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COMPUTATIONAL INTELLIGENCE APPROACHES FOR ENERGY
OPTIMIZATION IN MICROGRIDS

BY

TAMAL ROY

A thesis submitted in partial fulfillment of the requirements for the

Master of Science

Major in Electrical Engineering

South Dakota State University

2020

COMPUTATIONAL INTELLIGENCE APPROACHES FOR ENERGY
OPTIMIZATION IN MICROGRIDS

TAMAL ROY

This thesis is approved as a creditable and independent investigation by a candidate for the Master of Science in Electrical Engineering degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this thesis does not imply that the conclusions reached by the candidates are necessarily the conclusions of the major department.

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ABSTRACT

COMPUTATIONAL INTELLIGENCE APPROACHES FOR ENERGY
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TAMAL ROY

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The future electrical system termed as smart grid represents a significant paradigm shift for power industry. Nowadays, microgrids are becoming smarter with the integration of renewable energy resources (RESs) , diesel generators , energy storage systems (ESS), and plug-in electric vehicles (PEV or EV) . However, these integration bring with new challenges for intelligent management systems. The classical power generation approaches can no longer be applied to a microgrid with unpredictable renewable energy resources. To relive these problem, a proper power system optimization and a suitable coordination strategy are needed to balance the supply and demand. This thesis presents three projects to study the optimization and control for smart community and to investigate the strategic impact and the energy trading techniques for interconnected microgrids.

The first goal of this thesis is to propose a new game-theoretic framework to study the optimization and decision making of multi-players in the distributed power system. The proposed game theoretic special concept-rational reaction set (RRS) is capable to model the game of the distributed energy providers and the large residential consumers. Meanwhile, the residential consumers are able to participate in the retail electricity market to control the market price. Case studies are conducted to validate the system framework using the proposed game theoretic method. The simulation results show the effectiveness

and the accuracy of the proposed strategic framework for obtaining the optimum profits for players participating in this market. The second goal of the thesis is to study a distributed convex optimization framework for energy trading of interconnected microgrids to improve the reliability of system operation. In this work, a distributed energy trading approach for interconnected operation of islanded microgrids is studied. Specifically, the system includes several islanded microgrids that can trade energy in a given topology. A distributed iterative deep cut ellipsoid (DCE) algorithm is implemented with limited information exchange. This approach will address the scalability issue and also secure local information on cost functions. During the iterative process, the information exchange among interconnected microgrids is restricted to electricity prices and expected trading energy. Numerical results are presented in terms of the convergent rate of the algorithm for different topologies, and the performance of the DCE algorithm is compared with sub-gradient algorithm. The third goal of this thesis is to use proper optimization approaches to motivate the household consumers to either shift their loads from peaking periods or reduce their consumption. Genetic algorithm (GA) and dynamic programming (DP) based smart appliance scheduling schemes and time-of-use pricing are investigated for comparative studies with demand response.

CHAPTER 1 INTRODUCTION

1.1 Background

The generation of electricity is very essential to meet the consumer load demand. A dependable and consistent supply is necessary to facilitate economic and industrial growth and to advance the quality of life. The demand of electricity has been increasing day by day and is expected to double in value between 2000 and 2030 [1]. By considering the today's consumer view and environmental changes, it is important for the utility company to decrease the electricity buying cost of the consumers and to connect the distributed energy resources (DERs) such as renewable energy sources (RESs) with the traditional energy generation. The increasing load demand is overloading the traditional power grids and conventional solution strategies are facing the complexity of exiting networks [2]. The solution of these critical issues of the traditional power plant is the implementation of some new power grids. The new power grids use RESs instead of fossil fuels to eliminate the greenhouse gas emission. Additionally, the technologically developed new type of power grids are able to adjust the real time power generation based on demand of users. Smart grid is one of the technologically advanced power grid that uses two way communication to gather information of the users so as to improve the efficiency reliability, economics and stainability of the production and distribution of electricity [3]–[7]. The SG can adjust power generation or electricity consumption by using the smart meter installed in houses or buildings of the consumers so as to increase the energy efficiency and power system stability[8]–[10].

A smart micro-grid (MG) is a small scale grid that use distributed energy storage

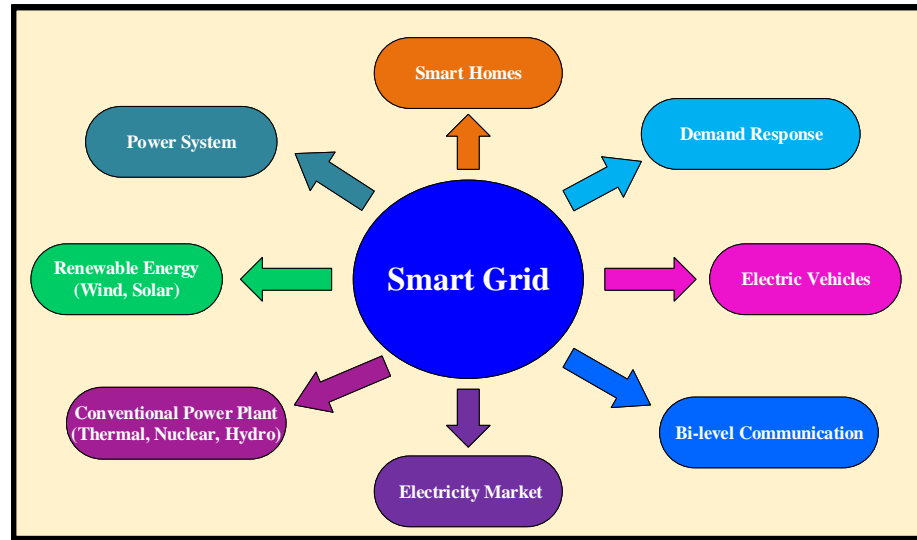


Figure 1.1. A general schematic diagram of smart grid with possible solutions.

and the integration of renewable energy (RE) resources to generate electricity [11]–[13]. The micro-grid can operate as standalone or islanded mode or in conjunction with main utility grid [14]–[16]. The micro-grid is intergraded near the end users. Therefore, the electricity buying cost of the consumer from the micro-grid is less than buying cost from the power whole seller (i.e., macro-station). The micro-grid can easily adjust the electricity generation. It can produce power based on the power demand of the consumers. Additionally, the micro-grid can be deployed or removed easily according to the load demand of the users.

Motivated by the above advantages of smart micro-grid, several researches all over the world have been conducted [17]–[21]. Although it will increase the green energy, these resources cannot ensure the stability and reliability of power production. The intermittent nature of renewable energy are introducing more uncertainties on the power system. For instance, the photovoltaic (PV) panel can not work at night and the wind farm can generate different power on different time. Also, the power consumption of

consumers are different in different time of a whole day. The peak demand period is considered the heaviest power consumption time while the remaining time is defined to as the off-peak. Furthermore, the peak time differs in different seasons. For instance, during summer, the peak time is usually observed in noon/ afternoon. On the other hand, during winter, spring and autumn, the afternoon defines as off-peak time.

Nowadays, due to the increasing level of the competition in the energy market, game theory has been recognized as one of the practically appealing solution approach to find the market equilibrium [22]–[24]. In the deregulated market, the providers and consumers are the active participants. Technological development of the power system leads to a significant increase in the number of active players in the market. These active market participants lead the market towards cost reduction and maximizing the profits of the players, increasing market reliability. Active market participants commence a bid by using and computing real market clearing price. Smart grid technologies have a great impact on the strategic decisions of consumers' behavior. The traditional electricity market has faced complex problems such as unbalanced information, strategic interference and the possibility of multi-phase equilibrium [25]–[27]. Smart competitive structures such as retail market structure based on electricity market agents are an alluring item for simulating such problems. Each market player is an autonomous agent with independent pricing strategies that can behave to match the outcome of the electricity market. In the classical electricity market, when the number of generators is higher than the number of sellers, that makes the market less efficient. In the recent electricity market, electricity buyers are no longer price takers since they are can influence the market by using different bidding strategies, as well as cooperating with other buyers. Therefore, in recent years, it

brings more attention to find a proper game theoretic approach to develop and investigate the multi-player decision making strategies in the retail electricity market with high penetration of renewable energy resources in the field of power system optimization.

In traditional power system, energy is generated by large generation plants in centralized fashion. In centralized system, the energy needs to be transported over long distance and through complex transportation meshes to the end users. Such complicated, inflexible structure can certainly create burden to the whole power system and make outages. The immense implications are responsible for recent grid failures in North America that have caused monetary losses and people discomfort [28]. The technological developed smart grid aims to develop traditional power grid by introducing the interconnected micro-grids system in distributed way. The distributed microgrid system allows the energy exchange with several micro-grids which are islanded from the utility grid. By using IMS, it is easy to ensure the full utilization of local energy resources, reduce the energy operation cost and achieve reliability of power delivery [29]–[31]. From the aspect of Energy trading game, the MGs can act as players from cooperative perspective. The MGs can be described as prosumers with both attributes of buyers and sellers. During different time periods, MGs can act as seller and buyer based on their respective load demand and aim at maximizing their individual benefits. Therefore, the distributed energy trading is necessary to accomplish the global operation goal of interconnected micro-grid system which preserves scalability and privacy issues.

Recently, the peak power consumption in household has caused adverse effects to the stability and reliability of the conventional electricity system [32]. Reducing the peak power consumption can reduce the instability of the power system [33]. The concept of

demand side management strategy can encourage the consumers to reduce the cost of electricity by reducing the peak demand by shifting the load from peak hour to off-peak hours [34]–[38]. In the United States, many demand response strategy are largely implemented by industrial and commercial consumers . These strategies are mainly direct load control, real-time pricing and time-of-use [39]. On the contrary, very few DR programs have been used for residential consumers. The traditional large scale based demand management program is applicable for industrial and commercial sector, it is not suitable for residential consumers to manage large number of residential houses without communication and automation [40]. The smart grid equipped with micro-grids can enable efficient and reliable bidirectional communication between utility operator and the end users. So, the intelligent energy management algorithm need to be investigated to balance the supply and demand.

1.2 Literature Review on Game Theoretic Approach for Distributed Electricity Providers in Deregulated Power Market

In the past several years, the majority of research of multi-player energy trading competition has been conducted on the supply side [36], [41]–[46] while demand side has not been concentrated. In this market structure, the participants of both sides of supply and consumption continuously adapt their strategies according to their objective function. In [47], the authors concentrated on controlling the locational marginal price (LMP) of buyers and by using different algorithms and strategic decisions based on game theory. In the proposed market structure, the market participants of both the supply and consumption sides conform their strategies according to their objective function. Moreover, power

market researchers have concentrated on dividing the market players inside coalitions such that the collaborative players' payoff becomes maximum [47]. The future distribution system, with high participation of renewable energy that has various non-convex objective functions including generation, storage device, and controllable load has been studied in past works of literature [48]–[51]. In [52], authors proposed a non-cooperative game to develop a trade mechanism through electricity trading at an electric vehicle to improve a decentralized market. However, existing works have been mainly focused on the control and operation problem of individual energy district (ED) with special attention to frequency stability and reliability improvement based on producers and prosumers is still considered as an promising area of research. In the retail electricity market which is inspired by the "Energy Internet" concept, consumption player play an active role in managing their load demands. This market allows to analyze consumers' reaction to price fluctuations. This is particularly essential in the demand side management, where consumer should change their demand through financial incentives.

In the last decade, the urgent need for a more efficient and reliable electricity market, which was triggered by environmental concern and estimations of high penetration of Plug-in Electric Vehicles (PEVs) into the market, has necessitated an intelligent construct within the electricity market. The future electricity markets is highly dependent on renewable energies. Renewable energy integration, coupled with volatile electricity prices, signify the importance of energy management in smart grids. The high penetration of distributed production agents in the residential sector eliminates the concerns regarding high load demand and sustainability issues. These production agents supply their own electricity demand and sell the rest to consumption agents, who can

manage their load demand in response to the spot market prices.

Therefore, to find market equilibrium, a state where all active market participants have made the most optimal decision is an objective for market participants [53]. The market equilibrium empowers all players to make an optimal decision, based on their competitors' choice. The multiple number of production agents and consumption agents in the retail market facilitate a game theoretic approach to find the market clearing prices.

1.3 Literature Review on Distributed Energy Trading for interconnected Micro-grids

Recent studies focus on the energy optimization strategy of IMS and proposed method can be divided into two types: centralized optimization and distributed optimization. Normally, if all the MGs share information on their respective load, generation and grid condition, the system could be easily implemented based on classical optimization such as optimal power flow (OPF). For instance, in [54] the authors consider a method of joint and distributed control of IMS. Alternatively, a method of Newton-like descend is proposed in this work [55] to solve the three-phase optimal power flow problems. For the security facts, these centralized solution may undergo from privacy issues [55], [56] which encouraged the authors [57], [58] to deploy distributed optimal power flow in the power system and most recently in [59]–[61]. However, the OPF problem is non-convex and the solution is too complicated to compute. In this work, conversely to the existing works, we will focus on trading mechanism of interconnected micro-grids rather than electrical operation of the utility grid. In the context of energy trading, distributed energy resources can make the current oligopolistic market to a flexible one [62]. For instance, the authors in [63] proposed a game theoretic approach to

trade the stored energy with other elements of the grid. In terms of demand response, the authors in [64] studied a generalized Nash equilibrium problem considering demand response where aggregators and micro-grids are formulated as non-cooperative game. However, majority of existing works [65]–[67] focus on energy trading mechanism based on architectural framework. [68], [69]

1.4 Literature Review on Optimization in Load Scheduling of a Residential Community Using Dynamic Pricing

Majority of studies investigated domestic energy management from theoretic perspective [70]–[77]. In [70], day-ahead scheduling and real-time regulation were connected to solve the uncertainties of the electricity price and hot water usage. In [71], the Monte Carlo simulation was enforced to solve RTP-based home energy management, and association with financial risks, modeled by the conditional value-at-risk. In [72], the scheduling of the household power consumption was taken as a Markov decision process, which directed to find decision thresholds for both controllable and uncontrollable appliances only with current prices and statistic knowledge about future prices. In [73], the uncertainty of the RTP was done through the robust optimization approach, which assumed that the unknown prices within the scheduling boundary had minimum and maximum limits. In [74], the day-ahead scheduling for the air conditioning (AC) was investigated in association to the uncertainties within the day-ahead electricity price and outdoor temperature forecasting, which were formed by fuzzy sets. In [75], the Lyapunov optimization approach was employed to reduce the long-term desired electricity cost for the household energy consumption, which comprised with renewable energy, controllable

loads, and uncontrollable loads. In [76], the demand response (DR) control strategy is proposed to control the total power consumption under the specified power limit during DR period. Appliances load demands are met according to priority of the load. In [77], a single objective optimization problem is performed to minimize the power consumption as well as the electricity cost. In this work, two optimization algorithms are compared with four appliances using external solver CPLEX.

In [78], optimization has been done for single house using particle swarm optimization to schedule the loads according to the priority placed by the customer. The authors estimate the schedule for hourly charging or discharging of the battery of electric vehicle, hours for turning on the heater for heating and hourly power of the pool pump and the water heater. In [73], the authors presented an optimization algorithm that ensures a residential consumer to adjust his or her cumulative hourly load level by varying hourly electricity prices. In [79], the authors proposed a multi-objective optimization model based on dynamic pricing, controllable load and a heuristic for household microgrids. The authors develop an evolution algorithm using hybrid differential coding to optimize the residential appliances and resource management. In paper [80], the authors proposed a hierarchical control scheme for distribution grids using the principles of organic computing to evaluate the results of simulations that handle variable tariffs and building energy management systems to facilitate demand response. However, the cost minimization considering different tariffs schemes, comfort of users, priority of loads of multiple houses have not been well-documented in the literature.

1.5 Motivations and Contributions

Motivated by the existing literature, we develop a game theoretic approach based on [48] to engage distributed electricity users and control the market price through load management. The objective is to maximize the production agents profit and minimize the consumption agents cost at Nash equilibrium point. Compared to prior works (e.g., [48], [49], [50], [52]), the main contributions of this work are: (i) A game theoretic approach is proposed based on ([48], [49], [50]) to analyze the behavior of production agents and consumption agents in the proposed market structure. Different from other prior works, the proposed model considers the control operation of market price through load management. The retail market electricity price is cleared at Nash equilibrium point. And (ii) the rational reaction sets (RRS) are used to model the game between production agents and consumption agents, and the economic operations of distributed electricity consumers are investigated of the future residential distributed system.

Motivated by aforementioned works, we have studied the energy trading mechanism between the islanded MGs without the need of a central coordinator. Each MGs buy/sell energy from/to adjacent MGs without sharing the local cost information. The objective of this work is to minimize the global operation cost (generation plus transmission costs) by preserving the local information. Compared with the previous works (e.g., [68], [69], [81]), the main contribution of this work include: (i) A distributed iterative algorithm based on deep cut ellipsoid method is proposed for energy trading between isolated MGs. Different from prior works, this work analyzes the comparative study between two distributed energy trading approaches using different topologies (Full, Line, Ring, Star).

(ii) the performance of two distributed algorithms are validated with different case studies.

In recent years, literature exhibits the cost minimization considering different tariff schemes, comfort of users, priority of loads of a single house. In this paper, considering the insufficient information of existing literature on community based energy management system, an optimization model is developed for a community. Genetic algorithm (GA) and dynamic programming (DP) are used as the optimization schemes to solve the load scheduling problems. The impact of priority of using residential appliances is also considered. The main objective is to comparative study of three optimization approaches as genetic algorithm (GA), aggressive dynamic programming (DP_{max}), conservative dynamic programming (DP_{min}) in terms of cost minimization of the utility. The DP_{max} (aggressive) and DP_{min} (conservative) are designed in terms of comfort of user and energy cost saving, respectively. Contribution of this work include: (a) A small community energy management system is developed with three houses considering the comfort level; (b) three types of houses with real-world appliances are implemented for a small community according to physical characteristics; (c) the three control approaches is evaluated on three case studies (fixed priority, with priority and without priority). The fixed priority is defined that the appliances will optimize the system according to their fixed priority order. With priority is specified that one appliance will work all the time and other appliances will be scheduled based on optimization approaches. For without priority, no priority order of using the appliances is set up for optimizing the energy consumption. d) The robustness of three different control approaches is validated for a residential community load scheduling problem.

1.6 The Structure of Thesis

The rest of the thesis is organized as follows. Chapter 2 discusses a game-theoretic optimization scheme to analyze the behavior of power production agents and consumption agents as well as to find the market clearing price at Nash equilibrium. A distributed iterative algorithm based on deep cut ellipsoid method for multiple micro-grids is demonstrated in Chapter 3. In Chapter 4, the power system optimization in a residential community for multiple houses considering comfort of users is discussed. A detailed description of the appliances model and performance comparison of the two optimization approaches are provided. The algorithm is discussed and applied to various topologies. Finally, conclusions of the thesis and possible future works are presented in Chapter 5.

