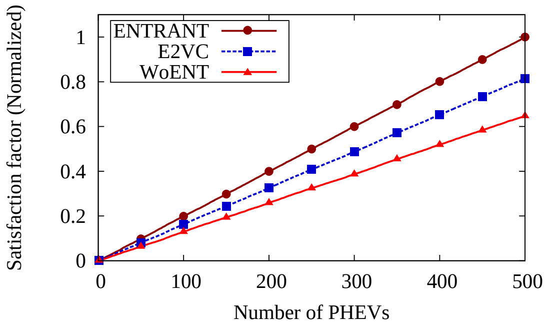


Figure 5.5: Satisfaction factor of the PHEVs

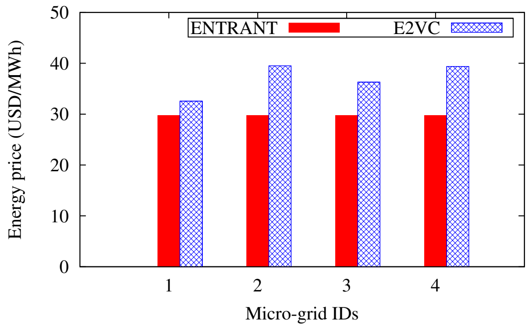


Figure 5.6: Energy price per micro-grid

35-65 MWh. The residual energy of the PHEVs are also selected randomly in between 10 MWh and the maximum storage capacity of each PHEV, individually. Here, we consider that each PHEV is the collection of 100 electric vehicles (EVs). We took 500 PHEVs, and 4 micro-grids for simulation purpose.

Figure 5.3 shows that the cumulative energy consumed per iteration is higher using the proposed scheme, ENTRANT, than using E2VC. Therefore, we conclude that within a coalition, each PHEV consumes higher amount of energy using ENTRANT, than using E2VC. Therefore, utilization of generated energy is much higher using ENTRANT, than using E2VC.

In Figure 5.4, the variation of the price paid by the PHEVs within a coalition is shown. Using ENTRANT, the PHEVs have to pay less, as the energy is properly distributed within the available micro-grids within a coalition. Hence, we conclude that in a coalition, the PHEVs gets the required energy by paying less while using the proposed scheme, ENTRANT, than using E2VC and WoENT.

Figure 5.5 shows that the cumulative satisfaction factor is much higher using ENTRANT, than using E2VC. Therefore, we conclude that using the proposed scheme, ENTRANT, each PHEV consumes higher percentage of energy of its requirement to charge its battery fully.

Though the total price paid by the PHEVs is almost similar using the approaches âĂŞ

ENTRANT and WoENT, as shown in Figure 5.4, the amount of consumed energy by the PHEVs, i.e., the satisfaction factor of the PHEVs, is higher using ENTRANT, than using WoENT, as shown in Figure 5.5. Therefore, we conclude that using the proposed scheme, ENTRANT, the PHEVs consume higher amount of energy while paying less, than using E2VC and WoENT.

Figure 5.6 shows that the price per unit energy, i.e., USD/MWh, is lower using ENTRANT, than using E2VC. Using ENTRANT, the price per unit energy is almost similar for each micro-grid, as the energy load is properly distributed within the available micro-grids within a coalition.

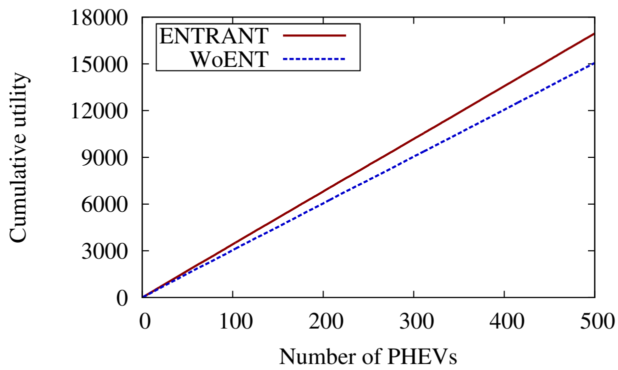


Figure 5.7: Utility value of the PHEVs

Figure 5.7 shows that the payoff, i.e., utility, of the utility function of each PHEV is much higher using ENTRANT, than using WoENT. Hence, we conclude that each PHEV can get higher quality of energy service using ENTRANT, than using WoENT.

5.3 Virtual Energy Cloud Topology Control (VELD) Scheme

5.3.1 System Model

We consider an energy distribution topology consisting two-layered architectures — *mobile macro-grid*, and *virtual energy-cloud*. Mobile macro-grid architecture consists of multiple mobile plug-in hybrid electric vehicles (PHEVs), and a single energy-cloud service provider [42]. On the other hand, a virtual energy-cloud architecture consists of a single energy-cloud service provider, and multiple micro-grids. The PHEVs demand the required amount of energy to the energy-cloud service provider. Hence, based on the mobility pattern of the PHEVs, the energy-cloud service provider maps the mobile PHEVs to the suitable energy generation units, i.e., micro-grids, such that the loss of energy through the transmission line, and energy service delay are minimum. In addition, if a PHEV travels long distance for an energy charging station (ECS), which is defined in Definition 13, the residual energy of the PHEV is reduced and the delay in getting the energy service also increases. Therefore, the energy requirement of the PHEV increases, i.e., the PHEV has to consume higher amount of energy to charge its battery fully. The schematic diagram of the energy distribution topology is shown in Figure 5.8.

Definition 13. *An energy charging station (ECS) is used as an energy exchange point between the PHEVs and the micro-grids using a virtual energy-cloud. We consider that in a small geographical area, there are multiple ECSs such that the PHEVs within that region get prompt service as per their requirements.*

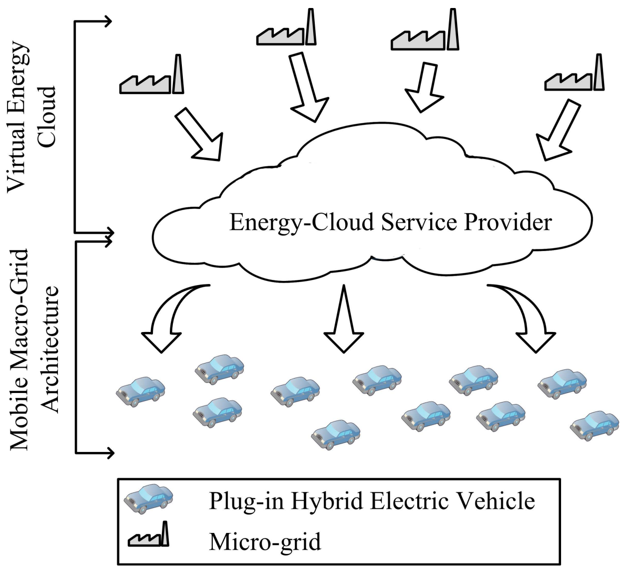


Figure 5.8: Schematic diagram of energy distribution topology

ReqMsgType	PHEV_ID	ReqEnergy	FinalSelFlag
1 byte	4 byte	2 byte	1 byte

(a) Request Message

AckMsgType	CSP_ID	Price	AckFlag
1 byte	4 byte	2 byte	1 byte

(b) Acknowledgement Message

Figure 5.9: Message format in proposed VELD scheme

ReqMsgType	CSP_ID	ReqEnergy	AckFlag
1 byte	4 byte	2 byte	1 byte

(a) Request Message

AckMsgType	MicroGrid_ID	SelectionFlag
1 byte	4 byte	1 byte

(b) Acknowledgement Message

Figure 5.10: Message format in virtual energy-cloud game

5.3.1.1 Mobile Macro-Grid Architecture

We consider that at time instant $t \in [0, \mathbb{T}]$, where $\mathbb{T}$ is the number of time instants in a day, the energy-cloud service provider supplies energy to each PHEV $n \in \mathcal{N}(t)$, where $\mathcal{N}$ is the total number of available PHEVs in mobile smart grid at time instant t. We assume that at time instant t, each PHEV $n \in \mathcal{N}(t)$ demands $d_n(t)$ amount of energy to the energy-cloud service provider to fulfill its energy requirement. On the other hand, the energy-cloud service provider charges each PHEV $n \in \mathcal{N}(\cdot)$ based on the energy consumption profile. Hence, we consider that the energy-cloud service provider uses a linear pricing mechanism for deciding on the amount of price to be paid by each PHEV $n \in \mathcal{N}(\cdot)$, individually. We discuss about the pricing scheme of the energy-cloud service provider in Section 5.3.1.1.

Pricing Scheme of the Energy-Cloud Service Provider: The energy-cloud service provider decides the price per unit energy, i.e., $p_n(\cdot)$, to be paid by each PHEV $n \in \mathcal{N}(\cdot)$ based on the amount of energy request by PHEV $n \in \mathcal{N}(\cdot)$, i.e., $d_n(\cdot)$. As the energy cloud service provider tries to maximize its revenue by considering a trade-off between the price per unit energy and the amount of energy supplied, while maintaining its minimum revenue. Therefore, the energy-cloud service provider uses convex pricing function, i.e., $\mathscr{P}_n(\cdot)$, for its pricing scheme, as follows:

$$\begin{aligned} \mathscr{P}_n(\cdot) &= p_n(\cdot)d_n(\cdot), \quad \forall n \in \mathcal{N}(\cdot) \\ &= \left[c^{avg} + \tan^{-1}\left(e^{\sum d_n(\cdot)}\right)\right] d_n(\cdot) \end{aligned} \tag{5.27}$$

where c^{avg} is the average energy generation cost per unit energy of the micro-grids connected with energy-cloud service provider. We define the average energy generation cost of the micro-grids, i.e., c^{avg}, mathematically, as follows:

$$c^{avg} = \frac{\sum\limits_{m \in \mathcal{M}} c_m}{|\mathcal{M}|} \tag{5.28}$$

where $\mathcal{M}$ is the available micro-grids connected with the energy-cloud service provider, and c_m is the energy generation cost per unit energy of each micro-grid $m \in \mathcal{M}$.

5.3.1.2 Virtual Energy-Cloud Architecture

The energy-cloud service provider provides the users *Energy-as-a-Service* (EaaS) defined in Definition 14. In EaaS, the users, i.e., the PHEVs, request the energy-cloud service provider to fulfill their energy demands. Based on the demand, the energy-cloud service provider distributes the energy request to the available micro-grids using a load balancing algorithm. Therefore, the energy-cloud service provider enables an infrastructure to provide the energy service to the available PHEVs, i.e., it provides the infrastructure for enegry service. The energy-cloud service provider serves energy to the PHEVs based on the demanded energy by the PHEVs on a real-time basis.

Definition 14. *Using Energy as a Service (EaaS), the energy-cloud service provider distributes energy to the PHEVs from the micro-grids. The PHEVs communicate with the micro-grids only through the cloud interface, and the PHEVs do not concern about the availability of energy, as the responsibility of providing energy service solely depends on* *the energy-cloud service provider. On the other hand, the PHEVs pay depending on the pay-per-use mechanism, i.e., each PHEV has to pay based on the amount of consumed energy decided using the pricing scheme in Section 5.3.1.1.*

5.3.1.3 Mobility Model for Cloud-based Mobile Smart Grid

We consider that the mobile PHEVs follow the Gauss-Markov mobility model. According to the mobility model, each PHEV updates its location after traveling a certain distance. The velocity and the position of each PHEV are considered as the correlated functions which are time dependent in nature. Therefore, the velocity and the position of a PHEV at time instant $t \in \mathbb{T}$ depend on the velocity and the position of that PHEV at time instant $(t-1)$. We assume that the PHEVs are mobile in a two-dimensional plane, i.e., 2D plane. The Gauss-Markov mobility model is represented as in [39]:

$$\vec{\nu}_n(t) = \nu_n^x(t)\vec{i} + \nu_n^y(t)\vec{j}, \quad \forall n \in \mathcal{N}(\cdot) \tag{5.29}$$

where $\vec{i}$ and $\vec{j}$ are the unit vector, $\vec{\nu}_n(\cdot)$ is the velocity vector of PHEV n, and $\nu_n^x(\cdot)$ and $\nu_n^y(\cdot)$ are the velocity components of PHEV $n \in \mathcal{N}(\cdot)$ in X-direction and Y-direction, respectively. We define the velocity components in X-direction and Y-direction, i.e., $\nu_n^x(\cdot)$ and $\nu_n^y(\cdot)$, are as follows:

$$\nu_n^x(t) = \beta\nu_n^x(t-1) + (1-\beta)\gamma^x + \theta(t-1)\sigma^x\sqrt{1-\beta^2} \tag{5.30}$$

$$\nu_n^y(t) = \beta\nu_n^y(t-1) + (1-\beta)\gamma^y + \theta(t-1)\sigma^y\sqrt{1-\beta^2} \tag{5.31}$$

where β is the variance over time; γ^x and γ^y are the mean velocity in X-direction and Y-direction, respectively; σ^x and σ^y are the standard deviation of velocity components in X and Y-direction, respectively; and $\theta(\cdot)$ is the time independent uncorrelated Gaussian process with zero-mean with unit variance. In the virtual energy cloud topology control