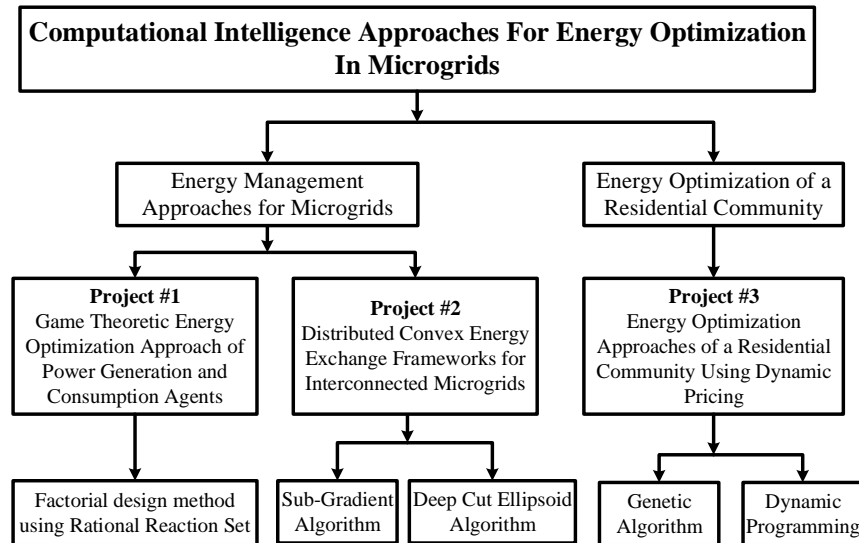


Figure 1.2. The structure of thesis.

CHAPTER 2 GAME THEORETIC ENERGY OPTIMIZATION APPROACH OF POWER GENERATION AND CONSUMPTION AGENTS

2.1 Introduction

Recently, electricity market has changed largely due to environmental and economic situations. In the deregulated market, the providers and consumers are the active participants. Technological development of the power system leads to a significant increase in the number of active players in the market. These active market participants lead the market towards cost reduction and maximizing the profits of the players, increasing market reliability [82]-[83]. Active market participants commence a bid by using and computing real market clearing price.

Smart grid technologies have a great impact on the strategic decisions of consumers' behavior. The traditional electricity market has faced complex problems such as unbalanced information, strategic interference and the possibility of multi-phase equilibrium [25]–[27]. Smart competitive structures such as retail market structure based on electricity market agents are an alluring item for simulating such problems. Each market player is an autonomous agent with independent pricing strategies that can behave to match the outcome of the electricity market. In the classical electricity market, when the number of generators is higher than the number of sellers, that makes the market less efficient. In the past several years, the majority of research has been on the supply side. In [84]-[85], the market players are played individually and cooperatively, and their cooperation resulted in a great profit, although the free-rider issue may also have appeared. In the comprehensive market, electricity purchasers are no longer price takers,

since they can leverage the market by introducing different bidding strategies as well as cooperating with other purchasers. Hence, it is important to investigate and advance the individual and cooperative strategies of electricity purchasers. In this chapter, the control operation of electricity market price through load management is investigated on the retail electricity market which allows high integration of small renewable production agents in a competitive manner instead of market price set by regulations. Compared to prior works (e.g.,[48],[49],[52]), the main contributions of this work are:

- A energy optimization problem for retail electricity market is formulated for each distributed production agent, where the wind energy, the solar energy, the energy storage (ES), and the diesel generator models are taken into consideration. A proper game theoretic approach is proposed to analyze the behavior of production agents and consumption agents in the proposed market structure. Different from other prior works, the proposed model considers the control operation of market price through load management. The retail market electricity price is cleared at Nash equilibrium point.
- The rational reaction sets (RRS) are used to model the game between production agents and consumption agents, and the economic operations of distributed electricity consumers are investigated of the future residential distributed system.

2.2 Proposed Model Description

The proposed benchmark for electricity market is represented based on [48] in Figure 4.1. In this proposed energy market, small production agents which are equipped with various generation and storage units, like photovoltaic systems, wind turbine, diesel

generators and distributed energy storage devices. The DER's agents can communicate and share information with each other. This communication results in maximizing profits and improves market stability and reliability. The smart grid enable bidirectional communication for the consumers to easily access the grid and the production agents and collects information regarding storage units, generating units and loads [86]. In the proposed framework, the small production agents are autonomous entities than traditional suppliers. This market structure facilitates large integration of renewable resources, which is important to ensure more sustainable future electricity market.

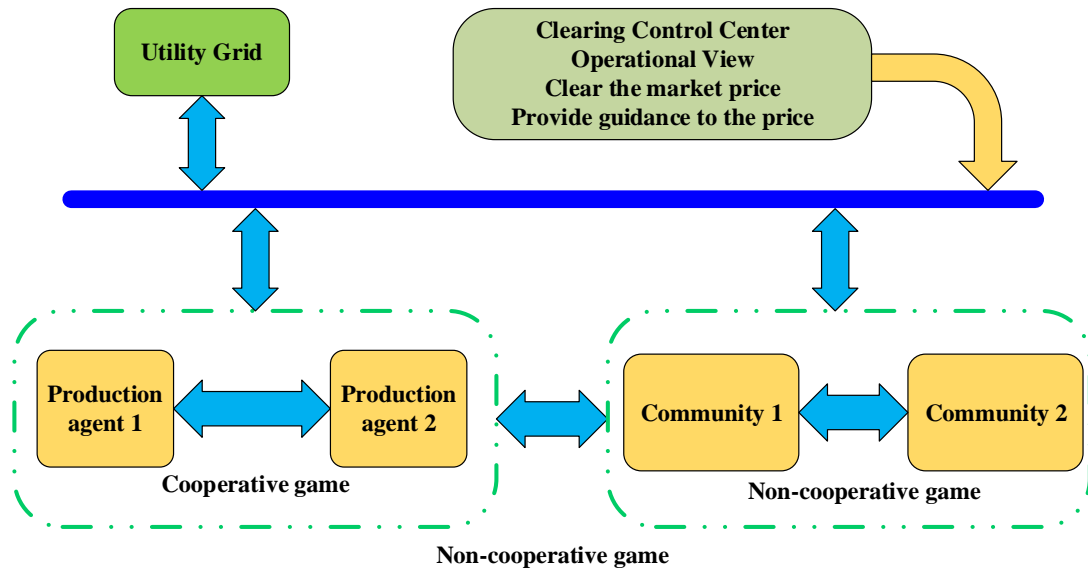


Figure 2.1. Proposed smart grid hierarchy model including DER's production agents, multiple communities, utility grid and bi-directional communications [48]

The developed retail market model enables the active participation of the household consumers with exploitation and management of distributed energy resources (DER). The small production agents can cooperate each other to obtain more profit. On the other hand, customers are participating in the market by managing their shift-able load demand to reduce final electricity price. The consumers are regularly involved in setting the market

prices. In this work, DER's production agents have no control in setting the market price. The role of the grid is different than in conventional electricity market model. In such retail electricity market, the utility grid no longer occupies power plant. The utility grid is considered an independent unit to meet the shortage of power from small production agents. It also provides ancillary services to the consumption agents and small DER's production agents. In this work, the utility grid is not considered as the active player in the game model. The game exists among a large number of production agents and consumption agents.

2.3 Objective Functions and Constraints

This section represents the mathematical formulation of the key concept of the highly competitive retail electricity market. This proposed framework allows a high penetration of distributed generators (DG) and energy storage. The participants of the market can be categorized into three groups: small production agents, consumption agents, and the utility grid. But, the utility grid has not participated in the market.

2.3.1 Objective functions

For the i^{th} (e.g. $i=1,2$) production agent, the objective function can be defined as the summation of differences between revenue and cost over 24 hours in the one-hour interval. The profit function of production agent 1:

$$P_1 = \sum_{t=1}^{t=24} (R_{1,t} - C_{1,t}). \quad (2.1)$$

The profit function of production agent 2:

$$P_2 = \sum_{t=1}^{t=24} (R_{2,t} - C_{2,t}). \quad (2.2)$$

The production agents objective function:

$$\arg \max J_{productionagents} = P_1 \times P_2 \quad (2.3)$$

where $R_{1,t}$, $C_{1,t}$ and $R_{2,t}$, $C_{2,t}$ are the revenue function of t^{th} hour of production agents 1 and 2 respectively.

The retail electricity price is a function of aggregated load demand. This price function is considered to be identical for all the players following a singular distribution system [87].

$$\lambda(Pd_{total}) = (-\alpha \times Pd_{total}) + \beta, \alpha \geq 0 \quad (2.4)$$

where λ is the electricity price in $\$/kWh$, Pd_{total} is the total load demand and α and β are the load demand coefficients.

The revenue function of every single production agent at t^{th} hour can be expressed as:

$$R_{i,t} = \lambda(Pd_{total}) \times [P_{wind,i}(t) + P_{solar,i}(t) + P_{DG,i}(t) + P_{ES,i}(t)] \quad (2.5)$$

where $P_{wind,i}$ is the output power of the i^{th} supplier, $P_{solar,i}$ is the solar output power of the i^{th} production agent, $P_{DG,i}$ is the diesel generator output power of the i^{th} production agent and $P_{ES,i}$ is the battery output power of the i^{th} production agent. $P_{ES,i}$ can be positive

and negative based on discharging and charging mode respectively. The cost function of i^{th} production agent at t^{th} hour can be defined as:

$$C_{i,t} = [\psi_{wind}P_{wind}(i,t) + \psi_{solar}P_{solar}(i,t) + \psi_{DG}P_{DG}(i,t) + \psi_{ES}P_{ES}(i,t)], \quad (2.6)$$

where ψ is production cost of energy generation units. Wind and solar power generators are considered as non-manageable units, and their power output depends on uncertain and variable energy resources. In this work, the production cost of renewable energy resources (i.e, wind and solar) is assumed to be negligible in long term such that $\psi_{solar} = 0$ and $\psi_{wind} = 0$. The degradation cost of the storage device is beyond the scope of this paper. so, the cost of energy storage units, $\psi_{ES} = 0$. Since the small-scale DGs have negligible startup and shutdown time, the startup and shutdown cost is assumed as a constant for each DG units. The cost of DG unit (ψ_{DG}) can be formulated a strictly convex quadratic function as:

$$C_{i,t} = \psi_{DG} = a_i P_{DG}^2(t) + b_i P_{DG}(t) + c_i. \quad (2.7)$$

For the residential community, the objective function is to minimize the operating cost by managing their own displaceable loads. For i^{th} community at t^{th} hour, the objective function is defined as:

$$\arg \min J_{community} = \sum_{t=1}^{t=24} \lambda(P_{total}) \times Pd_{i,t} \quad (2.8)$$

2.3.2 Local and global constraints

Each player can make decisions on their own subject to local as well as global constraints.

The local constraints include the following relation:

2.3.2.1 Local regulation of wind generation

The wind output power can be determined from power function based on wind speed according to following relation:

$$P_{wind}(i, t) = \begin{cases} 0 & v < v_{ci} \text{ or } v > v_{co} \\ \frac{P_r(v-v_{ci})}{(v_r-v_{ci})} & v_{ci} \leq v \leq v_r \\ P_r & v_r \leq v \leq v_{co} \end{cases}$$

The wind turbine need to maintain the power output ($P_{wind}(i, t)$) within the specified range $[P_{wind,i,min}, P_{wind,i,max}]$ for the i^{th} player at t^{th} hour.

$$P_{wind,i,min} \leq P_{wind}(i, t) \leq P_{wind,i,max} \quad (2.9)$$

where $P_{wind}(i, t)$ is the power output and $P_{wind,i,min}$ and $P_{wind,i,max}$ are the minimum and maximum power output of wind energy resources for the i^{th} player at t^{th} hour.

2.3.2.2 Local regulation of solar generation

Solar energy system power distribution can be calculated using solar Irradiation.

The solar energy system output power is determined as follows:

$$P_{solar}(i, t) = A_c \times \eta \times I_t \quad (2.10)$$

The power generation ($P_{solar}(i, t)$) of solar panel should control within the specified range $[P_{solar,i,min}, P_{solar,i,max}]$ for the i^{th} player at t^{th} hour.

$$P_{solar,i,min} \leq P_{solar}(i, t) \leq P_{solar,i,max} \quad (2.11)$$

where $P_{solar}(i, t)$ is the power generation and $P_{solar,i,min}$ and $P_{solar,i,max}$ are the minimum and maximum power output of solar energy system for the i^{th} player at t^{th} hour.

2.3.2.3 Diesel generator technical limits

The DG of i^{th} player at any given t^{th} hour must operates with the expected power output within the specified boundary $[P_{DG,i,min}, P_{DG,i,max}]$.

$$P_{DG,i,min} \leq P_{DG}(i, t) \leq P_{DG,i,max} \quad (2.12)$$

where $P_{DG,i,min}$ and $P_{DG,i,max}$ are the minimum and maximum output power of i^{th} player diesel generator. The high operating cost of diesel generator bound the suppliers to turn on the generator at any given output. Especially, the expected power output must be greater than minimum power output ($P_{DG,i,min}$) of diesel generator.

2.3.2.4 Energy storage technical limits

Every energy storage power output ($P_{ES}(i, t)$) must be satisfied within the specified range $[P_{ES,i,maxd}, P_{ES,i,maxc}]$ for the discharge and charging mode respectively, at t^{th} hour for the i^{th} player.

$$P_{ES,i,maxd} \leq P_{ES}(i, t) \leq P_{ES,i,maxc} \quad (2.13)$$

where $P_{ES,i,maxd}$ and $P_{ES,i,maxc}$ are the maximum energy storage power in kW of discharge and charge mode respectively. For restricting over-discharging and over-charging, the state of charge of each battery must maintain safe range otherwise the energy storage unit will switch to a standby mode.

The SOC in the energy storage at t^{th} for i^{th} player should remain within ceratin range $[SOC_{ES,i,min}, SOC_{ES,i,max}]$ to avoid damaging the energy storage lifespan.

The SOC at the next hour can be determined using the capacity of the energy storage $[E_{capacity,i}]$ in the ($\Delta t = 1$ hr) interval and battery power output ($P_{ES}(i, t)$). $P_{ES}(i, t)$ might be negative or positive depending on charging and discharging modes respectively.

$$SOC_{ES,i,min} \leq SOC_{ES}(i, t) \leq SOC_{ES,i,max} \quad (2.14)$$

$$SOC_{ES,i}(t+1) = SOC_{ES}(i, t) - P_{ES}(i, t) \times \frac{\Delta t}{E_{capacity,i}} \quad (2.15)$$

where $SOC_{ES,i,min}$ and $SOC_{ES,i,max}$ are the minimum and maximum state of charge (SOC) of ES , $E_{capacity,i}$ is the battery capacity in kWh and Δt is considered to be 1 hour.

$P_{ES}(i, t)$ might be negative or positive depending on charging and discharging modes

respectively. To ensure certain amount of electricity store in ES at the beginning of the next day (24^{th} hour), the minimum SOC at 24^{th} hour is defined as:

$$SOC_{ES,24} \geq SOC_{ES,end} \quad (2.16)$$

2.3.2.5 Upstream utility grid constraints

The considered market structure allows the production agents to buy and sell electricity from the utility grid. Every player must satisfy the following relation when try to sell electricity:

$$P_{Grid}(i,t) \leq \eta \times (P_{wind}(i,t) + P_{solar}(i,t) + P_{DG}(i,t) + P_{ES}(i,t)) \quad (2.17)$$

where $P_{Grid}(i,t)$ is the power sold to the utility grid by i^{th} production agent at t^{th} hour. The negative $P_{Grid}(i,t)$ implies the selling electricity to the grid. On the other hand, positive $P_{Grid}(i,t)$ indicates the buying electricity from the grid in extreme cases.

2.3.2.6 Residential community load constraints

The consumers of each residential community have the ability to control and manage their responsive loads (RLD) at t^{th} hour within the certain range.

$$\zeta_1 P_{RL}(i,t) \leq P_d(i,t) \leq \zeta_2 P_{RL}(i,t) \quad (2.18)$$

where $P_{Base}(i,t)$ is the base load demand of the i^{th} player at t^{th} hour. ζ_1 and ζ_2 are the minimum and maximum percentage of responsive load (RL) respectively.

2.3.2.7 Global constraints of the system

According to the concept of conservation of energy, the power generated by production agents must be equivalent to the consumptions agents.

$$\sum_{i \in N} [P_{wind}(i,t) + P_{solar}(i,t) + P_{DG}(i,t) + P_{ES}(i,t) + P_{Grid}(i,t)] = \sum_{j \in N} Pd(j,t) \quad (2.19)$$

where the left-hand side indicates the produced power in the market. $P_{Grid}(i,t)$ is the buying or selling electricity from the grid. The total consumption by residential community reflects on the right-hand side.

2.4 Proposed game theoretic solution

In the proposed electricity market model, all the players strategically interact with each other by setting their power and load demand. Power production agents and residential consumers choose strategies to achieve the maximum payoff. The power production agents can maximize the profit by reducing the cost associated with power generation. The consumers of the residential community can minimize the cost by managing their load demand. The nature of the considered electricity market fit into the n-person game. The production agents can communicate and share their knowledge with each other to form a coalition. This collaboration can increase the market efficiency and stability. This work considers non-cooperative game among the residential communities. The game between production agents and residential communities can be iteratively solved using special game-theoretic methodologies (e.g. Rational reaction set and Deign of experiment- Response Surface method (DOE-RSM)) to find the Nash equilibrium. The

n-person game is defined by three components as $N, X_i, \varphi_i, i \in N$. Each i^{th} player belongs to a set $N = 1, 2, 3, \dots, n$ players. X_i is the strategy space of player i^{th} player. The set of collective strategies is defined as:

$$X = X_1 \times X_2 \times \dots \times X_n \quad (2.20)$$

where, φ_i is the i^{th} player payoff function who calculates their benefit by setting its own strategy based on the strategy space of others. The term $(y_i|x)$ denotes the element $(x_1, \dots, x_{i-1}, y_i, x_{i+1}, \dots, x_n)$. It states that the $(x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$ players are playing the game while the other i^{th} player takes the action y_i . The Nash equilibrium for each i^{th} player is defined as:

$$x^* = (x_1^*, \dots, x_n^*) \quad (2.21)$$

In other words, a Nash equilibrium solution is existed if x^* is at least as good as for player i as the action profile (x_i, x_{-i}^*) ; where every other player chooses x_j^* while other player chooses x_i .

$$\varphi_i(x_i^*|x^*) \geq \varphi_i(x_i|x_{-i}^*) \quad (2.22)$$

This defines that if all players choose the equilibrium profile, no strategy profile generates a preferable outcome for the i^{th} player than the Nash equilibrium. The game theoretic-rational reaction set is used to find Nash equilibrium of each player. In this work, factorial design method in DOE is used to find the sensitivity of each generating units to total load demand. Using the factorial design method, the rational reaction set of each

residential community load demand by taking the consideration of other community load demand.

2.4.1 Rational reaction set and Nash equilibrium

In the non-cooperative game, player 1 and player 2 are considered. The player 1 and player 2 select strategies x and y where $x \in X$ and $y \in Y$. X and Y are the set of all possible strategies each player can select. The objective function $f_1(x, y)$ and $f_2(x, y)$ represents the cost function for player 1 and 2, respectively.