(VELD) scheme, we consider that the variance over time, i.e., the value of β, is within zero and one. Mathematically,

$$0 \leq \beta \leq 1 \tag{5.32}$$

Hence, we define the magnitude and angle of direction of the velocity of each mobile PHEV $n \in \mathcal{N}(\cdot)$ as given below:

$$|\vec{\nu}_n(\cdot)| = \sqrt{[\nu_n^x(\cdot)]^2 + [\nu_n^y(\cdot)]^2} \tag{5.33}$$

$$\alpha_n(\cdot) = \tan^{-1}\left(\frac{\nu_n^y(\cdot)}{\nu_n^x(\cdot)}\right) \tag{5.34}$$

where $|\vec{\nu}_n(\cdot)|$ and $\alpha_n(\cdot)$ are the magnitude and the angle of direction of the velocity of each PHEV $n \in \mathcal{N}(\cdot)$.

5.3.1.4 Communication Model for Cloud-based Mobile Smart Grid

We consider that in EaaS, the energy-cloud service provider communicates with the plug-in hybrid electric vehicles (PHEVs) using wireless mesh network (WMN). We use IEEE 802.11b protocol for the communication purpose. Initially, each PHEV requests the energy-cloud service provider to supply the required amount of energy by sending a request message, as shown in Figure 5.9(a). Thereafter, the energy-cloud service provider sends an acknowledgment message to the PHEV, as shown in Figure 5.9(b). Each acknowledgment message is unicasted by the energy-cloud service provider. After getting conformation message, i.e., `FinalSelFlag` in Request message is set, the energy-cloud service provider (ECSP) sends the Request messages, as shown in Figure 5.10(a), to the connected micro-grids. On getting the request messages, the micro-grids cooperates within themselves, and send an acknowledgment message, as shown in Figure 5.10(b), while ensuring that each micro-grids connected with the energy-cloud service provider gets the same payoff.

5.3.2 Proposed Virtual Energy Cloud Topology Control Game

5.3.2.1 Game Formulation

To study the interaction between the PHEVs, and the energy-cloud service provider, i.e., for EaaS, we use a single leader multiple follower game theoretic approach in *virtual energy cloud topology control* (VELD) scheme. In this game, the energy-cloud service provider acts as leader, and decides the price per unit energy based on the amount of energy to be consumed by the PHEVs $\mathcal{N}(\cdot)$. On the other hand, the PHEVs act as the followers. Each PHEV $n \in \mathcal{N}(\cdot)$ decides on the amount of energy to be consumed to fulfill its energy requirement. We consider that each PHEV $n \in \mathcal{N}(\cdot)$ decides to consume $d_n(\cdot)$ amount of energy from the energy-cloud service provider. Therefore, the total energy requested, i.e., $\mathcal{D}(\cdot)$, to energy-cloud service provider is defined as follows:

$$\mathcal{D}(\cdot) = \sum_{n=1}^{n \in \mathcal{N}(\cdot)} d_n(\cdot) \tag{5.35}$$

Based on the total amount of energy requested by the PHEVs, i.e., $\mathcal{D}(\cdot)$, the energy-cloud service provider decides the price per unit energy, i.e., $\mathcal{P}(\cdot)$, using a convex function defined as follows:

$$\mathcal{P}(\cdot) = c^{avg} + \tan^{-1}\left(e^{\mathcal{D}(\cdot)}\right) \tag{5.36}$$

Hence, from Equation (5.27), we conclude that the price per unit energy paid by each PHEV $n \in \mathcal{N}(\cdot)$, i.e., $p_n(\cdot)$, is same for the PHEVs connected with the energy-cloud service provider. Mathematically,

$$\mathcal{P}(\cdot) \triangleq p_1(\cdot) \triangleq \cdots \triangleq p_n(\cdot) \triangleq \cdots \triangleq p_{|\mathcal{N}(\cdot)|}(\cdot) \tag{5.37}$$

The price per unit energy paid by each PHEV n, $p_n(\cdot)$, is not only dependent on the amount of energy requested by PHEV n, $d_n(\cdot)$, but also dependent on the amount of energy requested by the PHEVs other than PHEV n, i.e., $\boldsymbol{d}_{-n}$, where $\boldsymbol{d}_{-n} = \{d_1, d_2, \cdots, d_{n-1}, d_{n+1}, \cdots, d_{|\mathcal{D}(\cdot)|}\}$.

Hence, each PHEV $n \in \mathcal{N}(\cdot)$ decides the amount of energy to be consumed with non-cooperation. We define the components of the mobile macro-grid game as follows:

(i) Each PHEV $n \in \mathcal{N}(\cdot)$ acts as a follower, and needs to decide the optimum value of the amount of energy to be consumed, i.e., $d_n(\cdot)$.

(ii) The utility function of each PHEV n, i.e., $\phi_n(\cdot)$, needs to be maximized while depending on the amount of energy to be consumed by PHEV n, i.e., $d_n(\cdot)$, and the price per unit energy, $\mathcal{P}(\cdot)$, decided by the energy-cloud service provider.

(iii) The price per unit energy, $\mathcal{P}(\cdot)$, depends on the total amount of requested energy by the PHEVs, as shown in Equation (5.36).

(iv) The utility function of the energy-cloud service provider, i.e., $\varphi(\cdot)$, depends on the decided price per unit energy, i.e., $\mathcal{P}(\cdot)$, and the amount of requested energy by each PHEV n, i.e., $d_n(\cdot)$, where $\forall n \in \mathcal{N}(\cdot)$.