The Nash equilibrium exists where each player calculates its set of optimal solutions based on the choices made by other players. This feasible set of solution for each player is called rational reaction set (RRS) ([88],[48]). The RRS for player 1 and 2 can be structured as:

$$f_1(x^N, y) = \min f_1(x, y) \rightarrow x^N(y) \quad (2.23)$$

$$f_2(x, y^N) = \min f_2(x, y) \rightarrow y^N(x) \quad (2.24)$$

x^N is the optimal solution of player 1 that varies depending on the strategy y chosen by player 2. The function $x^N(y)$ is the RRS for player 1. Similarly, $y^N(x)$ is the RRS of player 2. If, the intersection of these two sets exists, then that point would be the Nash equilibrium solution for the non-cooperative game. Therefore, if the parametric equations $x^N(y)$ and $y^N(x)$ are solved simultaneously, the resulting equilibrium solution is the Nash equilibrium solution.

2.4.2 Consumption agents game

The 30 levels of load demand value of residential community 1 and 2 are generated which satisfy consumption agents' load demand constraints. The residential community 1 solves its own problem for every level of other community load demand. Similarly, the solution residential community 2 can be found. Then, each community load demand can be modeled as through machine learning model (linear regression) as a linear equation:

$$Pd_{1,t} = A \times Pd_{2,t} + B \quad (2.25)$$

$$Pd_{2,t} = C \times Pd_{1,t} + D \quad (2.26)$$

where, $Pd_{1,t}$ and $Pd_{2,t}$ define the load demand of community 1 and community 2 at t^{th} hour respectively. A,B,C and D are the coefficients of linear equations. Finally, the intersection of two linear equation sets of community 1 and 2 provides the Nash equilibrium solution.

2.4.3 Production agents game

Due to the cooperative game, suppliers made a coalition. That's why there is one combined objective function of production agents. The factorial design method had also applied here. The problem is solved for the production agents with each and every set of data from consumption agents. The optimized values for $P_{wind}(i)$, $P_{solar}(i)$, $P_{DG}(i)$, $P_{ES}(i)$, $P_{Grid}(i)$ were gained for each set of consumption data. Then, a linear regression model can be applied through the following formula:

$$P_{prod}(n,t) = A \times P_{total} + B \quad (2.27)$$

where the above equation represents the RRS of the n^{th} production agent as a function of the total load demand at t^{th} hour.

Finally, the optimal demand value (P_{total}) of residential communities at Nash equilibrium were substituted into the production agents problem to find the Nash equilibrium from the production agents.

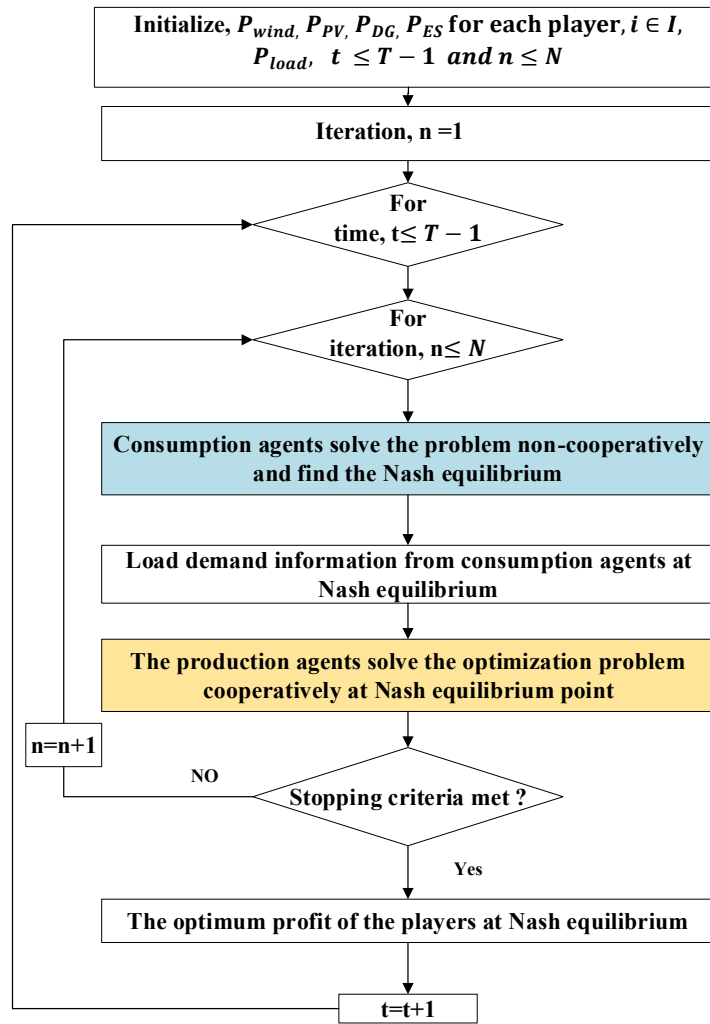


Figure 2.2. Proposed game theoretic algorithm flowchart

2.5 Result and Discussion

The benchmark under study includes a collection of production resources (WT, PV, DG, and ES) and consumers as the shift-able load. The system consists of 100 consumers. That is equally divided into two community. The consumer's load demand has been taken from [89]. The cost coefficients (a,b and c) and (α, β) , are summarized in Table 3.1. The $\sigma_1 = 20(\%)$ and $\sigma_2 = 80(\%)$ are minimum and maximum percentage of manageable load demand respectively.

Table 2.1. Cost and Price coefficient

Coefficients	α	β	a	b	c
Units	\$/kWh	\$/h	\$/kW ² h	\$/kWh	\$/h
Production agent 1	0.001	1.3	6×10^{-6}	0.010	0
Production agent 2	0.001	1.3	7×10^{-6}	0.015	0

For investigating the performance of the retail energy market (REM) based on design of experiment-rational reaction set approach, three cases have been implemented in the considered framework: case 1: Normal operating condition, case 2: Abundant renewable energy resources (RES) and case 3: Shortage of renewable energy resources.

All the production agents have renewable energy resources and generator units that summaries in Table 2.2.

2.5.1 Real time optimization

In the case of abundant renewable energy resources, the wind speed and solar radiation are in good condition. Due to the large availability of renewable energy provides the production agents higher profit than normal condition. Because the production cost of renewable energy is assumed to be negligible. During the less available renewable energy

Table 2.2. Production agents resources

Production agents	Generation	Type	Quantity	Capacity
Production agent 1	WT	30 kW	18	540 kW
	PV	180 W	1840	350 kW
	ES	24 V/84 Ah	631	1262 kW
	DG	100 kW	7	700 kW
Production agent 2	WT	30 kW	8	240 kW
	PV	180 W	1667	330 kW
	ES	24 V/84 Ah	631	1262 kW
	DG	260 kW	2	520 kW

hours, the production agents make a strategic decision not to turn on diesel generator because of high operating cost at any given output and relies on utility grid to secure the load demand. In other words, the expected power output of diesel generator should be greater than the $P_{DG,i,min}$. In those hours, the utility grid sells more electricity and the production agents get less profit. In the case of shortage of RES, the solar radiation and wind energy are in weak condition, the pursuit of maximizing the renewable energy utilization can push the energy storage and diesel generator to operate all day. Also due to the limitation of the capacity of energy storage and diesel generator, the shortage of generated power can be given by utility grid. That's why the profit is less than the normal condition. Figure 4.2 shows the convergence of the payoff function values for the production agents under different conditions. By iteratively solving the considered problem, the payoff function values of production agents are gradually converging to an equilibrium point in all scenarios. The payoff function values of production agents are converged to a high value in case of abundant RES. On the other hand, the payoff function values are converged to lower values because of buying electricity from the utility grid. Therefore, the equilibrium payoffs of considered cases are found to be $[2.06 \times 10^6]$,

2.74×10^6 and 1.46×10^6] respectively at 2^{nd} hour and $[2.25 \times 10^6, 3.26 \times 10^6$ and $1.41 \times 10^6]$ respectively at 10^{th} hour.

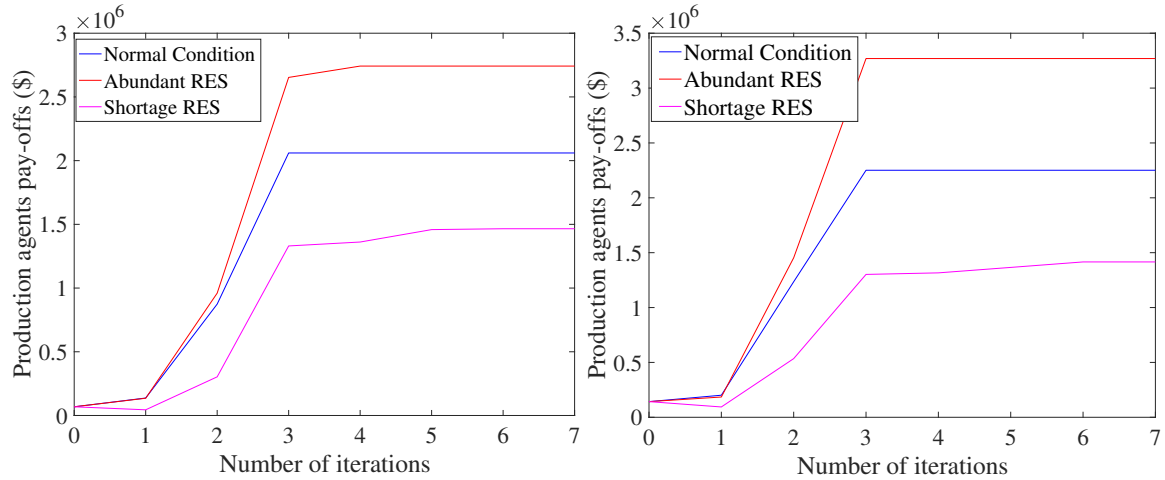


Figure 2.3. Pay-off function values of production agents at 2^{nd} hour (left) and 10^{th} hour (right).

In case of the non-cooperative game, the residential communities solve their own problem individually. Similarly, the production agents problem, both of the residential communities pay-off functions are converged to a lower cost [Figure 4.14 and 4.15] for the large availability of renewable energy hours. In the off-peak hours, the payoff function is converged to the higher cost because of expensive electricity buying from the utility grid.

Using the equilibrium solution, the electricity market price can be cleared for the future residential distribution system with multiple residential communities satisfying local and global constraints. The clearing price of restructured electricity market can be found at Nash equilibrium in Table 2.3.

2.5.2 Day ahead optimization

The day-ahead optimization is also completed in the proposed framework. Figure 4.16 and 2.7 show the convergence of the payoff function values for the players on the

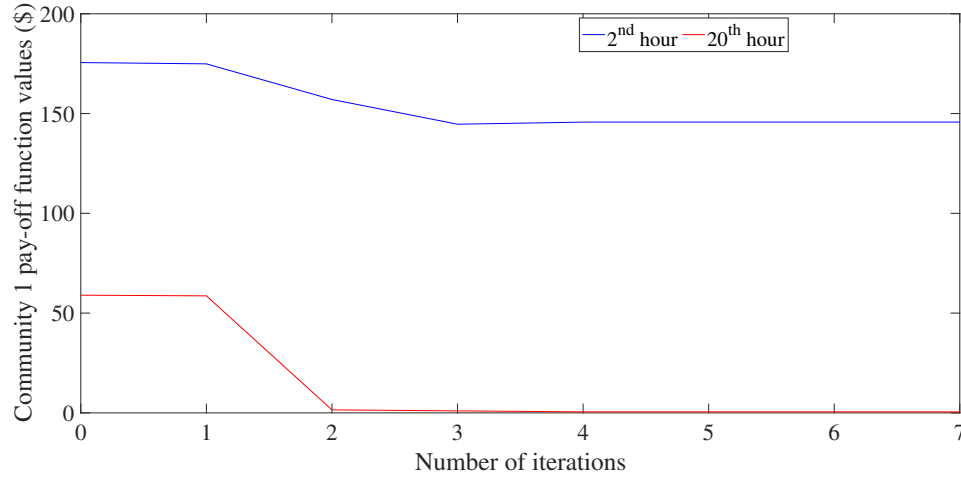


Figure 2.4. Pay-off function values of community 1

Table 2.3. Hourly electricity prices at Nash equilibrium

t	Price (\$/kWh)	t	Price (\$/kWh)	t	Price (\$/kWh)
1	0.9564	9	0.7513	17	0.5423
2	0.9641	10	0.9293	18	0.3369
3	0.9699	11	0.8530	19	0.1654
4	0.9446	12	0.8680	20	0.0889
5	0.9397	13	0.8845	21	0.1645
6	0.7831	14	0.9234	22	0.4099
7	0.7558	15	0.9243	23	0.4766
8	0.7695	16	0.7895	24	0.8519

production side and the consumption side with considered case studies. The payoff function values iteratively achieved by production agents using the cooperative game. While, consumption agents' pay-offs can be obtained through non-cooperative game. The payoff function values for all players gradually converged to an equilibrium point. The equilibrium pay-offs for the consumption players are found to be [3352, 3456].

The optimum pay-offs at Nash equilibrium of the day ahead optimization of the production agents for three considered cases are resulted to be $[9.0422 \times 10^5, 9.0830 \times 10^5 \text{ and } 8.8135 \times 10^5]$.

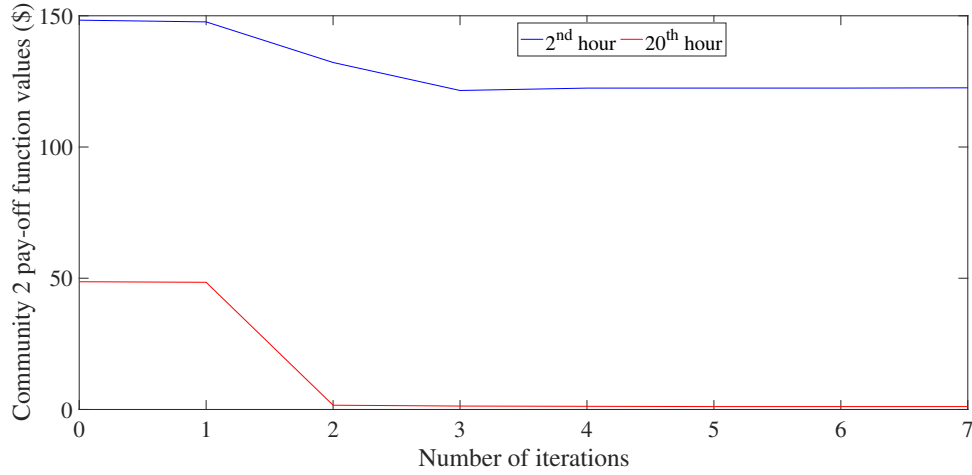


Figure 2.5. Pay-off function values of community 2

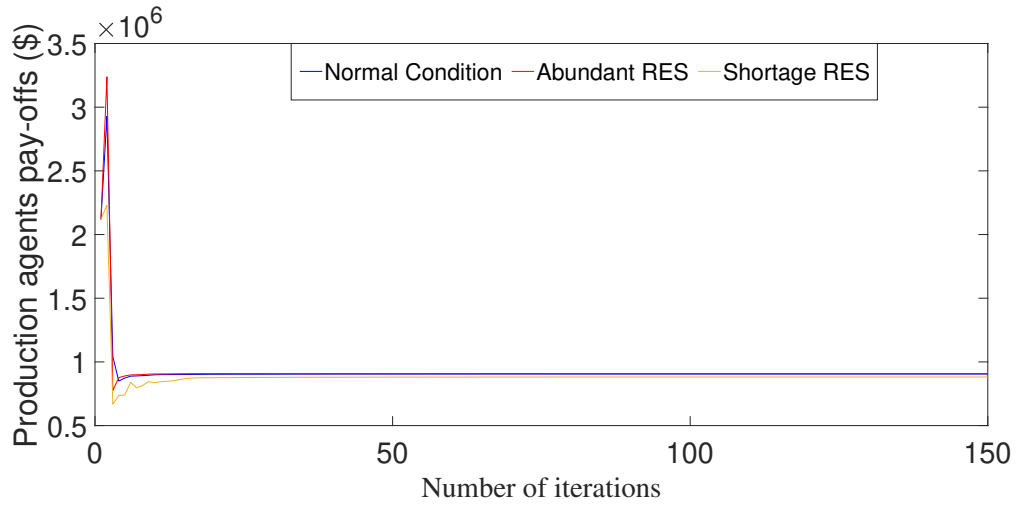


Figure 2.6. Pay-off function values of production agents

2.6 Concluding Remarks

In this chapter, a game-theoretic method is proposed based on [48] to analyze the behavior of the power generation and consumption players in the power system. The proposed framework enables the distributed operators and residential consumers to efficiently integrate a wide range of renewable energy resources. The residential consumption agents play an important role in the market to control the electricity price.

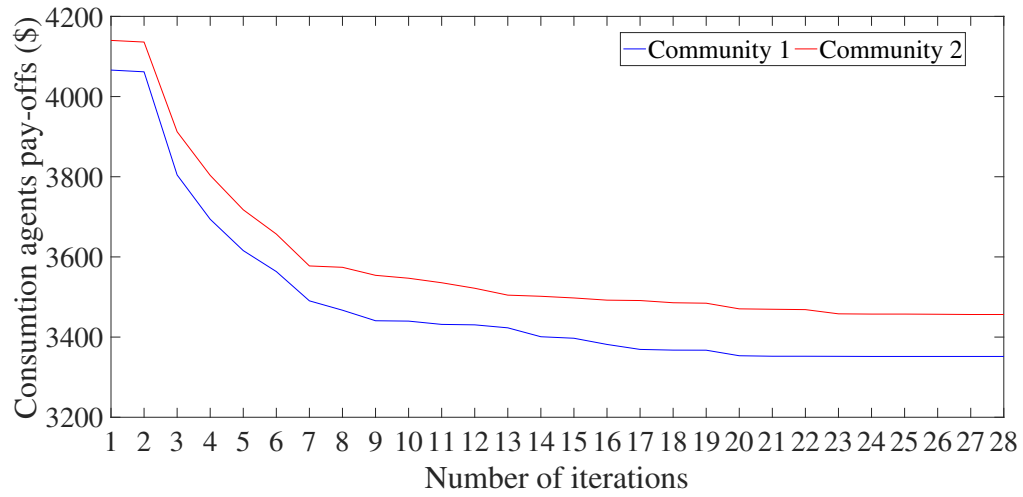


Figure 2.7. Pay-off function values of consumption agents

The consumption agents are not only able to find market clearing price at Nash equilibrium point but also reduce the electricity cost individually (non-cooperatively). Simulation case studies are conducted to validate the proposed game theoretic approach. The proposed approach can be effectively used as a tool for investigating the retail electricity market.

2.7 Acknowledgment

In this chapter, the work is developed and implemented based on the model of [48].

CHAPTER 3 DISTRIBUTED CONVEX ENERGY EXCHANGE FRAMEWORKS FOR INTERCONNECTED MICROGRIDS

3.1 Introduction

Distributed energy management with direct energy exchange among microgrids is promising approach to improve the economy, reliability and efficiency of system operation. In the interconnected microgrids system, each microgrid not only schedules its local power supply and demand, but also trades energy with other microgrids. Specifically, microgrids with excessive DERs generations can trade with other microgrids which has deficit of power for mutual benefits. This cooperation of multiple microgrids (MGs) can reduce the mismatch problem between distributed generation and demand, improve the system performance, decrease the total cost of the power system. However, existing strategies on microgrid energy trading only concentrate on simulation studies and modeling issues.