Utility function of a PHEV: The utility function of PHEV $n \in \mathcal{N}(\cdot)$, i.e., $\phi_n(\cdot)$, is defined as a concave function, and signifies the satisfaction level of PHEV n by consuming $d_n(\cdot)$ amount of energy with a optimum price per unit energy, $p_n(\cdot)$. The satisfaction level of each PHEV n is defined in Definition 15. For requesting $d_n(\cdot)$ amount of energy to the energy-cloud service provider, the net utility of PHEV n, i.e., $\phi_n(\cdot)$, is expressed as the difference between the revenue function of PHEV n, i.e., $\mathscr{R}_n(\cdot)$, and the cost function of PHEV n, i.e., $\mathscr{C}_n(\cdot)$. Mathematically,

$$\phi_n(\cdot) = \mathscr{R}_n(\cdot) - \mathscr{C}_n(\cdot), \quad \forall n \in \mathcal{N}(\cdot) \tag{5.38}$$

Definition 15. *The satisfaction level of PHEV $n \in \mathcal{N}(\cdot)$, i.e., $\mathcal{S}_n(\cdot)$, is defined as the amount of energy consumed by the PHEV n, i.e., $d_n(\cdot)$, and the amount of required energy, i.e., $\mathcal{E}_n^{max} - \mathcal{E}_n^{res}(\cdot)$. Mathematically,*

$$\mathcal{S}_n(\cdot) = \frac{d_n(\cdot)}{\mathcal{E}_n^{max} - \mathcal{E}_n^{res}(\cdot)}, \quad \forall n \in \mathcal{N}(\cdot) \tag{5.39}$$

where $\mathcal{E}_n^{max}$ *is the maximum battery capacity of each PHEV* n*, and* $\mathcal{E}_n^{res}(\cdot)$ *is the amount of stored energy present in the battery of PHEV* n*.*

Each PHEV $n \in \mathcal{N}(\cdot)$ requests the energy-cloud service provider to supply $d_n(\cdot)$ amount of energy to maximize its satisfaction factor. If $PHEV_1$ and $PHEV_2$ consume $d_1(\cdot)$ and $d_2(\cdot)$ amount of energy, respectively, while their energy requirements are same, the PHEV consumes higher amount of energy, has higher satisfaction level. Mathematically,

$$\begin{aligned} \mathcal{S}_1(\cdot) \geq \mathcal{S}_2(\cdot), \quad \text{if } d_1 \geq d_2, \text{ and} \\ [\mathcal{E}_1^{max} - \mathcal{E}_1^{res}(\cdot)] = [\mathcal{E}_2^{max} - \mathcal{E}_2^{res}(\cdot)] \end{aligned} \tag{5.40}$$

Therefore, the utility function of PHEV $n \in \mathcal{N}(\cdot)$, i.e., $\phi_n(\cdot)$, must satisfy the inequalities as discussed below:

(i) The utility function of each PHEV $n \in \mathcal{N}(\cdot)$, $\phi_n(\cdot)$, is considered to be a non-decreasing function, as each PHEV n tries to consume high amount of energy, $d_n(\cdot)$, to maximize its satisfaction level, $\mathcal{S}_n(\cdot)$. We consider that the amount of energy requested to the energy-cloud service provider changes from $d_n(\cdot)$ to $\hat{d}_n(\cdot)$. Here, $d_n(\cdot)$ and $\hat{d}_n(\cdot)$ represent the current and new amount of requested energy by PHEV n. Hence,

$$\frac{\delta \phi_n(\cdot)}{\delta \hat{d}_n(\cdot)} \geq 0 \tag{5.41}$$

(ii) At marginal condition, the utility function of each PHEV n, $\phi_n(\cdot)$, is considered to be decreasing. Therefore, each PHEV n does not increase the amount of requested energy, $\hat{d}_n(\cdot)$, on reaching the marginal condition. Mathematically,

$$\frac{\delta^2 \phi_n(\cdot)}{\delta [\hat{d}_n(\cdot)]^2} < 0 \tag{5.42}$$

(iii) The amount of requested energy, $\hat{d}_n(\cdot)$, decreases with the increase in the price per unit energy, $p_n(\cdot)$. Therefore, with the increase in price per unit energy, $p_n(\cdot)$, the utility of each PHEV n, $\phi_n(\cdot)$ decreases. Mathematically,

$$\frac{\delta \phi_n(\cdot)}{\delta p_n(\cdot)} < 0 \tag{5.43}$$

We consider that the revenue function of each PHEV n, $\mathscr{R}_n(\cdot)$, is a concave function. Hence, we define the revenue function, $\mathscr{R}_n(\cdot)$, of PHEV n as follows:

$$\mathscr{R}_n(\cdot) = \mathcal{E}_n^{max} \tan^{-1}\left(e^{-\frac{\hat{d}_n(\cdot)-d_n(\cdot)}{d_n(\cdot)}}\right) \tag{5.44}$$

The cost function of PHEV n, $\mathscr{C}_n(\cdot)$, is defined as a linear function of amount of requested energy, $\hat{d}_n(\cdot)$, with price coefficient $p_n(\cdot)$, i.e., $\mathcal{P}(\cdot)$, defined in Equation (5.36). Mathematically,

$$\mathscr{C}_n(\cdot) = p_n(\cdot)\hat{d}_n(\cdot) \tag{5.45}$$

Therefore, considering the Equation (5.38), we define the utility function, $\phi_n(\cdot)$, of each PHEV n as follows:

$$\phi_n\left(\hat{d}_n(\cdot), \boldsymbol{d}_{-n}(\cdot), p_n(\cdot)\right) = \mathcal{E}_n^{max} \tan^{-1}\left(e^{-\frac{\hat{d}_n(\cdot)-d_n(\cdot)}{d_n(\cdot)}}\right) - p_n(\cdot)\hat{d}_n(\cdot) \tag{5.46}$$

where $\boldsymbol{d}_{-n}(\cdot) = \{d_1(\cdot), \cdots, d_{n-1}(\cdot), d_{n+1}, \cdots, d_{|\mathcal{N}(\cdot)|}(\cdot)\}$.