This chapter tries to provide a extensive analytical solution for energy management problem among microgrids, can be implemented distributely without need of central agent. More clearly, our distributed system model consists of N microgrids in which (a) Each microgrids has own energy generation cost, (b) The distribution network operator imposes the cost for transferring energy between adjacent microgrids, (c) each microgrid owns power demand that must be fulfilled. Considering all of these issues, we have to find the optimal amount of energy to be traded by the microgrids in order to minimize the total operating cost of the considered system. In this work, a distributed iterative algorithm based on dual decomposition is proposed that solve the problem distributely. For ensuring

the safeguard, the information exchange among microgrids is limited to Lagrange multiplier and expected buying energy. First, each microgrids individually enumerates the amount of energy it should produce, sell and buy to minimize the local cost in terms of current energy prices. Then, a energy prices are adjusted according to law of demand after the energy bids between microgrids. This two-step proceeds until global agreement is met about prices and transferred energy. The performance of the proposed algorithm is compared with existing approaches in [68] and [90] in terms of computational time and iteration with different topologies.

3.2 System Model

A system composed of $N = 4$ interconnected MGs through a power interconnection infrastructure and a communication network is considered which represents in Figure 3.1 .

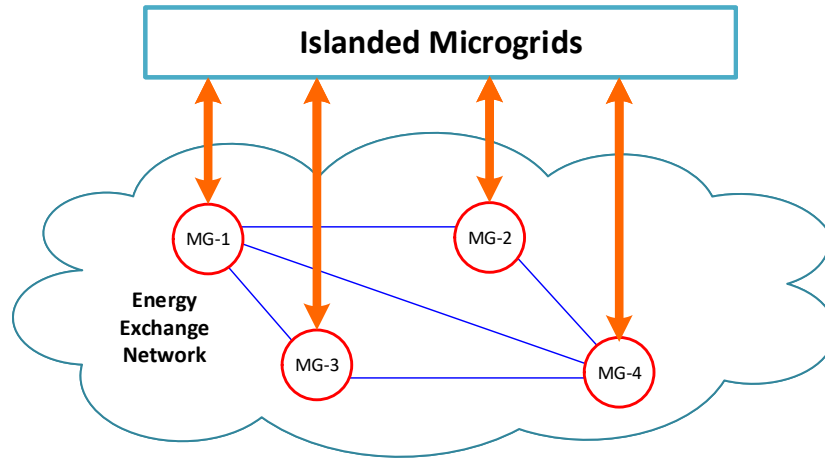


Figure 3.1. A energy exchange network composed of multiple interconnected MGs, distribution power line and communication network

During each scheduling time, $E_i^{(g)}$ and $E_i^{(c)}$ are the generation and consumption of MG i respectively. Moreover, MG i is allowed to sell energy $E_{i,j}$ to MG j , $j \neq i$, and to

buy energy $E_{k,i}$ from MG k , $k \neq i$. Then, The power balance within the MG requires

$$E_i^{(g)} + e_i^T \mathbf{A}^T \mathbf{E}_i^{(b)} = E_i^{(c)} + e_i^T \mathbf{A} \mathbf{E}_i^{(s)} \quad (3.1)$$

where the two N-dimensional column vectors

$$E_i^{(b)} = \begin{bmatrix} E_{1,i} \\ \cdot \\ \cdot \\ \cdot \\ E_{N,i} \end{bmatrix}$$

and

$$E_i^{(s)} = \begin{bmatrix} E_{1,i} \\ \cdot \\ \cdot \\ \cdot \\ E_{N,i} \end{bmatrix}$$

In order to introduce the connection between MGs, an adjacency matrix $\mathbf{A} = [a_{i,j}]_{N \times N}$ is defined. If there exists a connection between MG i to MG j , element $a_{i,j}$ is set as 1 and zero otherwise. Note that \mathbf{A} may be non-symmetric, meaning that at least two MGs are allowed to share energy in one direction only. Moreover, we fix $a_{i,i} = 0$, and if $a_{i,j} = 0 \rightarrow E_{i,j} = 0$ for all $i, j = 1, \dots, N$.

The objective of this problem is to minimize the total operating cost of

interconnected microgrid system, consisting of power generation and transmission cost.

So, the energy exchanged by interconnected MGs form the equilibrium point of the following minimization problem:

$$\begin{aligned}
 & \underset{E_{i,j}}{\text{minimize}} && \sum_{i=1}^{N=4} C_i(E_i^{(g)}) + \sum_{i=1} e_i^T \mathbf{A}^T \beta(E_i^{(b)}) \\
 & \text{subject to} && E_{i,j} \geq 0, \forall i, j \\
 & && E_i^{(c)} + e_i^T (\mathbf{A} E_i^{(s)} - \mathbf{A}^T E_i^{(b)}) \geq 0, \forall i
 \end{aligned} \tag{3.2}$$

where $C_i(E_i^{(g)})$ is defined the cost of generating $E_i^{(g)}$ units of energy at MG i ; $\beta(E_i^{(b)})$ is the cost of transferring $E_{i,j}$ units of energy between MG i and MG j ; \mathbf{e}_i is the i th column of the $N \times N$ identity matrix; $E_i^{(b)}$ is the vector composed of the energy bought from other MGs by MG i ;

$$\beta(E_i^{(b)}) = [\beta(E_{1,i}), \dots, \beta(E_{N,i})]^T \tag{3.3}$$

The multiple MGs in one interconnected microgrid system, which have their set of strategies, should be coordinated in order to achieve the global objective of the system and meet power demands.

3.2.1 The cost functions

In the system model mentioned above, two cost functions have been introduced, namely cost function $C_i(E_i^{(g)})$ is the price MG i spend to generate the energy $E_i^{(g)}$, and the cost function $\beta(E_i^{(b)})$ is the cost of transferring energy between MG i to MG j . Both cost functions are positive valued, monotonically increasing, convex and twice differentiable.

The cost function $C_i(E_i(g))$ of a diesel generator (DG) is modeled as a quadratic polynomial. So, the fuel cost is represented as follows:

$$C_{dgi} = a_i + b_i P_{dgi} + c_i P_{dgi}^2 \quad (3.4)$$

where a_i , b_i and c_i are the fuel cost coefficients of DG; and P_{dgi} is the output power of DG i .

The total operation cost $C_i(E_i^{(g)})$ includes the cost of all DG units of MG i ,
 $C_i(E_i^{(g)}) = \sum_{N=1}^{N=4} C_{dgi}$.

For the transportation cost, many factors may have influence on the model, i.e, the investment and construction cost of the network, etc. For simplicity, we imagine that the cost of all connection topologies of the system is same. The transmission cost also is quadratic; $\beta(x) = px + qx + rx^2$.

However, it is needed to comment on the cost functions, we need to describe how they can be used to introduce a upper bound constraint on the energy generated by the MGs or supported by the transfer connections. Indeed, one can design the cost function by introducing *soft* constraints with a sharp rise at nominal maximum value. The benefit of doing this design is twofold: first, we can make flexible system by avoiding further complexity to the minimization problem and the resulting constraint on the maximum energy is *soft*. By introducing soft upper bound, a MG of the system can generate more energy than the nominal maximum power, but the MG needs to pay an (significant) extra cost. This circumstance arises in the actual systems when backup generator activated.

3.3 Distributed model and algorithm

3.3.1 Distributed optimal scheduling model

When considering the minimization problem (3.2), one can readily identify that the objective function is strictly convex. Moreover, a centralized unit needs a control unit that is aware of all system informations. This fact implies a considerable amount of data traffic to gather all the information and can miss some annoying privacy issues. In this regard, we propose a distributed iterative approach by decomposing the problem N local subproblems, which can be implemented by the MGs in an autonomous and cooperative manner.

By utilizing Lagrangian method and duality theorem, a multiplier strategy is introduced as the exchanged information between MGs to solve the subproblem for each MG. Thus, the distributed iterative solution (3.2) can be rewritten as:

$$\begin{aligned}
 C^* = \underset{\boldsymbol{\varepsilon}_i^{(s)}, E_{i,j}}{\text{minimize}} \quad & \sum_{i=1}^{N=4} C_i(E_i^{(g)}) + \sum_{i=1} e_i^T \mathbf{A}^T \boldsymbol{\beta}(E_i^{(b)}) \\
 \text{subject to} \quad & E_{i,j} \geq 0, \forall i, j \\
 & E_i^{(g)} + e_i^T \mathbf{A}^T \mathbf{E}_i^{(b)} = E_i^{(c)} + e_i^T \mathbf{A} \mathbf{E}_i^{(s)}, \forall i \\
 & \boldsymbol{\varepsilon}_i^{(s)} = e_i^T \mathbf{A} \mathbf{E}_i^{(s)}, \forall i
 \end{aligned} \tag{3.5}$$

The only difference with respect to (3.2) is the introduction of new variable $\boldsymbol{\varepsilon}_i^{(s)}$ to represent the energy sold by MG i and later it will be equal to all the energy bought by other MGs from MG i . The coupling constraint can be represented as $\boldsymbol{\varepsilon}_i^{(s)} = e_i^T \mathbf{A} \mathbf{E}_i^{(s)}$.

Due to the convexity of primal dual problem (3.2), Lagrange multipliers are introduced to relax the coupling constraints and solving the dual problem.

$$C^* = \max_{\lambda} C(\lambda) \quad (3.6)$$

where, $C(\lambda) = \sum_{i=1}^N C_i^l(\lambda)$

$$\begin{aligned} C_i^l(\lambda) &= \min_{\epsilon_i^{(s)}, E_i^{(b)}} C_i(\epsilon_i^{(s)}, E_i^{(b)}, \lambda) \\ \text{subject to} \quad & E_{i,j} \geq 0, \epsilon_i^s \geq 0, \forall j \\ & E_i^{(g)} + e_i^T \mathbf{A}^T \mathbf{E}_i^{(b)} = E_i^{(c)} + e_i^T \mathbf{A} \mathbf{E}_i^{(s)} \end{aligned} \quad (3.7)$$

For each MG, we have:

$$C_i(\epsilon_i^{(s)}, E_i^{(b)}, \lambda) = C_i(E_i^g) + e_i^T \mathbf{A}^T \beta(\mathbf{E}_i^{(b)}) + e_i^T \mathbf{A}^T \text{diag} \lambda \mathbf{E}_i^{(b)} - \lambda_i \epsilon_i^{(s)} \quad (3.8)$$

that is the contribution of MG i to the Lagrangian function relative to (3.2). The parameter λ gathers all the Lagrange multipliers λ_i corresponding to coupling constraints $\epsilon_i^{(s)} = e_i^T \mathbf{A} \mathbf{E}_i^{(s)}$, respectively and for all $i = 1, \dots, N$. Based on above analysis, each Lagrange multiplier λ_i can be defined as the marginal cost of MG i , namely the selling price of a unit of power to neighboring MGs. Thus, Lagrange function can be seen as net expenditure. The net expenditure of each MG has four parts: (i) $C_i(E_i^{(g)})$ is the generation unit cost function; (ii) $e_i^T \mathbf{A}^T \beta(\mathbf{E}_i^{(b)})$ is the transmission network cost resulted from transferring energy bought from other MGs; (iii) $e_i^T \mathbf{A}^T \text{diag} \lambda \mathbf{E}_i^{(b)}$ is the cost due to buying energy; and (iv) $\lambda_i \epsilon_i^{(s)}$ is the income by selling energy.

3.3.2 Distributed algorithm

The problem can be transformed to maximum dual problem. To this end, the optimal Lagrangian multiplier converge to the optimal point of dual problem (3.5), $\lambda^* = \operatorname{argmax}_{\lambda} C(\lambda)$. More specifically, at each point $\lambda[k]$, each MG minimizes its corresponding contribution to the Lagrange function by solving the local subproblem (3.7) and determining the minimum point $(\epsilon_i^{(s)}[k], \mathbf{E}_i^{(b)}[k]) = (\epsilon_i^{(s)}(\lambda[k]), \mathbf{E}_i^{(b)}(\lambda[k]))$.

In the previous work [68], the *Sub – Gradient Algorithm* is used to solve the optimization problem. In this algorithm, the Lagrange multiplier are updated according to

$$\lambda_i[k+1] = \lambda_i[k] + \alpha[k] \begin{bmatrix} e_1^T A E_1^{(s)}[k] - \epsilon_1^{(s)}[k] \\ \vdots \\ e_N^T A E_N^{(s)}[k] - \epsilon_N^{(s)}[k] \end{bmatrix} \quad (3.9)$$

where, $\alpha[k]$ is a positive step factor. However, the Sub-Gradient (SG) Algorithm needs the initial assumption of price (λ) and step size (α). Initial assumption is restrictive in the Sub-Gradient Algorithm to find a optimal solution set. This initial assumption often makes the algorithm slower. Moreover, without the initial assumption, Sub-Gradient Algorithm fails to find a feasible solution. So, there is a need to find a faster algorithm to improve the system performance.

The approach proposed in this work is based on the Deep Cut Ellipsoid (DCE) Algorithm. According to [91], the *DCE* is used to determine the feasibility of a system of

linear inequalities. The *DCE* Algorithm generates a "decreasing" sequence of ellipsoids that contain a minimizing point. The update of the dual variables may also be done in this algorithm. The idea of choosing initial ellipsoid is to localize the set of candidate λ 's within a closed and bounded set. Therefore, This algorithm releases the users to initialize the price values (λ) at the first iteration and from choosing the step size (α).

The size and shape of the ellipsoid can be represented as λ and matrix P respectively. The sub-gradient of $C(\lambda)$ in $\lambda = \lambda[k]$ need to be computed from $k - th$ can be described as

$$\varsigma[k] = [e_N^T A E_N^{(s)}[k] - \varepsilon_N^{(s)}[k]]_{N \times 1}, \forall \lambda \quad (3.10)$$

Then we have, $C(\lambda) \leq C(\lambda[k]) + \varsigma_T(\lambda - \lambda[k]), \forall \lambda$, Then, the sub-gradient needs to be normalized as,

$$v[k] = \frac{\varsigma[k]}{\sqrt{\varsigma^T \times P[k] \times \varsigma[k]}} \quad (3.11)$$

First, The Lagrange multiplier (λ) can be represented as,

$$\lambda_i[k+1] = \lambda_i[k] + \frac{1 + N \times \alpha}{N + 1} \times P[k] \times v[k] \quad (3.12)$$

Second, the shape (matrix P) of the ellipsoid can be updated as:

$$P[k+1] = \frac{N^2}{N^2 - 1} \times (1 - \alpha^2) \times (P[k] - \frac{2(1 + N\alpha)}{(N + 1)(1 + \alpha)} \times P[k] \times v[k] \times (v[k])^T \times P[k]) \quad (3.13)$$

where, α is a positive step factor, $P[k]$ is the shape of solution space; and k is the iteration number.

Next, the updated Lagrange multiplier (λ) will check the original bounds. If it is within the bound, then it is converged else it will take next iteration according to (3.10),

(3.11), (3.12), (3.13).

Algorithm 1 summarizes are the steps of the proposed distributed iterative algorithm. For solving the (3.7), each MG should aware of $\varepsilon_i^{(s)}[k]$ and $E_i^{(b)}[K]$, namely the

Algorithm 1 Distributed optimal scheduling algorithm

- 1: Initialize $\lambda_{min}, \lambda_{max}, \lambda_i[0], P[0], M = 4, \alpha = 0, k=0$
 - 2: At k^{th} iteration
 - 3: At any MG i
 - 4: Compute the sub-gradient $\varsigma[k] = [e_N^T A E_N^{(s)}[k] - \varepsilon_N^{(s)}[k]]_{N \times 1}, \forall \lambda$
 - 5: Normalize the sub-gradient $v[k] = \frac{\varsigma[k]}{\sqrt{\varsigma^T \times P[k] \times \varsigma[k]}}$
 - 6: MGs exchange $\lambda_i[k]$ with neighboring MG
 - 7: MG i computes $\varepsilon_i^{(s)}[k]$ and $E_i^{(b)}[K]$ using (3.5) with $\lambda[k]$.
 - 8: MG i informs MG $j(j \neq i)$ the energy it expects to buy namely $E_{j,i}[k]$, at the given price $\lambda_j[k]$.
 - 9: According to the expected purchasing energy $E_{j,i}[k]$ from other MGs, MG i obtains
 - 10: $E_i^{(s)}[k] \Rightarrow [E_{i1}[k] \dots E_{iN}[k]]^T$
 - 11: MG i updates according to step 12 and 13
 - 12: $\lambda_i[k+1] = \lambda_i[k] + \frac{1+N \times \alpha}{N+1} \times P[k] \times v[k]$
 - 13: $P[k+1] = \frac{N^2}{N^2-1} \times (1 - \alpha^2) \times (P[k] - \frac{2(1+N\alpha)}{(N+1)(1+\alpha)} \times P[k] \times v[k] \times (v[k])^T \times P[k])$
 - 14: At any MG i
 - 15: If $\lambda_i < \lambda_{min}$
 - 16: $\varsigma[k] = -1, v[k] = \frac{\varsigma[k]}{\sqrt{P[k]}}, \alpha = \frac{(\lambda_{min} - \lambda_i)}{\sqrt{P[k]}}$
 - 17: Then, MG i updates according to step 18 and 19
 - 18: $\lambda_i[k+1] = \lambda_i[k] + \frac{1+N \times \alpha}{N+1} \times P[k] \times v[k]$
 - 19: $P[k+1] = \frac{N^2}{N^2-1} \times (1 - \alpha^2) \times (P[k] - \frac{2(1+N\alpha)}{(N+1)(1+\alpha)} \times P[k] \times v[k] \times (v[k])^T \times P[k])$
 - 20: $k = k + 1$
 - 21: Until stopping criteria is met.
-

total energy it sold and the vector composed of energy bought from other MGs. Moreover, we can compute $E_i^{(s)}$ from $E_i^{(b)}$. Combined with Algorithm 1, the Lagrangian multipliers can be updated. Therefore, all necessary data can be computed by each MG without a centralized controller. Also, the information traded between MGs is bounded to Lagrange multipliers λ_i and the expected buying energy $E_{j,i}$, which is interacted to the

corresponding MG j . Hence, the privacy of MGs can be secured. According to Algorithm 1, each Lagrange multiplier λ_i can be interpreted as the price per energy unit requested by MG i to sell energy to its neighboring MGs. Using the Lagrangian function (3.8), each MG pays for generating energy, for purchasing energy and for transferring the energy it purchases. On the other hand, the MG is paid for the energy it sells. By solving the problem (3.7), MG is maximizing its profit for some given selling ($\lambda_i[k]$) and buying ($\lambda_j, j \neq i$) prices per unit energy. Based on the Algorithm 1, the price λ_i would be modified constantly until the energy demand matches energy offer. As reported by (3.12), if the energy offered by MG i is less than the requested energy from other MGs, the price must be increased as the demand exceeds the supply. Conversely, when the demand by MG i is less than the supply, the price will be decreased. However, the price does not changed when the supply and demand are equilibrium.