Lemma 3. *The satisfaction level of each PHEV n, i.e., $\mathcal{S}_n(\cdot)$, holds the following constraint:*

$$0 < \mathcal{S}_n(\cdot) \leq 1 \tag{5.47}$$

Proof. As we assume that each PHEV n requests an amount of energy, $\hat{d}_n(\cdot)$, that is positive. Mathematically,

$$d_n(\cdot) > 0 \tag{5.48}$$

Hence, the satisfaction level of each PHEV $n \in \mathcal{N}(\cdot)$, i.e., $\mathcal{S}_n(\cdot)$, follows the following inequality:

$$\begin{aligned} \mathcal{S}_n(\cdot) &= \frac{\hat{d}_n(\cdot)}{\mathcal{E}_n^{max} - \mathcal{E}_n^{res}} \\ \mathcal{S}_n(\cdot) &> 0, \quad \text{as } \hat{d}_n(\cdot) > 0 \end{aligned} \tag{5.49}$$

Each PHEV does not consume excess energy than its maximum battery capacity, as that results in increase the temperature of the battery, and shorten the lifetime of the battery. Hence, the amount of requested energy, $\hat{d}_n(\cdot)$, must satisfy the following inequality:

$$\hat{d}_n(\cdot) \leq \mathcal{E}_n^{req}(\cdot) = \mathcal{E}_n^{max} - \mathcal{E}_n^{res}(\cdot) \tag{5.50}$$

where $\mathcal{E}_n^{req}(\cdot)$ is the maximum amount of required energy to charge-fully the battery of PHEV n. Therefore,

$$\mathcal{S}_n(\cdot) \leq 1 \tag{5.51}$$

Therefore, the satisfaction level of each PHEV $n \in \mathcal{N}(\cdot)$, i.e., $\mathcal{S}_n(\cdot)$, satisfies the condition: $0 < \mathcal{S}_n(\cdot) \leq 1$ $\square$

Utility function of energy-cloud service provider: The utility function of energy-cloud service provider, i.e., $\varphi(\cdot)$, signifies the earned capital of the energy-cloud service provider by supplying $\hat{d}_n$ amount of requested energy to the PHEV $n \in \mathcal{N}(\cdot)$. By supplying $\hat{d}_n(\cdot)$ amount of energy to each PHEV n with price per unit energy, $p_n(\cdot)$, the energy-cloud service provider earns $\hat{d}_n(\cdot)p_n(\cdot)$ amount of capital. Therefore, the total amount of earned capital of energy-cloud service provider is defined as follows:

$$\varphi(\cdot) = \sum_{n=1}^{n \in \mathcal{N}(\cdot)} \hat{d}_n(\cdot)p_n(\cdot) \tag{5.52}$$

Considering Equation (5.37), we rewrite Equation (5.52) as follows:

$$\varphi\left(\mathcal{P}(\cdot), \hat{d}_n(\cdot)\right) = \mathcal{P}(\cdot) \sum_{n=1}^{n \in \mathcal{N}(\cdot)} \hat{d}_n(\cdot) \tag{5.53}$$

The energy-cloud service provider tries to maximize its revenue by increasing the payoff of the utility function $\varphi(\cdot)$. Hence, the main objective of the energy-cloud service provider is as follows:

$$\arg\max \varphi\left(\mathcal{P}(\cdot), \hat{d}_n(\cdot)\right) \tag{5.54}$$

5.3.2.2 Existence of Generalized Nash Equilibrium

We determine the generalized Nash equilibrium for virtual energy-cloud topology control game in the proposed scheme, VELD, using the variational inequality condition, as discussed in Theorem 6.

Theorem 6. *Given the pricing function of the energy-cloud service provider, i.e., $\mathcal{P}(\cdot)$, there exists a variational equilibrium, i.e., generalized Nash equilibrium, for the utility function, $\phi_n(\cdot)$, for each PHEV $n \in \mathcal{N}(\cdot)$, and the condition for generalized Nash equilibrium is as follows:*

$$\phi_n\left(\hat{d}_n^*(\cdot), \boldsymbol{d}_{-n}^*(\cdot), p_n(\cdot)\right) \geq \phi_n\left(d_n(\cdot), \boldsymbol{d}_{-n}^*(\cdot), p_n(\cdot)\right) \tag{5.55}$$

Proof. We know that the utility function of each PHEV n, i.e., $\phi_n(\cdot)$, needs to be maximized in order to reach the generalized Nash equilibrium. Hence, applying Karush-Kuhn-Tucker condition, we try to find out the variational equilibrium solution. Hence, we get:

$$\nabla_n \phi_n(\cdot) = 0 \tag{5.56}$$

Therefore, considering the overall utility function of the macro-grid, we can rewrite

Equation (5.56) as follows:

$$\nabla \sum_{n \in \mathcal{N}(\cdot)} \phi_n(\cdot) = 0 \tag{5.57}$$

By performing the Jacobian transformation of the matrix derived by first-order derivative on Equation (5.57), we get a non-positive diagonal matrix. Hence, there exists a variational equilibrium for the proposed scheme, VELD. Therefore, we conclude that the proposed scheme, VELD, holds a generalized Nash equilibrium solution. □

5.3.2.3 The Proposed Algorithms

For virtual energy-cloud topology control using the proposed scheme, VELD, we propose two different algorithms — for each PHEV, and for the energy-cloud service provider, as discussed in Algorithms 5.3 and 5.4, respectively. Using Algorithm 5.3, each PHEV $n \in \mathcal{N}(\cdot)$ decides the optimum amount of energy to be requested to the energy-cloud service provider. Based on the requested energy by the $\mathcal{N}(\cdot)$ PHEVs, the energy-cloud service provider decides the price per unit energy using Equation (5.36).

Algorithm 5.3: VELD algorithm for each PHEV

Inputs : E_n^{max}: Maximum battery capacity of PHEV $n \in \mathcal{N}(\cdots)$
$d_n(\cdot)$: Previous amount of energy requested by PHEV n
$\mathcal{P}(\cdot)$: Price decided by the energy-cloud service provider
Output: $\hat{d}_n(\cdot)$: Current amount of energy requested by PHEV n

Decide the current amount of energy to be requested using following equation:
$\hat{d}_n(\cdot) = d_n(\cdot) + 0.01$ // `Energy request incremented by 0.01` kWh
if $\left(\phi_n\left(\hat{d}_n^*(\cdot), \boldsymbol{d}_{-n}^*(\cdot), p_n(\cdot)\right) \geq \phi_n\left(d_n(\cdot), \boldsymbol{d}_{-n}^*(\cdot), p_n(\cdot)\right)\right)$ **then**
  Request $\hat{d}_n(\cdot)$ amount of energy to energy-cloud service provider
else
  Request $d_n(\cdot)$ amount of energy to energy-cloud service provider
  // `Nash equilibrium reached`
end

Algorithm 5.4: VELD algorithm for each energy-cloud service provider

Inputs : $\hat{d}_n(\cdot)$: Current amount of energy requested by each PHEV $n \in \mathcal{N}(\cdot)$
$c_m(\cdot)$: Energy generation cost per micro-grid $m \in \mathcal{M}$

Output: $\mathcal{P}(\cdot)$: Price decided by the energy-cloud service provider

Calculate $\mathcal{D}(\cdot) = \sum_n \hat{d}_n(\cdot)$
Calculate average energy generation cost, c^{avg}, using following equation:
$c^{avg} = \frac{\sum_m c_m(\cdot)}{|\mathcal{M}|}$
Decide the new price unit energy, $\mathcal{P}(t)$, using the following equation:
$\mathcal{P}(t) = c^{avg} + \tan^{-1}(e^{\mathcal{D}(\cdot)})$
Broadcast the new price per unit energy, $\mathcal{P}(t)$

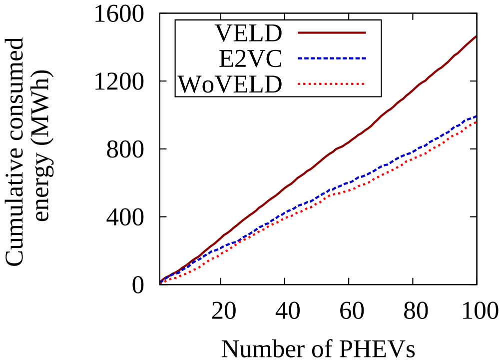


Figure 5.11: Energy consumed by the PHEVs

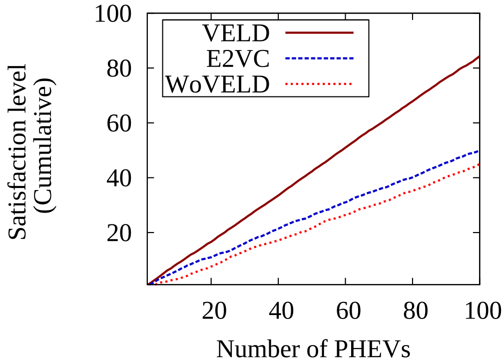


Figure 5.12: Satisfaction level of the PHEVs

5.4 Performance Evaluation

5.4.1 Simulation Parameters

We consider that the PHEVs follow the Gauss-Markov mobility model, and moves in a two-dimensional plane simulated in MATLAB-based simulation platform. The PHEVs request the energy-cloud service provider to supply energy based on their requirements, considered as random value as shown in Table 5.2.

5.4.2 Benchmark

The performance of the proposed scheme, virtual energy cloud topology control (VELD), is evaluated by comparing the results with other energy distribution policies such as the

Table 5.2: Simulation Parameters: VELD

Parameter	Value
Simulation area	10 km×10 km
Number of PHEVs	100
Maximum battery capacity	35-65 MWh
Residual energy of each PHEV	>10 MWh
Excess energy per micro-grid	99 MWh

economics of electric vehicle charging (E2VC) [4], and the energy distribution without any game-theoretic approach (WoVELD). We refer to these different energy trading policies as VELD, E2VC, and WoVELD, through the rest of the work. In E2VC [4], the authors proposed a non-cooperative game theoretic approach. Though the authors did not consider the choice of any energy-cloud service provider for the PHEVs available in the coalition. In WoVELD, we considered that each PHEV requests the energy-cloud service provider based on their requirements. Thus, we can improve the satisfaction factor of the PHEVs, and the energy load to the micro-grids using our proposed scheme, VELD, than using other approaches, i.e., E2VC and WoVELD.

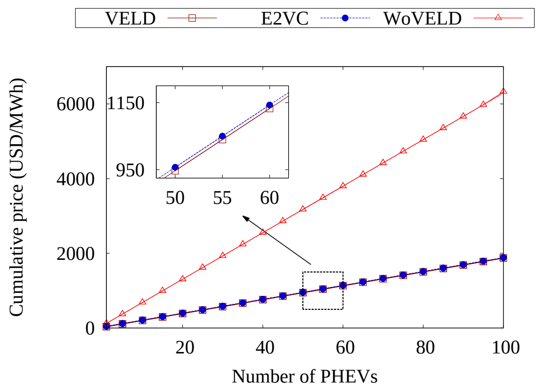


Figure 5.13: Price for the PHEVs

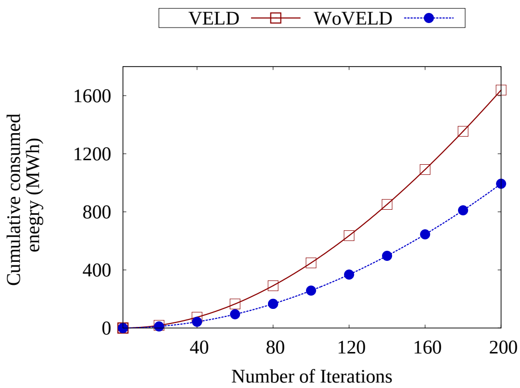


Figure 5.14: Energy consumed per iteration

5.4.3 Results and Discussions

For simulation, we assume that the energy-cloud service provider calcualtes the real-time supply and demands in every 5 seconds interval. Figure 5.11 shows that the amount of

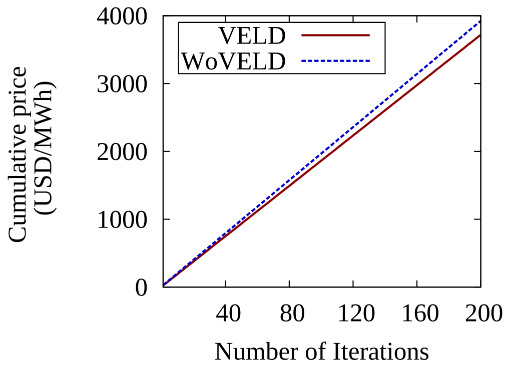


Figure 5.15: Price per iteration

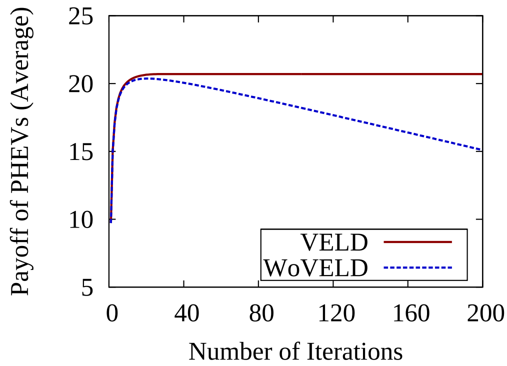


Figure 5.16: Utility per iteration

energy consumed by the PHEVs is higher using the proposed scheme, VELD, than using E2VC and WoVELD. Therefore, the satisfaction levels of the PHEVs are much higher using the proposed scheme, VELD, than using the other schemes such as E2VC and WoVELD, as shown in Figure 5.12. In Figure 5.13, we evaluated the cumulative price per unit energy which is almost same using the proposed scheme, VELD, and E2VC, and higher using WoVELD. Using the proposed scheme, VELD, the PHEVs consume 47.49% and 52.96% higher amount of energy than using E2VC and WoVELD, respectively.