3.3.3 Solution of The Local Subproblem

In this section, the solution of local subproblem is reported to support the global minimization problem of the system. The minimization subproblem (3.7) at MG i behaves according to six possible cases. Table (3.1) expresses these six different cases to support the local subproblem as the intention of MG i to minimize local cost or equivalently, to maximize net profits, when λ_i s are interpreted as exchanging prices per energy unit. In the first case, the MG i is generating all and only the energy it consumes, that is $\epsilon_i^{(s)} = 0$ and $E_i^{(g)} = E_i^{(c)}$. So, the MG i is not interested to sell energy since the selling price is lower than marginal generation cost. Indeed, the income will be lower than the extra production cost. In addition, purchasing is not beneficial either since the purchasing price is higher

Table 3.1. Possible Cases of Local Subproblem of MGi

Cases	Generation	Buy	Sell
1	✓	—	—
2	—	✓	—
3	✓	✓	—
4	✓	—	✓
5	—	✓	✓
6	✓	✓	✓

than the marginal production cost. Therefore, as for case 1, the MG i should remain self constrained.

However, MG i is always willing to trade energy since their local cost $(C_i(E_i^{(c)}) + \beta(0))$ is higher than the net payment. This case holds only in case 6. Similar considerations hold for other cases.

3.4 Result and Discussion

Several case studies have been considered based on proposed energy trading mechanism. A interconnected test system consisting of four different MGs, including DG units only. The interconnection topology of interconnected microgrid system is represented in Figure 1. The fuel coefficients of DG are $a = 86.3852$ \$, $b = 56.5640$ \$/MW and $c = 0.328412$ \$/(MW)². The coefficients of transfer cost function are $p = 0$, $q = 0$, $r = 3.6828$. The cable capacity assumes 100 MW. We have introduced a soft upper bound $E_{max} = 5MW$ as motivated by Section 3.2.1. The transfer cost function is set without the upper bound.

3.4.1 Trading prices

Figure 3.2 represents the iterative process of electricity price of each MG. The curves refer to a fully connected system, where microgrid loads are $E^{(c)} = [1, 6, 6, 6]$ and

each MG generation capacity is $P_{max} = 5MW$. The result shows that the DCE algorithm converges after 58 iterations. The prices of MG1, MG2, MG3 and MG4 are 59.3530 $\$/MWh$, 67.3156 $\$/MWh$, 67.3156 $\$/MWh$ and 67.3156 $\$/MWh$, respectively. However, the electricity prices of MGs converge to different values with same initial prices. Besides, Figure 3.2 depicts the final selling prices of MGs which have direct relationship of their own loads, that means, the MG that consumes more electricity has a higher selling price after the convergence is achieved. For example, MG1 earns more money by selling energy to the other MGs with a lower price, because it has lower power demand. In fact, the MG1

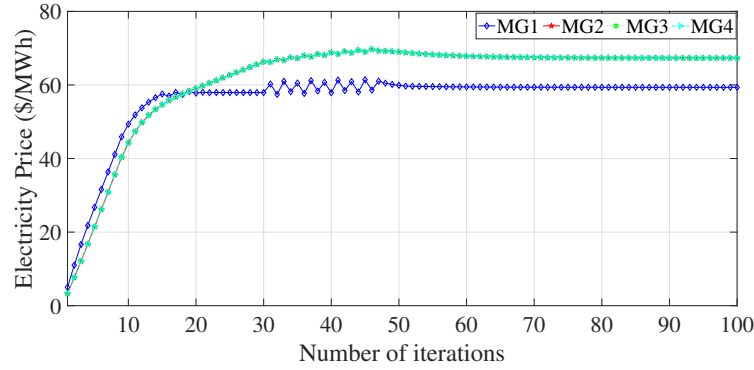


Figure 3.2. Iterative process of the electricity price of each MG.

only generates and sells energy, whose local cost function is :

$$C_1 = C_{DG1}(P_{DG1}) - \lambda_1 \varepsilon_1^{(s)} \quad (3.14)$$

The optimal $\lambda_1 = \lambda_1^*$ can be give in the form of marginal cost:

$$\lambda_1^* = C'(P_{DG1}) \quad (3.15)$$

On the other hand, the MG2, MG3 and MG4 only generate and buy energy from MG1.

They are all buying same amount of energy from MG1 and their local cost functions can be represented as:

$$C_2 = C_{DG2}(P_{DG2}) + \beta(E_{1,2}) + \lambda_2 E_{1,2} \quad (3.16)$$

$$C_3 = C_{DG3}(P_{DG3}) + \beta(E_{1,3}) + \lambda_3 E_{1,3} \quad (3.17)$$

$$C_4 = C_{DG4}(P_{DG4}) + \beta(E_{1,4}) + \lambda_4 E_{1,4} \quad (3.18)$$

Moreover, from the perspective of MG2, MG3 and MG4, λ_2^* , λ_3^* and λ_4^* can be expressed as:

$$\lambda_2^* = C'(P_{DG2}) - \beta'(E_{1,2}) \quad (3.19)$$

$$\lambda_3^* = C'(P_{DG3}) - \beta'(E_{1,3}) \quad (3.20)$$

$$\lambda_4^* = C'(P_{DG4}) - \beta'(E_{1,4}) \quad (3.21)$$

Therefore, MG2, MG3 and MG4 should reduce its net expenditure by purchasing energy from MG1. The price of MG1 after convergence can be calculated according to (3.15), (3.19), (3.20) and (3.21), which is consistent with the result of Algorithm 1.

3.4.2 Trading energy

The iterative process of the energy trading between MGs is shown in Figure (3.3), (3.4), (3.5) and (3.6). The energy trading after convergence at current time slot can be explained as follows: MG2, MG3 and MG4 buy 1.07994 MWh energy from MG1 respectively. And the MG1 offer 3.25039 MWh energy to sell to other MGs. As we can see, the total energy sold is equal to total energy purchased in the system. The coupling

constraints $\epsilon_i^{(s)} = e_i^T A E_i^{(s)}$ is fulfilled after convergence, which justifies that the algorithm works well. During the optimization, the cost by power transmission between MGs is

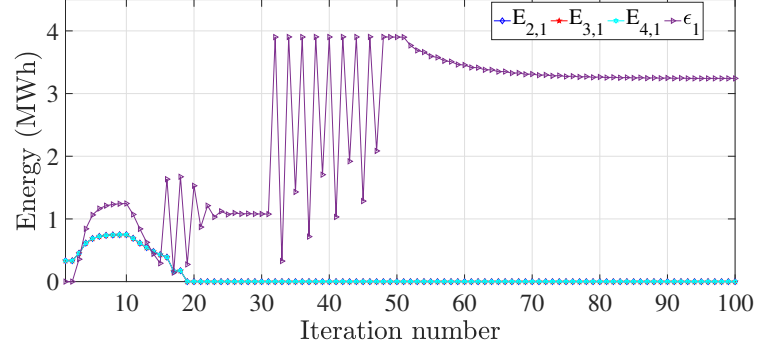


Figure 3.3. Iterative process of the trading energy of MG1.

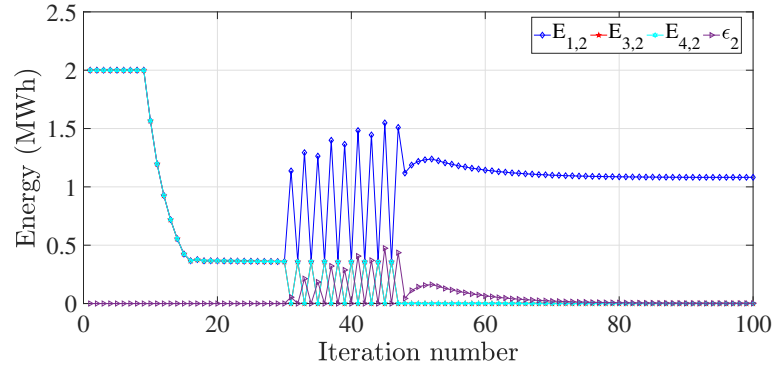


Figure 3.4. Iterative process of the trading energy of MG2.

covered by the electricity buyer. In the current time slot, MG2 buys energy from MG1 to meet its load demand, as marginal cost of its own generating unit is higher than the sum of selling price and the transmission cost of MG1.

Similarly, the marginal cost of MG3 and MG4 is not economical. So, it is beneficial to work on lower generation limit.

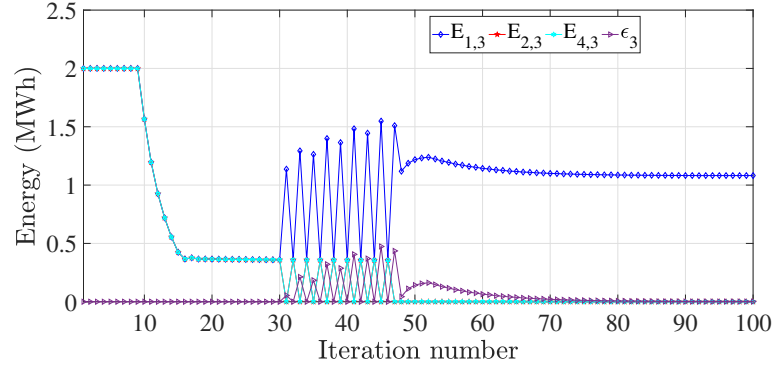


Figure 3.5. Iterative process of the trading energy of MG3.

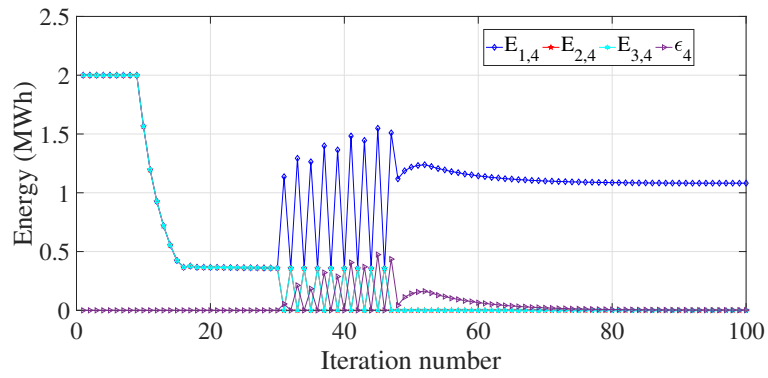


Figure 3.6. Iterative process of the trading energy of MG4.

3.4.3 Iterative process of variables

All optimal variables including the buying energy, selling energy, generation can be solved by Algorithm 1. For instance, Figure (3.7) shows the iterative process of variables of MG3. After convergence, MG3 buys 1.07995 MWh energy from MG1. The generation of DG3 is 4.9184 MWh. According to power balance constraint, supplied power is equal to net load demand. Moreover, supplied energy is 6 MWh, which is equal to the load demand of MG3. Similarly, the supplied power can be satisfied in MG1, MG2 and MG4. Having gained more insight into the iterative process, the decision of MG3 is affected by the trading prices with MG2, MG4 and MG1. Initially, MG3 intends to buy a large

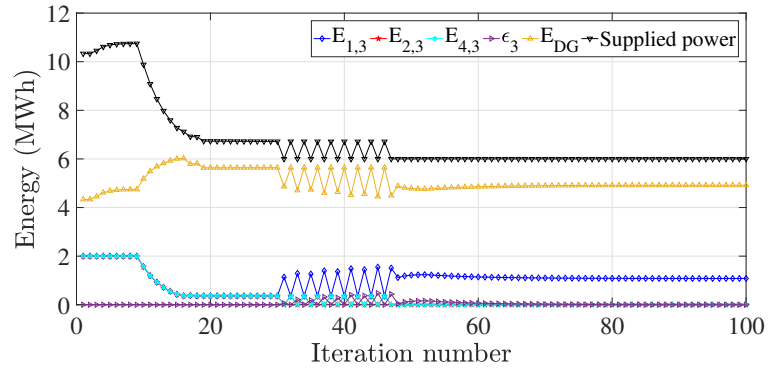


Figure 3.7. Iterative process of the variables of MG3.

quantity of energy. However, selling prices of MG1 is increased with iterations, the expected buying energy of MG3 has also been reduced, whereas the generation of DG is increased. Finally, all the variables of MG3 converged to stable values. From this result, we can find that each MG can decide to adjust generation of DG, or trade with other MGs with a extensive consideration of the generation cost, trading price and load characteristics, which ultimately reduces the total operation costs and makes power usages flexible and interactive.

3.4.4 Benefits of interconnection

Given the same setting, each MG can also be operated autonomously. Table 3.2 represents the cost comparison of each MG between autonomous and interconnected operation.

Table 3.2. Cost comparison of each MG between autonomous and interconnected operation

Microgrid ID	Cost (\$)				
	MG1	MG2	MG3	MG4	Total
Autonomous operation	143.278	4610.83	4610.83	4610.83	13975.78
Interconnected operation	332.114	377.017	376.998	376.998	1463.11

The results show that energy trading not only decreases the global operation cost, but

also decreases the the local expenditure of individual MG which has less generation.

Therefore, MG1 gains revenue by selling energy where as MG2, MG3 and MG4 reduce their cost by purchasing energy.

3.4.5 Performance comparison with existing work

In order to interpret the benefits and advantages of the distributed model and deep cut ellipsoid (DCE) algorithm, the results are compared with the existing work [68] in terms of exchanged information, the number of MGs, solution algorithm and performance. The results show that the DCE algorithm features advantages in several aspects, especially in algorithm performance. The DCE algorithm has shown a better convergence performance as compared with the algorithm proposed in [68].

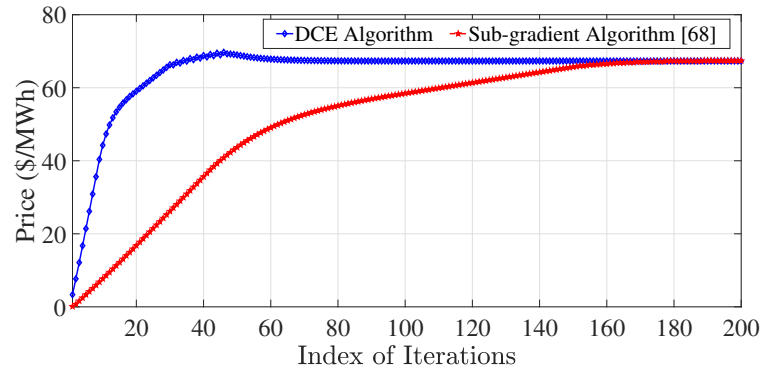


Figure 3.8. Iterative process comparison of price in MG3 between this work and that in [68]

Finally, the optimal operation cost achieved by Algorithm 1 is almost equal to centralized optimization, which is shown in (3.3).

As for the exchanged information, the centralized optimization requires all measured data of sources and load to be transferred to the system central coordinator, which results in more requirements on the overall communication cost. However, sharing

Table 3.3. Comparison between centralized optimization and Distributed optimization

MG	Cost (\$)	
	Centralized optimization	Distributed optimization
MG 1	332.112	332.114
MG 2	377.08	377.017
MG 3	376.984	376.998
MG 4	376.971	376.988
Total	1463.147	1463.120

information of load and sources can lead to serious privacy and business issues, since MGs may belong to different business owners. In this work, the DCE algorithm is developed based on the distributed optimization framework of [68], the information shared among MGs is limited to Lagrange multipliers and the expected buying energy quantities, which are only communicated with trading MGs.

As for the convergence performance of algorithms, the simulation results show that the DCE algorithm has an improved performance compared to the distributed sub-gradient algorithm of [68]. In order to show the detail iterative process comparison of price in MG3 between this work and [68] based on same test cases, as shown in Figure (3.8). The DCE algorithm release the system to make restrictive assumption which makes the system performance better. Because, the initial assumption makes the system slower. The deep cut ellipsoid (DCE) algorithm has the faster iteration speed due to faster shrinking. First, the initial assumption of price is made based on total cost function. Then , the price needs to be maintained within the bounded limit which makes the solution space even smaller that speeds up the system faster. Finally, the prices of MG3 in this work and [68] converge to the same value. For energy exchange network, four different topologies (e.g. Full, Ring, Line and Star) are considered as in Figure 3.9.

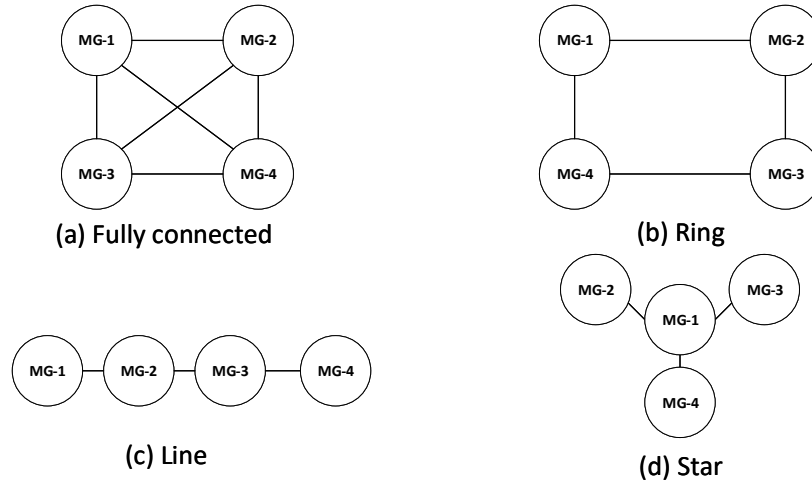


Figure 3.9. Considered four topologies

The performance comparison for sub-gradient algorithm and DCE algorithm has also been done for four topologies as in Figure 3.10. The four topologies are compared in terms of iteration and time to show the performance improvement of DCE algorithm.

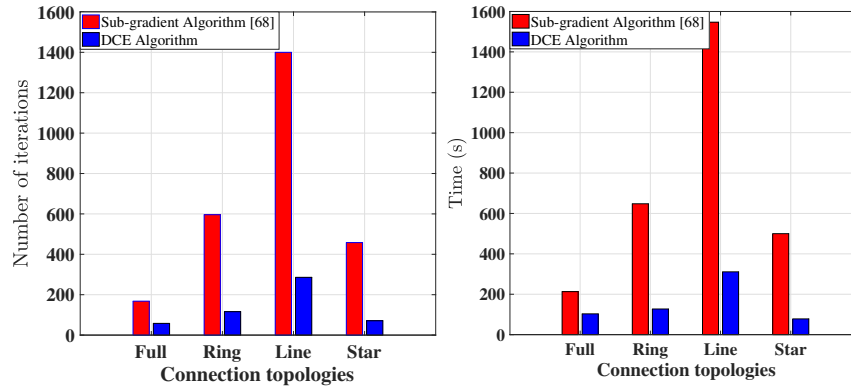


Figure 3.10. Comparison between Sub-gradient algorithm and DCE Algorithm with different topology in terms of iteration and time

According to Figure 3.10, it is clear that, the fully connected topology, topology (a) give the best performance. While for other three topologies, topology (d) has advantages over other two, since it improves the income for MG1, which achieve the highest cost reduction, although it has worst cost reduction performance for MG2, MG3 and MG4.