Figure 5.14 shows an incremented curve with cumulative energy consumed per iteration. From Figure 5.14, we conclude that the energy consumed per iteration is 64.87% higher using VELD than using WoVELD. The average price per unit energy in each iteration is also 5.52% lower using VELD than using WoVELD, as shown in Figure 5.15. Using the propose scheme, VELD, the payoff of the utility function is always equal or higher than using WoVELD, as shown in Figure 5.16.

5.5 Concluding Remarks

In this chapter, two distributed energy management schemes for the PHEVs are presented considering Gauss-Markov mobility model for the PHEVs.

In this chapter, we formulated a multi-leader multi-follower Stackelberg game theoretic approach to study the problem of ENTRANT. Based on the proposed approach, that is, ENTRANT, we showed how energy can be distributed within the PHEVs within a coalition having multiple micro-grids. The simulation results show that the proposed scheme, ENTRANT, yields improved results.

On the other hand, a single leader multiple follower Stackelberg game based VELD scheme studied the problem of energy distribution using virtual energy cloud. Based on the proposed scheme, VELD, we showed how each PHEV consumes high amount of energy with paying less price per amount of energy. The simulation results show that the proposed scheme, VELD, yields improved results.

Chapter 6

Conclusion

The objective of the thesis is to provide an efficient smart grid architecture, which is dynamic in nature, and different energy management schemes suitable for smart grid. We consider various challenges such as energy storage facilities at customer-end, Gauss-Markov mobility of the PHEVs, and the energy as a service provided by the energy cloud service provider. Chapters 3-5 presented the schemes proposed in this thesis. We discuss the summary of the thesis in Section 6.1. The major contribution of the thesis work are listed in Section 6.2. In Section 6.3, we discuss the limitations of our work. Finally, in Section 6.4, the thesis is concluded while citing directions for future work.

6.1 Summary of the Thesis

This thesis was presented in six chapters. The Chapter 1 presented a brief introduction to smart grid, and discussed the motivation of the work while citing the main objectives of this thesis.

In Chapter 2, we surveyed the existing literatures of smart grid architecture and energy management schemes. The existing schemes for both smart grid architectures and energy management schemes are discussed and analyzed. We summarized the problem area based on the limitations of the existing schemes.

Chapter 3 presented the schemes for the proposed dynamic smart grid architecture – *dynamic coalition formation* (*DCF*) and *dynamic DAU selection* (*DARTS*). The proposed scheme, DCF, is capable of handling the effect of the variation in energy demand and supply by forming the coalitions dynamically. The dynamic formation of the coalitions among the consumers and the micro-grids helps achieving high quality of energy service while ensuring proper distribution of energy and high profit of the micro-grids. On the other hand, the proposed scheme, DARTS, is capable of handling the variation in communication overhead by selecting the DAUs, dynamically. The DAUs are used to communicate with the meter data management system (MDMS). The proposed schemes were evaluated through simulation in MATLAB, and the results for various metrics were compared with benchmark schemes.

Chapter 4 presented the scheme for the proposed *home energy management with storage system* (*HoMeS*). The proposed scheme is capable of handling the storage devices at the customer-end. This scheme, HoMeS, helps utilizing the storage facility at the customer-end, while achieving maximum utilization of the generated energy by the micro-grids. The proposed scheme was evaluated through simulation in MATLAB, and the results for various metrics were compared with benchmark schemes.

In Chapter 5, two energy management schemes for the mobile PHEVs were presented. In both the schemes, i.e., ENTRANT and VELD, we considered that the PHEVs followed Gauss-Markov mobility model. In cloud-free energy management scheme for the PHEVs, i.e., *ENTRANT*, we exploited the energy management topology control to maximize the utilization of the generated energy while each PHEV is connected multiple micro-grids within a coalition. On the other hand, In cloud-based energy management scheme for the PHEVs, i.e., *VELD*, we exploited the energy management topology control using virtual energy cloud infrastructure. In VELD, the ECSP provides energy as a service (EaaS) to the available micro-grids. The proposed schemes were evaluated through simulation in MATLAB, and the results for various metrics were compared with benchmark schemes.

6.2 Contributions of Our Work

In this thesis, dynamic architecture and energy management schemes were proposed for smart grid impeded by various challenges. The proposed schemes were designed to cope with the main issues – energy storage facilities at customer-end, Gauss-Markov mobility of the PHEVs, and the energy as a service provided by the energy cloud service provider. We list the major contributions of this thesis as follows.

Dynamic Coalition Formation in Smart Grid: We propose a dynamic coalition formation scheme, which is capable of providing high quality of energy service to the consumers in smart grid while maximizing the utilization factor of generated energy.

Dynamic Data Aggregator Unit Selection in Smart Grid: We propose a dynamic data aggregator unit selection scheme, which is capable of providing a real-time communication by reducing the delay at DAU-end. Using this scheme, the communication overhead is also properly distributed.

Distributed Home Energy Management Scheme with Storage in Smart Grid: We propose a distributed home energy management scheme while considering that each customer is equipped with storage devices and connected with multiple micro-grids available within a coalition. Using this scheme, each customer consumes high amount of energy including the amount of energy required for storage.

Distributed Energy Trading Topology Control in Mobile Smart Grid: We propose a distributed energy management scheme for the mobile PHEVs. In this scheme, we assumed that each PHEV is connected with multiple micro-grids available within a coalition. This proposed scheme is capable of providing energy service with high satisfaction factor, while ensuring high profit of the micro-grids.

Distributed Virtual Energy Cloud Topology Control in Mobile Smart Grid: We propose a distributed virtual energy management scheme for the PHEVs. In this scheme, we assumed that each PHEV is connected with single energy cloud service provider (ECSP), and pays according to its usage. In this scheme, the ECSP provides energy service to the PHEVs while ensuring high utilization factor of the generated energy by the micro-grids, and high profit of the micro-grids.

6.3 Limitations

We made few assumptions while designing the proposed schemes.

- The consumers, i.e., customers and PHEVs, are connected with multiple micro-grids.
- Multiple DAUs are available for each smart meter to communicate with the MDMSs.
- The PHEVs follow the Gauss-Markov mobility model.
- In HoMeS, we assumed that the customers broadcasts their minimum energy consumption *a priori*.
- In VELD, the customers get the required amount of energy while paying as per usage of energy.

6.4 Future Scope of Work

- Future extension of the proposed scheme, DCF, includes understanding how the coalition can be formed in a more optimal way, so that the services provided by the grids to the customers can be improved, thereby yielding utilization of smart grids.

- Future extension of the problem, DARTS, includes understanding how the energy consumption information of the customers by a smart meter can be delivered to the MDMS using multi-hop communication through different DAUs available in the coalition.
- Future extension of the scheme, HoMeS, includes understanding how the energy distribution can be improved by exchanging less number of messages, so that the delay in energy supply can be reduced, and the service provided by the micro-grids to the customers can be improved, thereby improving the utilization of the micro-grids.
- Future extension of the problem, ENTRANT, includes understanding how the energy trading network topology can be controlled in advance based on the estimated trajectory of the PHEVs, so that scheduling in energy trading has less delay and the energy can be properly distributed within a single coalition, that is, multiple micro-grids, or multiple coalitions.
- Future extension of the last work, VELD, includes understanding of how the energy redistribution can be done in virtual energy cloud infrastructure by the energy-cloud service provider.

Publications

Journal

- **A. Mondal**, S. Misra, and M. S. Obaidat, "Distributed Home Energy Management System with Storage in Smart Grid Using Game Theory," *IEEE Systems Journal*, 2015, DOI: 10.1109/JSYST.2015.2421941. [Published on May 22, 2015]

- **A. Mondal** and S. Misra, "Game-Theoretic Energy Trading Network Topology Control for Electric Vehicles in Mobile Smart Grid," *IET Networks*, 2014, DOI: 10.1049/iet-net.2014.0089. [Available online on January 7, 2015]

Conference

- **A. Mondal** and S. Misra, "Dynamic Coalition Formation in a Smart Grid: A Game Theoretic Approach," in *Proceedings of IEEE ICC Workshop on Smart Communication Protocols and Algorithms* (*SCPA*), Budapest, Hungary, June 2013, pp. 1067–1071.

- **A. Mondal** and S. Misra, "Dynamic Data Aggregator Unit Selection in Smart Grid: An Evolutionary Game Theoretic Approach," in *Proceedings of the 11th IEEE India Conference on Emerging Trends and Innovation in Technology (INDICON)*, Pune, India, December 2014, pp. 1–6.

- **A. Mondal** and S. Misra, "Game-Theoretic Distributed Virtual Energy Cloud Topology Control for Mobile Smart Grid," in *Proceedings of the 6th IEEE International Conference on Cloud Computing Technology and Science (CloudCom)*, Singapore, December 2014, pp. 54–61.

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BIO-DATA

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   - **A. Mondal**, S. Misra, and M. S. Obaidat, "Distributed Home Energy Management System with Storage in Smart Grid Using Game Theory," *IEEE Systems Journal*, 2015, DOI: 10.1109/JSYST.2015.2421941. [Published on May 22, 2015]

- **A. Mondal** and S. Misra, “Game-Theoretic Energy Trading Network Topology Control for Electric Vehicles in Mobile Smart Grid,” *IET Networks*, 2014, DOI: 10.1049/iet-net.2014.0089. [Available online: January 7, 2015]
- S. Misra, T. Ojha, and **A. Mondal**, “Game-theoretic Topology Control for Opportunistic Localization in Sparse Underwater Sensor Networks,” *IEEE Transactions on Mobile Computing*, vol. 14, no. 5, July 2014.
- S. Misra, G. Mali, and **A. Mondal**, “Distributed topology management for wireless multimedia sensor networks: exploiting connectivity and cooperation,” *International Journal of Communication Systems*, vol.27, no. 3, March 2014.
- S. Misra, S. Bera, **A. Mondal**, R. Tirkey, H.C. Chao, and S. Chattopadhyay, “Optimal Gateway Selection in Sensor-Cloud Framework for Health Monitoring,” *IET Wireless Sensor Systems*, vol. 3, no. 4, December 2013.

6. **Conference Publications**:

- **A. Mondal** and S. Misra, “Dynamic Data Aggregator Unit Selection in Smart Grid: An Evolutionary Game Theoretic Approach,” in *Proceedings of the 11th IEEE India Conference on Emerging Trends and Innovation in Technology (INDICON)*, Pune, India, December 2014, pp. 1–6.
- **A. Mondal** and S. Misra, “Game-Theoretic Distributed Virtual Energy Cloud Topology Control for Mobile Smart Grid,” in *Proceedings of the 6th IEEE International Conference on Cloud Computing Technology and Science (CloudCom)*, Singapore, December 2014, pp. 54–61.
- A. Roy, **A. Mondal**, and S. Misra, “Connectivity Re-establishment in the Presence of Dumb Nodes in Sensor-Cloud Infrastructure: A Game Theoretic Approach,” in *Proceedings of Emerging Issues in Cloud (EIC) workshop in conjunction with the 6th IEEE International Conference on Cloud Computing Technology and Science (CloudCom)*, Singapore, December 2014, pp. 847–852.
- S. Misra, **A. Mondal**, S. Banik, M. Khatua, S. Bera, and M. S. Obaidat, “Residential Energy Management in Smart Grid: A Markov Decision Process-Based Approach,” in *Proceedings of IEEE International Conference on Internet of Things (iThings)*, Beijing, Chaina, August 2013, pp. 1152–1157.
- **A. Mondal** and S. Misra, “Dynamic Coalition Formation in a Smart Grid: A Game Theoretic Approach,” in *Proceedings of IEEE International Workshop on Smart Communication Protocols and Algorithms (SCPA) in conjunction with IEEE International Conference on Communications (ICC)*, Budapest, Hungary, June 2013, pp. 1067–1071.

7. **Achievements**:

- **Winner** in *Poster presentation* on the 6th Research Scholars’ Day 2015 of School of Information Technology, Indian Institute of Technology Kharagpur

- **Nominated** as *Departmental Research Scholar Representative* of School of Information Technology, Indian Institute of Technology Kharagpur for academic year 2014-2015.
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- **Nominated** for *Merit scholarship* by Government of India Ministry of Human Resource Development Department of Higher Education based on performance in Higher Secondary Examination.
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- **Ranked** 49^{th} in *Secondary Examination* from State - West Bengal, India.
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