Based on above all the topologies, the DCE algorithm performs better than the slow sub-gradient algorithm in terms of iteration and time. Therefore, the MGs should be operated in distributed manner which lower the interaction time with less data exchanges.

Having achieved some more insight into the result, the search routine of sub-gradient algorithm seems zigzag shaped. Besides, the sub-gradient algorithm is the fastest direction for the increasing of objective function value. Therefore, it could be a good choice to search on sub-gradient direction in the local space. However, this algorithm's convergence speed is slowed down in global space due to its zigzag shaped search direction. For this drawback, the deepest cut ellipsoid algorithm with a sequence of shrinking ellipsoids that is polynomial in time is studied in this work. During each iteration, the sequence of each ellipsoid is more smaller in volume than its predecessor due to its deepest cut; after that it is easy to find feasible point within this smallest global space. So, the DCE algorithm has addressed the problem by the zigzag typed searching direction and eventually quicken the convergence.

3.5 Concluding Remarks

In this section, a distributed energy trading algorithm is studied based on deep cut ellipsoid method to minimize the global cost of the interconnected MG system. This algorithm is not only efficient in distributed energy trading but also speeds up the system performance quite well. The performance of DCE algorithm was validated using different case studies for a system consisting of 4 MGs. Compared to existing work [69], the deep-cut ellipsoid approach shows the advantageous features of modeling and performance.

CHAPTER 4 ENERGY OPTIMIZATION APPROACHES OF A RESIDENTIAL COMMUNITY USING DYNAMIC PRICING

4.1 Introduction

Household electric power consumption in peak time has caused adverse effects to the stability and reliability of the conventional electricity system. Reducing the peak power consumption can decrease the risk of distribution and transmission network outages. In searching for viable solutions, Demand side management strategy has been recognized as one of the practically appealing solution to reduce the cost of electricity by reducing the peak demand by shifting the load from peak hour to off peak hours. It is also prevent network overloading because it provides the flexibility required to time shift the loads. In this chapter, an optimization model is studied for a smart residential community with the presence of smart residential appliances where the impact of priority of using residential appliances is also taken under consideration. Contribution of this chapter include:

- A small community energy management system is developed with three houses considering the comfort level;
- Three types of houses with real-world appliances are implemented for a small community according to physical characteristics;
- The three control approaches are evaluated on three case studies (fixed priority, with priority and without priority). The fixed priority is defined that the appliances will optimize the system according to their fixed priority order. With priority is specified

that one appliance will work all the time and other appliances will be scheduled based on optimization approaches. For without priority, no priority order of using the appliances is set up for optimizing the energy consumption.

4.2 Model Description

4.2.1 Residential Load Categorization

Electricity is used in residential houses in several ways. According to the residential energy consumption survey by USEIA (US Energy Information Administration) , 2009, Space cooling/ heating is the main household electricity consumer. Electric water heater is the second largest household electricity consumer. Other household appliances such as lighting, freezers, refrigerators, cloth dryer and entertainment devices consume rest of the electricity consumption. A typical survey of electricity consumption in residential households in U.S.A is displayed in Figure 4.1. According to figure, space heating accounts 41% of household electricity consumption and water heater accounts for 18%. Other appliances electronics (e.g. cloth dryer, electric vehicles) and lighting accounts for 6%.

4.2.2 Energy Management System of a Community

The benchmark model is represented in Figure 4.2. It exhibits the hand in hand gesture of information technology and electrical scenario in the present technological generation. In the model, the household loads are divided into two categories, non-critical or controllable loads and critical loads. Loads which are vital for the day to day activities of the consumers such as cooking, refrigeration and lighting etc. fall under critical loads. Controllable or non-critical power intensive loads can be interfered without noticeable

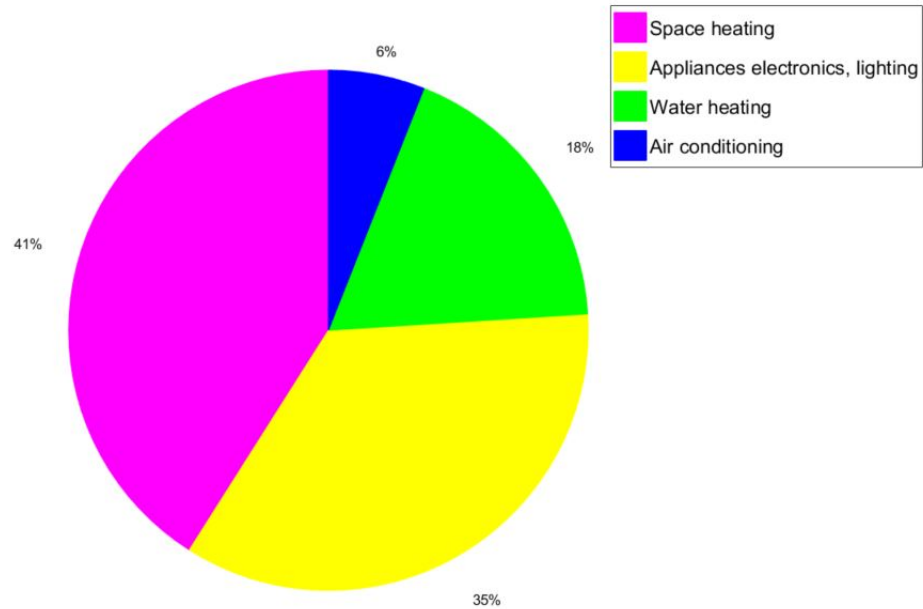


Figure 4.1. A typical residential energy usages survey

effect to the consumer's lifestyle.

Three types of houses including critical loads and controllable loads are considered in a small community. Since these power intensive loads account for a significant percentage of the total household demand, controlling these loads during peak hours will help to reduce the peak demand in the community.

4.3 Constraints For Individual Appliances

Residential controllable appliances such as air conditioning unit, water heater, clothes dryer, dishwasher and electric vehicle are modelled according to physical characteristics. The controllable appliances have high potential in the demand response events and to reduce cost. The manageable appliances are controlled by the central energy management system (CEMS). The energy management system unit is responsible to change the status of the non-critical loads in response to the demand limit specified by the

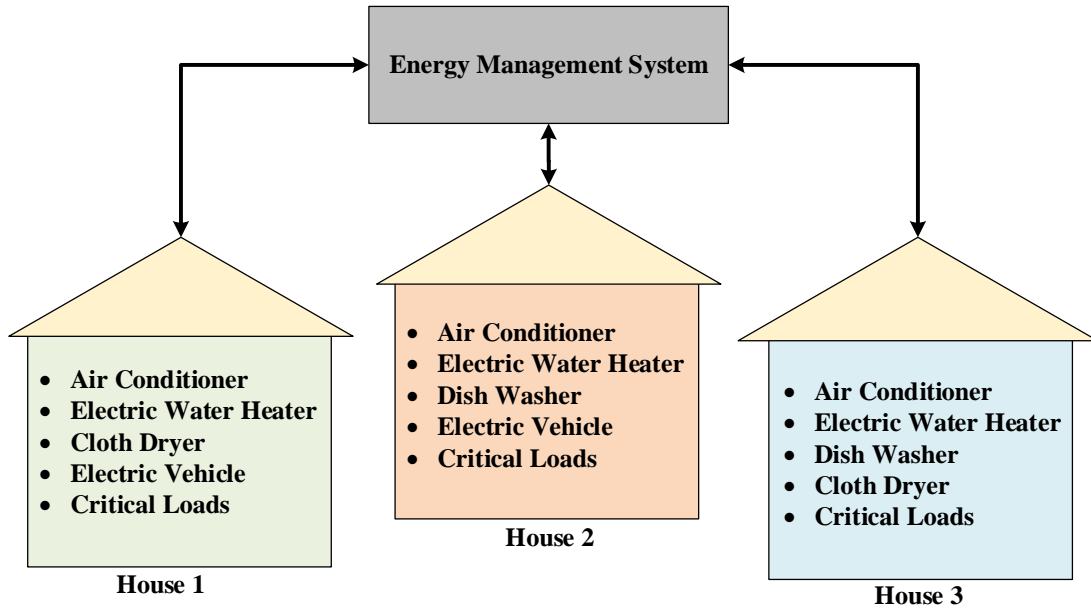


Figure 4.2. Community Based Energy Management System Model

utility.

4.3.1 Space Cooling Load Model

Space cooling unit load model is developed to adjust the power to fit preset temperature range. In this work, to simplify the constraints, the space cooling operates with "on-off" status W_{AC}^t and keeps the rated power equal to P_{AC} (kW) when turned on. For each time step t , the demand for electricity of space cooling unit is calculated as,

$$P_{AC}^t = P_{AC} \times W_{AC}^t \quad (4.1)$$

Also, there is a room temperature range $[T_{room}^{min}, T_{room}^{max}]$:

$$T_{room}^{min} \leq T_{room}^t \leq T_{room}^{max}. \quad (4.2)$$

The room temperature for time instance t is expressed as,

$$T_{room}^{t+\Delta t} = T_{room}^t + \Delta t \times \frac{G^t}{\Delta c} + \Delta t \times \frac{C_{AC}}{\Delta c} \times w_{AC,t} \quad (4.3)$$

where, T_{room}^t is the room temperature, Δt is the length(minute), G^t is the heat gain rate of the house, C_{AC} is the cooling capacity (Btu/h), Δc is the energy needed to change the temperature of the air in the room by $1^\circ F$ (Btu/ $^\circ F$).

4.3.2 Electric Heater Load Model

The Electric Water Heater (WH) has turn on-off mode (W_{WH}^t). When it's turned on, it operates with rated power P_{WH} (kW). The water temperature in the water heater has upper and lower bound $[T_{outlet}^{min}, T_{outlet}^{max}]$, so the operation of the electric water heater should maintain the temperature constraint:

$$T_{outlet}^{min} \leq T_{outlet}^t \leq T_{outlet}^{max}. \quad (4.4)$$

where, T_{outlet}^t is the mixed water temperature ($^\circ F$) in the water tank at time t . For each time step t , the demand for electricity of the water heater unit (P_{WH}) is expressed as,

$$P_{WH}^t = P_{WH} \times \eta_{WH} \times W_{WH}^t \quad (4.5)$$

The outlet water temperature of the tank is calculated as,

$$\begin{aligned} T_{outlet}^{t+\Delta t} = & \frac{T_{outlet}^t \times (V_{tank} - fr^t \times \Delta t)}{V_{tank}} + \frac{T_{inlet} \times fr^t \times \Delta t}{V_{tank}} + \frac{1gal}{8.34lb} \\ & \times [P_{WH}^t \times \frac{3412Btu}{kwh} - \frac{A_{tank} \times (T_{outlet}^t - T_{room}^t)}{R_{tank}}] \times \frac{\Delta t}{60\frac{min}{hr}} \times \frac{1}{V_{tank}} \end{aligned} \quad (4.6)$$

where, V_{tank} is the volume of the water tank (gallons), fr^t is the hot water consumption rate (gallons per minute), T_{inlet} is the temperature of the inlet water ($^{\circ}F$), P_{WH}^t is the power of the WH (kWH), A_{tank} is the surface area of the tank (ft^2), T_{room}^t is the room temperature ($^{\circ}F$), and R_{tank} is the heat resistance of the tank ($^{\circ}F.ft^2.h/Btu$).

4.3.3 Cloth Dryer Load Model

The typical cloth dryer (CD) load is task-based appliance. In the cloth dryer, the user set up work period $[T_{CD}^{start}, T_{CD}^{finish}]$ with the required working time $T_{CD}^{required}$. When the user turns on the cloth dryer, the cloth dryer works with rated power P_{CD}^t (kW). The power consumption of the cloth dryer is divided into two parts. One is as power consumption of the motor and another one is as the power consumption of the heating coil. Therefore, the cloth dryer should ensure the following constraints:

$$P_{CD}^t = k \times P_{hc} \times W_{CD}^t + P_m \times w_{CD}^t \quad (4.7)$$

$$W_{CD}^t \text{ and } w_{CD}^t = 0; \text{ (if } t < T_{CD}^{start} \text{ or } t > T_{CD}^{finish} \text{)}$$

$$\sum_{t=T_{CD}^{start}}^{T_{CD}^{finish}} W_{CD}^t = T_{CD}^{required} \quad (4.8)$$

where, P_{hc} is the rated power of the cloth-dryer heating coil (kW), k is the drying level ($k = 1/M, 2/M, \dots, M/M$), M is the total number of drying levels, P_m is the power consumption of the motor (kW), W_{CD}^t is the on/off status of the cloth-dryer heating coil and w_{CD}^t is the on/off status of the motor of the cloth-dryer where the status w_{CD}^t should on whenever the customer wants to turn on the cloth-dryer; however the on/off status of the W_{CD}^t depends on the signal from the optimization approaches.

4.3.4 Electric Vehicle Load Model

The user of electric vehicle (EV) sets up the time range of charging period $[T_{EV}^{start}, T_{EV}^{finish}]$ and the required charging time is $T_{EV}^{required}$:

$$\sum_{t=T_{EV}^{start}}^{T_{EV}^{finish}} W_{EV}^t = T_{EV}^{required} \quad (4.9)$$

$$W_t = \begin{cases} 0, & SOC^t \geq SOC^{max} \\ 1, & SOC^t \leq SOC^{max} \end{cases} \quad (4.10)$$

The electric vehicle charges with its rated power P_{EV} (kW):

$$P_{EV}^t = P_{EV} \times W_{EV}^t \quad (4.11)$$

Battery charge state at any time slot t depends upon the charge state of the battery in the previous time slot. Initial charge state depends on the energy used for driving. The initial charge state is assumed as 37.5% and the battery charge state at any time slot t can be calculated in the following equation:

$$SOC^t = SOC^{t-1} + P_{EV} \times \frac{\Delta t}{C_{battery}} \quad (4.12)$$

4.3.5 Dishwasher Load Model

Dishwasher (DW) is also task-based appliance like cloth dryer and electric vehicle; householders set up work period $[T_{DW}^{start}, T_{DW}^{finish}]$ and required working time $T_{DW}^{required}$.

Once the user turns on the dishwasher, the dishwasher works with rated power P_{DW} (kW).

Therefore, the dishwasher should follow the constraints:

$$W_{DW}^t = 0 \quad (t < T_{DW}^{start} \text{ or } t > T_{DW}^{finish})$$

$$\sum_{t=T_{DW}^{start}}^{T_{DW}^{finish}} W_{DW}^t = T_{DW}^{required} \quad (4.13)$$

4.3.6 Critical Loads

The critical loads may include freezing, cooking and refrigeration and other non-controllable electric appliances. The load profile is obtained from [76], where the maximum value and minimum values are considered as 2 kW and 1 kW, respectively in the simulation. A typical load profile variation with time for the critical loads considered in this work is represented in Figure 4.3.

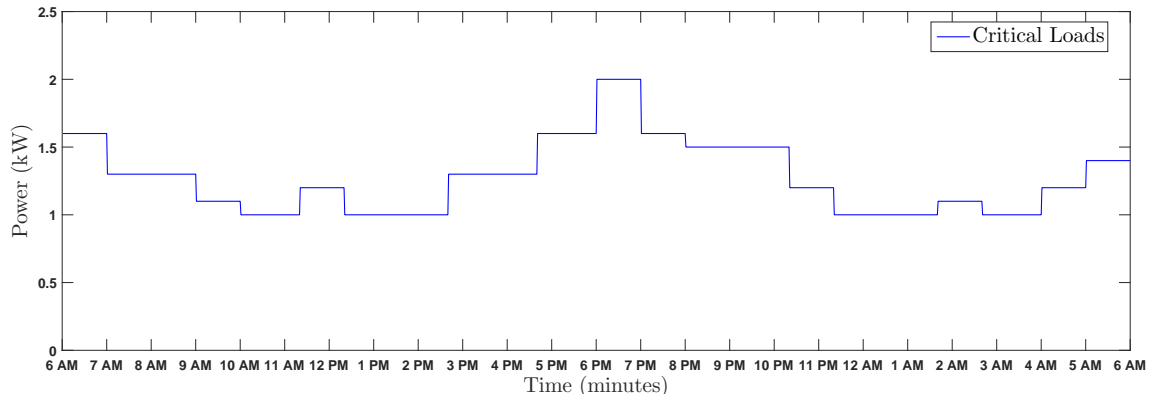


Figure 4.3. A load profile for critical loads during a day

4.4 Electricity Pricing Mechanism

The wholesale electricity prices differ notably from hour to hour. However the cost to produce electricity is different for each power plant, the cost of producing one kilowatt-hour (kWh) of electricity differs constantly, relying on the cost effective power

plants [92]. In the power system operation, the power plants are operated according to an economic dispatch i.e. in the time of low demand periods, the lowest operational cost effective power plants will operate. At the time of high peak periods, the costly fossil fuel based power plants have to be operated to balance demand and supply. Despite, almost all residential users nowadays are charged some flat-rate retail price [93], [94]. Hence, the electricity consumer use more electricity during peak hours. The domestic residential consumers also use higher amount of electricity during late afternoon where the demand of the electricity is high. The high peak-hour demand period induces high cost to the electricity retailers due to the high whole sale prices. It also has a negative impact on the reliability of the power grid [95].

In the literature, there are different electricity pricing mechanism which reflect the actual electricity market prices, such as Time of Use (TOU) and Real Time Pricing (RTP). These pricing methods encourage the users to schedule the loads to off peak hours. In the TOU pricing, the electricity price vary with the time of the day, the day of the week and season of the year. Normally, the high electricity price is used for peak demand periods and lower price is used for off-peak demand periods. The price which is between the lower and higher price is used for moderate demand periods. Using the TOU pricing, the electricity consumers know the electricity prices in the day-ahead basis, they can shift some of their loads to off peak periods which has a less electricity price. Controllable appliances such as water heater, air conditioners, dishwashers, cloth dryers and electric vehicles can be shifted to off peak periods and they will be able to reduce their electricity bill.

A typical TOU pricing mechanism [96] is considered in this work. In the considered

TOU pricing mechanism, the whole day is divided into three time periods and three different energy prices are used for these three time periods. The energy prices during each time periods are represented in Figure 4.4.

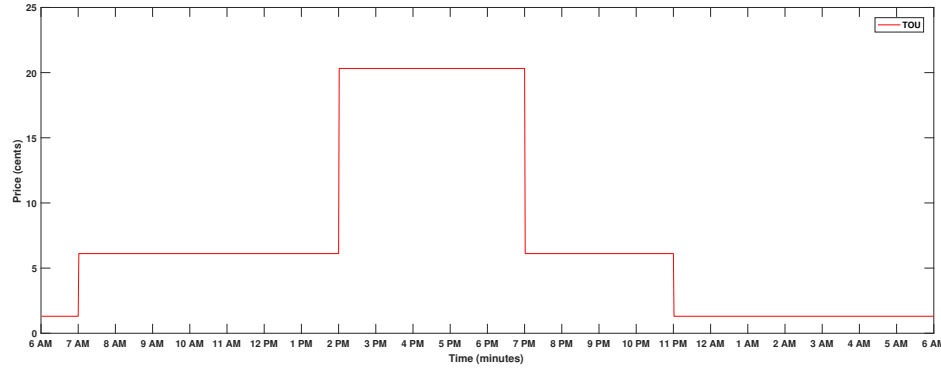


Figure 4.4. Variation of electricity prices using Time of Use pricing mechanism

Table 4.1. Time of Use energy prices [97]

Period	Time interval	Energy Price (cents per kWh)
On-peak period	2 p.m. - 7 p.m.	20.3217
Off-peak period	7 a.m. - 2 p.m. and 7 p.m.- 11 p.m.	6.1132
Super off-peak period	11 p.m.-7 a.m.	1.3063

4.5 Objective Function

In this paper, the energy management system (EMS) of the community is formulated as a power system optimization problem. All the controllable appliances are participated into the optimization where the power consumption of the house for a certain period of time is limited by the utility. For any time instance t , the total power consumption of a house at time t can be expressed as,

$$P^{nt} = [A^{1nt}, A^{2nt}, \dots, A^{int}] [x^{1nt}, x^{2nt}, \dots, x^{int}]^T \quad (4.14)$$

where, A , x , n and i represent the rated power consumption of the appliances, the status, the number of houses and the number of appliances, respectively. For an example, the power consumption of house 1 can be written as,

$$P^{1t} = [P_{AC}, P_{WH}, P_{CD}, P_{EV}, P_{Cri}] [W_{AC}^{1t}, W_{WH}^{1t}, W_{CD}^{1t}, W_{EV}^{1t}, W_{Cri}^{1t}]^T \quad (4.15)$$

where, the rated power of the each appliances are multiplied with the status of the appliances at time t . The value of the status W_i^t can be 0 (off) or 1 (on) which is depended on the optimization signal. In the optimization method, the power consumption is constrained by the inequality and equality constraints where the inequality constraint is used to keep the power consumption in a certain demand limit as,

$$\sum_{n=1}^{N=3} P^{nt} \leq D^t \quad (4.16)$$

And the equality constraint is used to set-up priority of the controllable appliances based on customer's priority. For an example, if the customer of house 1 wants to give priority to the air conditioner to keep the room temperature in a certain range, then the equality constraint can be expressed as,

$$[P_{AC}, 0, 0, 0, 0] [W_{AC}^{1t}, 0, 0, 0, 0]^T = P_{AC}^{1t} \quad (4.17)$$

In this paper, the objective is to maximize the power consumption considering the specified demand limit to keep the customer comfort level as good as possible as,

$$P^t = \max_{W^t} \sum_{n=1}^{N=3} P^{nt} \quad (4.18)$$

$$V = \sum_{t=1}^{T=1440} P^t C^t \quad (4.19)$$

where, P^t is the total power consumption of all the appliances at time t , W^t is the on-off status (0 = Off / 1 = On) set of the appliances at time t and C^t is the power consumption cost in \$/kWh at time t . The proposed optimization techniques can be solved with the equation (4.18) through binary decision variables W^{it} as there is a need for 5×1440 binary variables for each houses to describe the scheduling of the five appliances by taking the time resolution as minute.

4.6 Proposed Approaches

4.6.1 Genetic Algorithm

Solving the optimization problems optimally, genetic algorithm is a technique inspired by the principle of evolution. Genetic algorithm uses a "Chromosomal" representation that requires the optimal solution to be coded as a finite length string. In this work, the genetic algorithm optimization technique can be formulated using the fitness function FT_t as it is marked as the objective function to maximize the power consumption (P^{nt}) ignoring the discomfort of the user as,

$$FT_t = \max_{W^t} \sum_{n=1}^{N=3} (P^{nt}) \quad (4.20)$$

where, W^t is the status set. Five decision variables are introduced since there are five loads (four are controllable and one is critical). Inequality constraint is determined to ensure the maximum use of power of the five appliances of each houses. Equality constraint is specified the priority of the loads. Genetic algorithm toolbox [98] is used in MATLAB environment to get the maximum optimal power consumption of each house in a small community to shift the loads from peak hour off-peak hour to ensure the minimization of energy cost of each houses in a community.

4.6.2 Dynamic Programming

The DP is a widely-used mathematical technique for solving optimization problems that can be divided into sub-problems and where decisions are required in each stage [99]. In this paper, the optimization problem is formulated as a discrete decision problem using the traditional DP where the goal is to find a set of status (W^{nt}) for each houses so that the objective function can be maximized (DP_{max}) or minimized (DP_{min}) based on the customer's choice as,

$$W^{nt} = \arg \max / \min (P^{nt}) \quad (4.21)$$

Since, the status W_i^t is 0 (off) or 1 (on) for each appliances, the possible combination of five-dimensional decision vectors are found as $2^5 = 32$ for each time instances and for each houses. Then, the system is trained by the equality and inequality constraints. After training the constraints, the system selects 'k' number of decision vectors that obeys the constraints. For the DP_{max} , the system selects a decision vector that maximizes the power consumption which is suitable for customer's comfortability and in terms of the DP_{min} , the system selects a decision vector that minimizes the power consumption which is suitable

for minimizing the electricity bills.

The proposed optimization algorithm flowchart is illustrated in Figure 4.5.

According to control strategy, at each time, the system sends the household load profiles and user priorities to the energy management system. When the total power consumption of the community exceeds the generation (D_t) by utility grid, then it will go to the optimization stage of each houses and assign the demand limit (D_t) to the residents equally. According to the assignment of demand limit (D_t), the appliances are turned off based on their preferences and scheduled the appliances of each house to off-peak period. Then, the system calculates the total power consumption for each resident, and sends the information to the utility. Afterwards, the system check the next time period and if it is less than T , then the system follows the same procedure again.

4.7 Simulation and Results

In this section, the operations of controllable loads without and with demand limits for Time of use (TOU) pricing schemes are taken into consideration. First, the operation of power intensive non-critical loads are explored with and without energy management system. Second, three case studies are investigated to validate a demand response algorithm adopted from [76] and three optimization approaches (GA, DP_{max} , DP_{min}) for the three houses in a community. The numerical results are shown to evaluate the performance of the optimization techniques. The power need of the community is met by power from the grid. Twenty four (24) hours time horizon is assumed, starting from 6 AM to next day 6 AM. The power intensive controllable load models are modeled in MATLAB environment. All codes were run on an Intel Core i-7 2.7-GHz computer. All

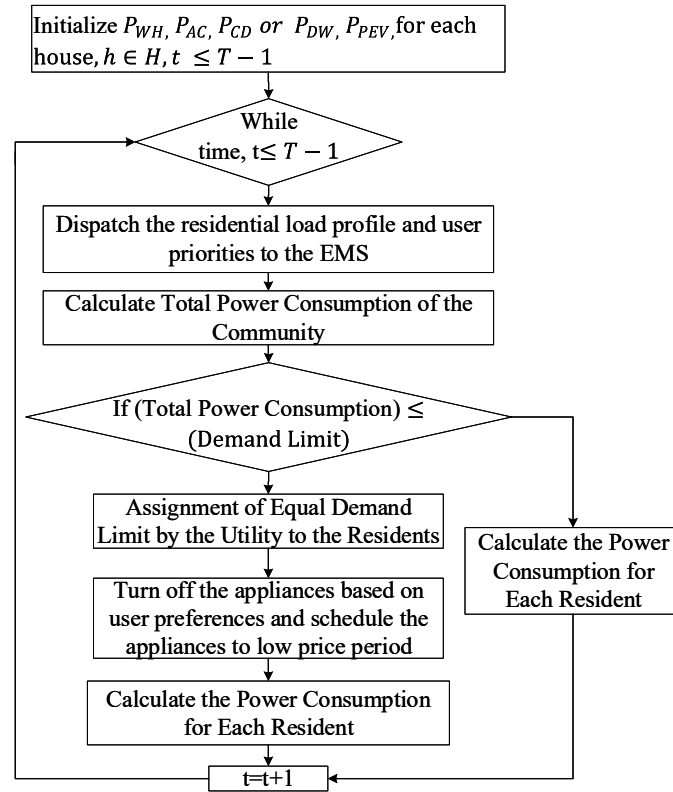


Figure 4.5. Proposed optimization algorithm for optimizing residential load demands.

the essential parameters of each house appliances are adopted from [100].

To validate the performance of genetic algorithm and dynamic programming, three cases are investigated under same environment. In the optimization period, the cloth dryer and dishwasher have started at 6 P.M. as specified by the user but due to demand limit, the operation of motor coil has started. The heating coil has started when the household power consumption is less than the demand limit. The Critical loads are the noncontrollable loads does not participate in the optimization event.

The Electric Vehicle (EV) should take 4 hours 10 minutes between 5:00 P.M. to 9:10 P.M. to fully charge the electric with 37.5% initial state of charge, the CD operates

Table 4.2. The Parameters of the appliances

Parameters	Values	Units	Parameters	Values	Units
Δt	$\frac{1}{60}$	minute	P_m	0.3	kW
C_{AC}	-33000	Btu/h	P_{hc}	3.7	kW
Δc	0.0195	$Btu/^{\circ}F$	P_{hc}^{DW}	2.7	kW
T_{room}^{min}	64.4	$^{\circ}F$	T_{CD}^{start}	6	pm
T_{room}^{max}	71.6	$^{\circ}F$	$T_{CD}^{required}$	90	minutes
T_{outlet}^{min}	107.6	$^{\circ}F$	T_{DW}^{start}	6	pm
T_{outlet}^{max}	118.4	$^{\circ}F$	$T_{DW}^{required}$	30	minutes
T_{set}	68	$^{\circ}F$	$T_{DW}^{required}$	20	minutes
P_{AC}	2.352	kW	T_{DW}^{start}	6	pm
V_{tank}	80	gallons	P_{EV}	3.6	kW
T_{inlet}	68	$^{\circ}F$	$C_{battery}$	24	kWh
P_{WH}	4	kW	SOC_{max}	100	%
A_{tank}	14	ft^2	SOC_0	37.5	%
R_{tank}	16	$^{\circ}F.ft^2.h/Btu$			

for 1.5 hours between 7:00 P.M. to 8:30 P.M. and the dishwasher (DW) works 30 minutes (for house 2) and 20 minutes (for house 3).

The operation results between 6 AM to next day 6 AM of the three cases are shown in Figure [4.14, 4.15, 4.16]. The purpose of the three cases is to evaluate the performance of the proposed approaches (genetic algorithm, dynamic programming) for three houses in a community. The cost savings are also analyzed and compared among these three approaches of the three houses.

4.7.1 Operation of power intensive controllable loads with and without EMS

4.7.1.1 Electric water heater

The operation of the electric water heater with and without EMS is described in this section. In this model, if the water temperature falls below the lower limit of the expected temperature value, then heating coils of water heater are turned on. If the water

temperature increases above the upper limit of expected temperature, then the water heater are switched off. If the temperature of the water maintains preset comfort range, the status of the water heater will keep as previous. To illustrate the model according to this work, the hot water draw event occur at around 7 A.M., 8 P.M., around 9 P.M. and around 11 P.M.- see the water temperature drops. Due to large water draw event occur at 8 P.M., around 9 P.M. and around 11 P.M. makes the outlet water temperature drops dramatically below the lower limit of desired water temperature in the tank. After finishing the large water draw event, the water heater controller operates to bring the water temperature within the preset comfort range (107.6-118.4 °F).

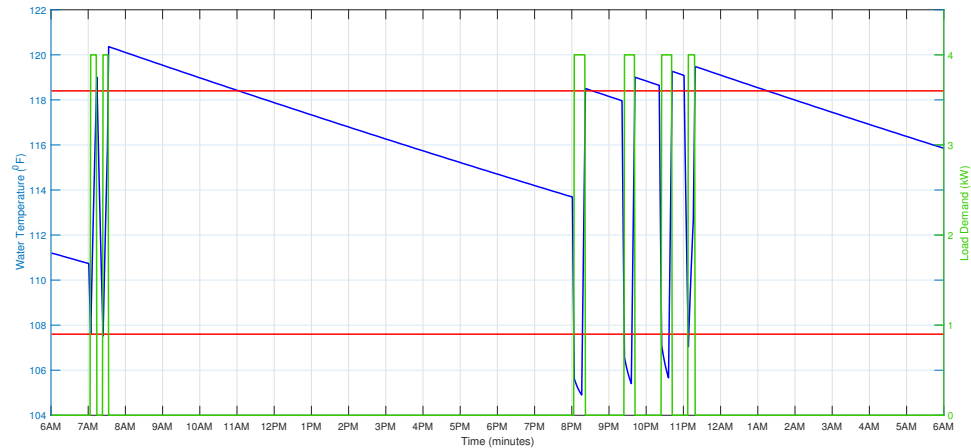


Figure 4.6. Operation of electric water heater unit without EMS

During the EMS control operation at peak period, the electric heater should operate first as the priority is high. For the period of 8-11 p.m., the water heater is operated along with the critical load consumption. However, the EMS controller deferred the other appliances according to their priority.

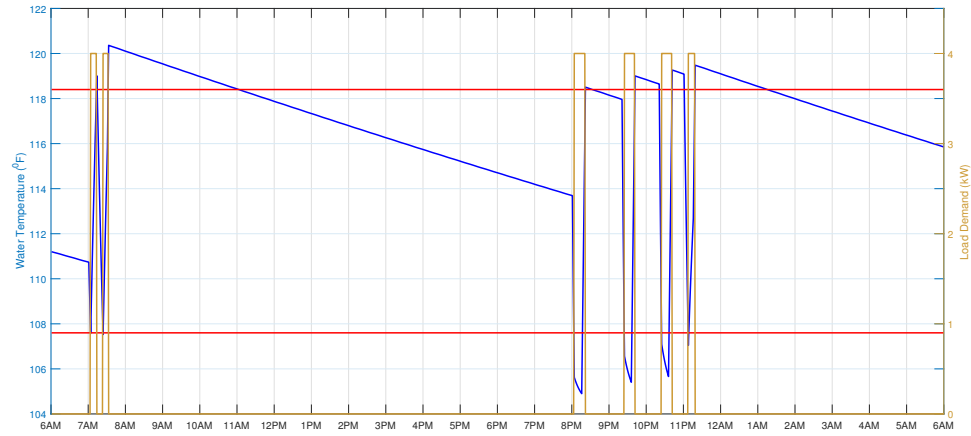


Figure 4.7. Operation of electric water heater unit with EMS

4.7.1.2 Air conditioning unit

The model of AC is presented in Section 4.3.1. For the AC unit, the preset comfort range is set between $66^{\circ}F$ to $70^{\circ}F$. From the Figure 4.8, it can be seen that if the room temperature is above the desired upper temperature limit of the comfort zone, the AC unit is turned on. As soon as, the temperature of the room drops down below the desired lower temperature limit, the space cooling unit is switched off. The AC unit's ON and OFF cycles repeated throughout the day to maintain room temperature within preset comfortable range.

At the peak demand period, the demand limit is fixed at 4 kW. Due to the 4 kW demand limit from 6-7 P.M., the room temperature rise up to $91.8^{\circ}F$ and violets the comfort range. The EMS controller tries to maintain the requested demand limit by prolonging loads according to their priority ($EWH > AC > CD > EV$). The EMS controller shut down the space cooling unit during the period (6-7 P.M.) by maintaining the total household load consumption within requested demand limit.



Figure 4.8. Operation of air conditioning unit without EMS

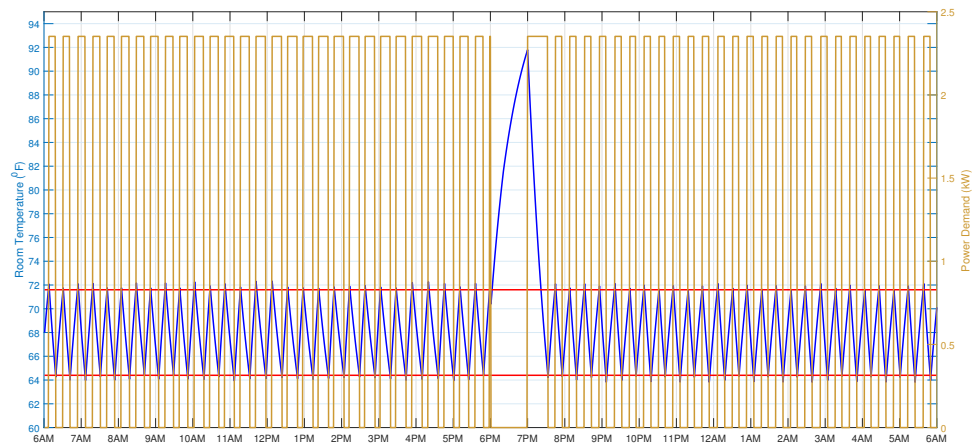


Figure 4.9. Operation air conditioning unit with EMS

4.7.1.3 Cloth dryer and dishwasher

The cloth dryer and dishwasher are the task based appliances that described in Section 4.3.3 and 4.3.5. These task based appliances models consists of two power consumption parts, motor and heating coils. The appliances (e.g. cloth dryer) should operated at specified time (90 minutes). Due to the demand limit at peak period, the motor of cloth dryer are started. However, the EMS controller can control the heating coils of

cloth dryer by considering load priorities and demand limit.

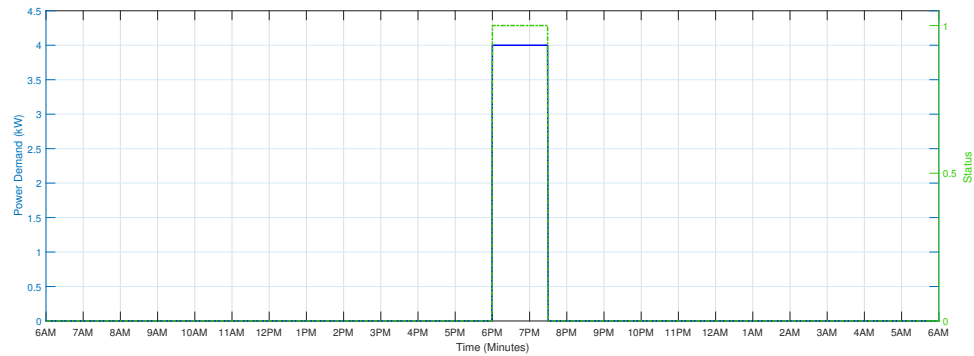


Figure 4.10. Operation of cloth dryer without EMS

The Figure 4.11 presented operation period during EMS control. The EMS controller turn on the heating coils at 7 P.M. for a short time as the total household load consumption is less than the demand limit at that time. Then, for next few minutes heating coils of cloth dryer are paused allowing the electric water heater to operate. The cloth dryer should operated in next two hours, when the water heater is not in operation and complete work at 9 P.M.

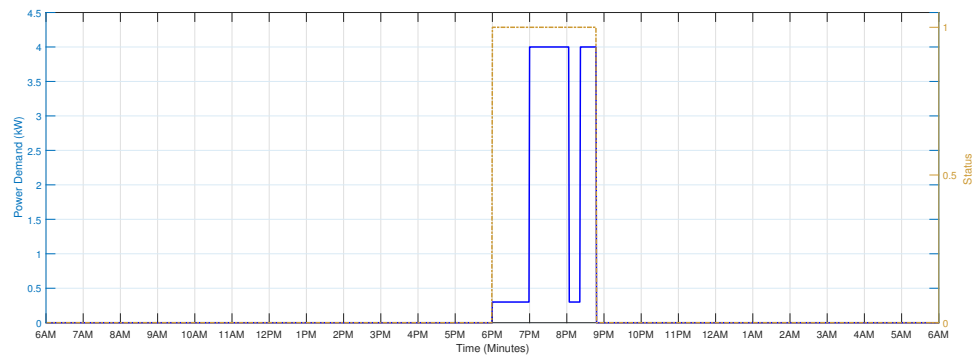


Figure 4.11. Operation of cloth dryer with EMS

4.7.1.4 Electric vehicle

The operation of electric vehicle model is described in Section 4.3.4. Without EMS, the electric vehicle started the charging at 5 P.M. and finished at 9:10 P.M. (Figure 4.12). Due to the restricted demand limit in the peak period and the preferences of the appliances, the EMS controller deferred the EV's charging period at 9 P.M. In Figure 4.13, it is noticed that the EV started charging after the cloth dryer operation time. Then for few minutes, the charging of electric vehicle is paused as the high priority water heater are turned on. After finishing the water heater job, the charging of EV again started and completed it's charging at 1:30 A.M.

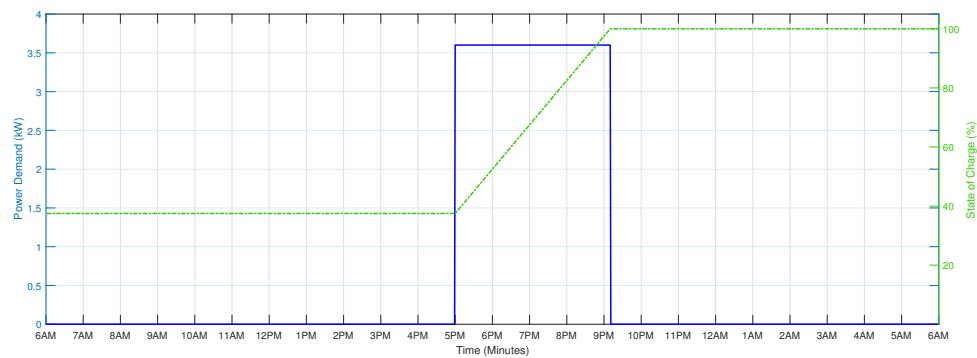


Figure 4.12. Operation of electric vehicle with EMS

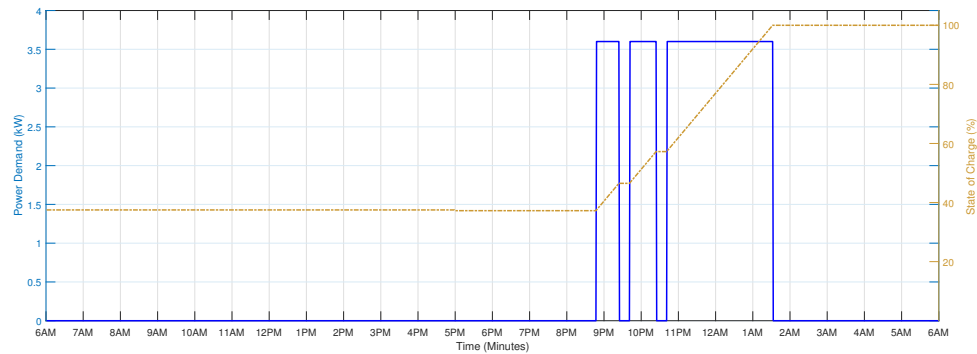


Figure 4.13. Operation of electric vehicle with EMS

4.7.2 Case Study 1: Fixed Priority

Considering case study 1, the total power consumption of the house 1 for unscheduled scenario is 5194.3 kW bought from grid owing to the additional power demand from cloth dryer, dishwasher and electric vehicle. When the optimization approaches and DR-Algorithm are in process, the power taken from grid does not exceed the demand limit. The power consumption for DR-algorithm, GA, DP_{max} and DP_{min} are given the identical values (5217.7 kW) since the priority of all appliances are fixed. The personal priorities of the resident are summarized in Table 4.3.

Table 4.3. Controllable load priorities

Controllable Loads	Priority
Water heater	4
Air conditioning unit	3
Cloth dryer	2
Electric vehicle	1

The results are summarized in Table 4.4. In this case, inequality constraints are not considered where the house 1 power consumption of P^{1t} at time t is specified by utility demand limit D^t . Equality constraints set up the priority of the appliances based on the consumer preferences to ensure that all the appliances are turned on at time t . In the optimization period, if the required power consumption of the house is greater than demand limit D^t , the certain appliances need to be turned off based on the optimization signal according to the priority order.

Figure 4.14 shows that while minimizing the cost of energy, the scheduling of appliances have moved in the time range where time of use tariff is low.

All the methods are given the same electricity consumption minimization results in

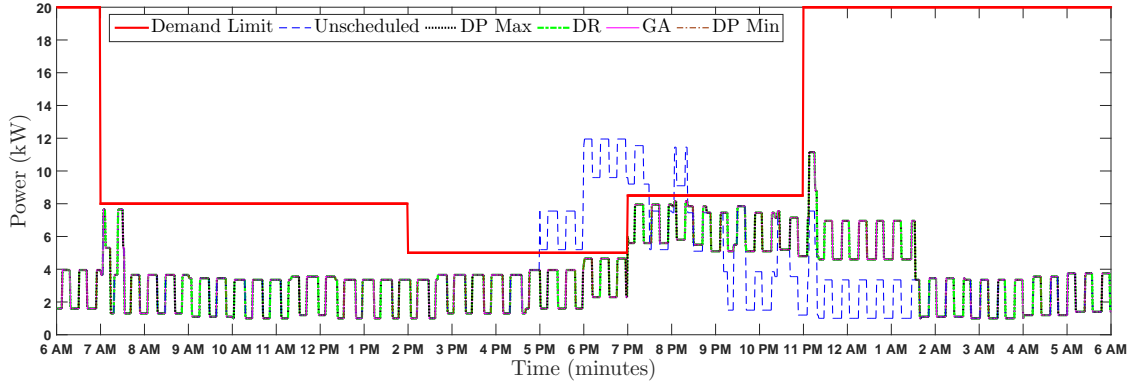


Figure 4.14. Household energy consumption for House 1 since the fixed priority is taken.

Table 4.4. Case A: Fixed priority for House 1

Appliances	Power Consumption (kW)				
	Unscheduled	DR	DP' max	DP' min	GA
Air conditioner	1768.7	1768.7	1768.7	1768.7	1768.7
Water heater	328	328	328	328	328
Cloth dryer	360	383.4	383.4	383.4	383.4
Electric vehicle	903.6	903.6	903.6	903.6	903.6
Critical loads	1834	1834	1834	1834	1834
Total	5194.3	5217.7	5217.7	5217.7	5217.7
Cost (\$)	8.0482	6.0764	6.0764	6.0764	6.0764
Time (s)	0	10	5	5.5	298

this case. As for computational time DP_{max} and DP_{min} are the fastest, and only takes 5s and 5.5s respectively. Required computational time for GA is $\sim 60 \times$ of DP_{max} and $55 \times$ of DP_{min} . The cost of electricity for unscheduled case is \$8.0482. When minimizing the energy cost, the cost of energy is \$6.0764 showing the energy savings of 24.5% in all the approaches.

4.7.3 Case Study 2: With Priority

As for case study 2, the power consumption and the energy cost are shown in Table 4.5 for genetic algorithm, DP_{max} and DP_{min} . In this case, the water heater is fixed as priority and other appliances set up their priority based on the optimization signal. The inequality constraints are considered to make the total power consumption P^t of the community within demand limit D^t . The equality constraint only sets up the priority of the water heater as constant at time t . The cloth dryer (house 1 and 3) and dishwasher (house 2 and house 3) work similarly as before. In this event, the cost reduction for three approaches are 18% ,17.82% and 33.45% than unscheduled case.

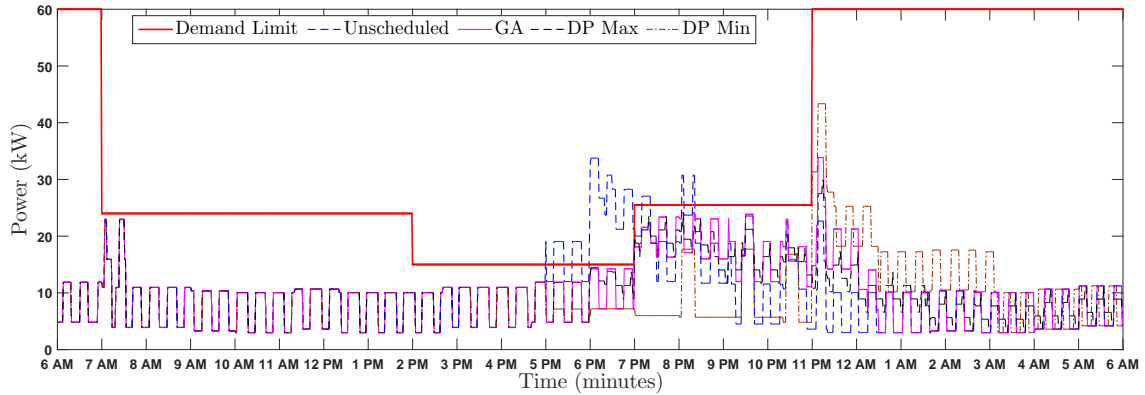


Figure 4.15. Total Household energy consumption for a small community since the priority is considered.

Figure 4.15 shows the power of the residential community in different approaches. In the peak period (2 p.m.-7 p.m.), the users of the community use less energy since the electricity price is high. During the off peak period (7 p.m.-11 p.m.) and the super off peak period (12 a.m.-6 a.m.), the electricity price is relatively low and the consumers should use more energy, contributing to bill reduction.

According to the Table 4.5, the DP_{min} reduces the significant amount of cost since it

Table 4.5. Case B: With priority for a community

Houses	Power Consumption (kW)			
	Unscheduled	GA	DP' max	DP' min
<i>House1</i>	5194.3	5284.3	5217.7	4903.3
<i>House2</i>	4909.3	4927.3	4888.1	4618.3
<i>House3</i>	4350.7	4398.1	4355.3	4217.9
<i>Total</i>	14454.3	14609.7	14535.9	13739.5
<i>Cost(\$)</i>	21.8061	17.85	17.92	14.51

curtails the loads in the peak hour as customer comfort level is violated. The other two approaches shift the loads from peak hour to off-peak hour by consuming the power as much as possible by maintaining the demand limit D' .

4.7.4 Case Study 3: Without Priority

Results for case study 3 are shown in Table 4.6. In this case, there are no priority of the appliances as there are no equality constraints have been set up. The inequality constraints work similarly as case study 2. The total cost savings for three approaches are 18.64%, 20.34% and 36.16%, respectively in the community.

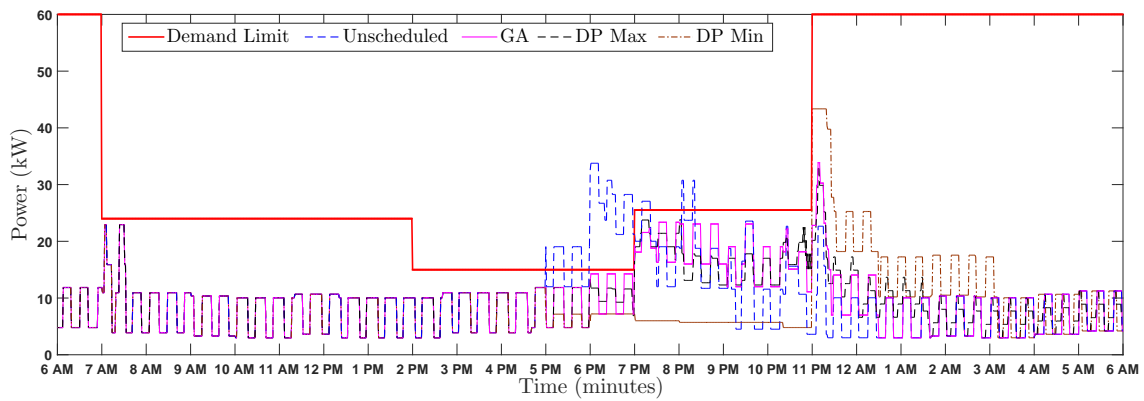


Figure 4.16. Total Household energy consumption for a small community since no priority is taken.

In this case, there are little higher cost savings in all the approaches in the residential community than in case studies 1 and 2.

Table 4.6. Case C: Without priority for a community

Houses	Power Consumption (kW)			
	Unscheduled	GA	DP' max	DP' min
<i>House1</i>	5194.3	5136.3	5200.3	4755.3
<i>House2</i>	4909.3	4779.3	4888.1	4470.3
<i>House3</i>	4350.7	4380.7	4169.4	4069.99
<i>Total</i>	14454.3	14296	14257.8	13295.59
<i>Cost(\$)</i>	21.8061	17.74	17.37	13.92

4.8 Concluding Remarks

In this section, a small residential community energy management system is proposed to schedule load from peak period to off-peak period without affecting consumers' life style. A residential community of three houses are considered with different electric appliances. Two heuristic approaches named Genetic algorithm (GA) and dynamic programming (DP) based smart appliance scheduling schemes and time-of-use pricing are proposed for comparative studies with demand response. Three case studies are demonstrated that all three control approaches can optimize energy consumption according to demand limit. The DP_{min} generally showed the smallest energy cost since it curtails the loads in the peak hour. Genetic algorithm can optimize the energy consumption hence reduce the cost but require higher computational time. The DP_{max} reduces the computational complexity as well as decreases the energy cost. The DP_{max} is suggested to be the best choice for real life application, due to good performance in cost optimization.

CHAPTER 5 CONCLUSIONS AND FUTURE WORK

In this chapter, the research reported an overview of the contributions of this thesis towards the aim of energy management of residential communities and interconnected micro-grids. The objective of the thesis is to investigate demand side management in residential communities, deregulated electricity market and energy trading among interconnected microgrids. We have considered the several challenging issues for improving the existing power system and provided intelligent solutions by using smart grid technologies and integrating and employing household appliances, plug-in-electric-vehicles (PEV), energy storage and distributed energy systems. Throughout the thesis, a couple of optimization schemes were developed to accomplish the objectives the smart grid. In each proposed approach, the numerical analysis was performed to show the effectiveness of the proposed model. Various simulation programs have been developed and displayed the results to evaluate the performance of proposed mechanisms.

5.1 Summary of the Thesis

This thesis was presented in four chapters. Chapter 1 presented a brief introduction to smart grid, demand side management, electricity market and transactive energy among microgrids. In this chapter, the literatures of energy management schemes and electricity markets are also analyzed. The motivation of the work was discussed while citing the main objectives of the thesis. We summarized the problem based on the limitation existing works.

Chapter 2 presented a new game-theoretic scheme to study the optimization and

decision making of multi-players in the distributed power system. The proposed game theoretic special concept-rational reaction set (RRS) is capable to model the game of the distributed energy providers and the large residential consumers. This scheme helps the residential consumers to participate in the retail electricity market by controlling the market price. The proposed approach also enables the distributed operators and residential consumers to efficiently integrate a wide range of renewable energy resources. The consumption agents are not only able to find market clearing price at Nash equilibrium point but also reduce the electricity cost individually (non-cooperatively). The proposed game theoretic approach were evaluated through simulation in MATLAB by various case studies. The simulation results have shown that the proposed approach can be effectively used as a tool for investigating the retail electricity market.

Chapter 3 presented a distributed energy trading approach based on deep-cut ellipsoid method under a distribution network. The problem is formulated as energy management problem to minimize the total system cost. An hour-ahead optimization model is constructed and the objective function includes the operation of DGS and network tariff. A distributed iterative algorithm is studied based on deep cut ellipsoid method considering descent search direction. The convergence of DCE algorithm was proved and verified with numerical results. Moreover, the results have been shown that each MG can adjust generation of DGs or trade with other MGs with a extensive consideration of generation cost and trading price and load characteristics. The distributed energy trading based on DCE algorithm has also been applied to four topologies and found that certain topologies were more beneficial than others. Compared with the existing work [69], the DCE algorithm has been shown the advantageous features on

modeling and performance.

Chapter 4 presented the optimization schemes for the residential community with multiple houses based on smart appliances scheduling- *genetic algorithm (GA)* and *dynamic programming (DP)* . In the proposed schemes, the time of use (TOU) pricing mechanism is used to identify the electricity cost. The optimization control approaches are capable of solving load scheduling problem of a small community. Three different house with real-world non critical appliances, with different power consumption are compared under energy management benchmark problem. Three case studies are demonstrated that all three control approaches can optimize energy consumption according to demand limit. The DP_{min} generally showed the smallest energy cost since it curtails the loads in the peak hour. On the other hand, genetic algorithm and aggressive dynamic programming (DP_{max}) are capable to reduce energy cost but differs the computational complexity. Genetic algorithm takes higher computational time than DP_{max} to solve this problem. The simulation results have shown that the aggressive dynamic programming (DP_{max}) is suggested to be the best choice for real life application, due to good performance in cost optimization.

5.2 Original Contribution of the Work

In this thesis, community energy management approaches and strategic electricity market architecture were proposed for smart grid retarded by various challenges. The proposed strategies were designed to cope with main issues- price control facilities at customer end and load scheduling schemes of distributed operator. We have listed the following major contributions of this thesis.

5.2.1 Distributed Game Theoretic Scheme of Electricity Market

We proposed a game theoretic framework to study the optimization and decision making of multilayer in the distributed power system. We apply the game theoretic special concept- rational reaction set (RRS), which is capable to model the game of distributed energy provider and the large residential consumers. In this scheme, the consumption agents are not only able to find market price at Nash equilibrium but also reduce the electricity cost non-cooperatively.

5.2.2 Distributed Energy Trading Approach for Interconnected Micro-grids

We studied a distributed energy trading framework to minimize the global cost of the interconnected MG system. The convex optimization technique called deep cut ellipsoid method, which is capable to model the distributed energy trading approach for islanded MGs. The DCE algorithm was validated using different case studies for a system consisting of 4 MGs. The performance of DCE algorithm is compared with sub-gradient approach, which provides the faster performance in DCE approach.

5.2.3 Intelligent Energy Management Approaches of Residential Community

We proposed a optimization model for a residential community with real world appliances. The two computational intelligence schemes- genetic algorithm and dynamic programming are used to solve the optimization problem. Using those schemes, each consumer can achieve the highest reduced electricity cost and good performance for energy scheduling.

5.3 Future Scope of the Work

- Future extension of the problem, includes understanding the incentive based energy trading mechanism can be applied between small energy providers and buyers to encourage proactive energy trading and fair benefit sharing. Another interesting direction of game theoretic trading approach to find the computationally efficient solution of large-scale distributed power systems.
- Future extension of of the energy trading problem, includes considering the indeterminacy of renewable energy generation, demand response and load demand, for which current deterministic approach would be no longer applicable.
- Future extension of the proposed work, includes understanding how the energy scheduling can be improved by introducing distributed renewable resources at the customer-end and the distributed system operator can be offered fair reimbursement to the customers by participating efficient demand response program, thereby improving the system efficiency and reliability.

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