A NOVEL DEMAND RESPONSE MECHANISM IN SMART COMMUNITY WITH LEARNING-BASED NEURAL NETWORK MODELING

by

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A THESIS

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ABSTRACT

This thesis investigates how to develop a learning-based demand response mechanism for a novel smart community that can minimize the energy cost both for the smart community system operator and for the residents while meeting all requirements for all entities.

The thesis first proposes a demand response centralized energy management strategy for the grid-connected smart community with distributed energy resources. The results show that the energy management system can make proper day ahead schedule based on forecasted load and weather information, utility curtailment condition and user priority settings.

Then the thesis proposed a novel learning-based NARX (nonlinear autoregressive network with exogenous inputs) energy consumption model for the Smart Community. The mode consists of a certain size of smart homes all equipped with smart meters and typical controllable electric appliances. Different modeling methods for HVAC, electric water heater, cloth dyer, electric vehicle and energy storage system are analyzed. The performance of the NARX model shows the accuracy of applying NARX to Smart Community modeling.

After that, the thesis proposed a genetic algorithm based optimal method to solve the energy cost function. After simulation under different load curtailment conditions, the validation of the proposed method is proved as it can greatly lower the total energy cost from the grid.

DEDICATION

This thesis is dedicated to everyone who helped me and guided me through the process of doing the experiments and writing this thesis. Among them, such as Dr. Li, my dear laboratory mates, I would especially like to give the credit to my parents without whom I could not keep myself together and be motivated all the time.

LIST OF ABBREVIATIONS AND SYMBOLS

SC	Smart Community
DR	Demand Response
HVAC	Heating, Ventilation, and Air Conditioning
EWH	Electric Water Heater
CD	Cloth Dryer
EV	Electric Vehicle
ESS	Electric Storage System
DER	Distributed Energy Resources
NARX	Nonlinear autoregressive network with exogenous inputs
GA	Genetic Algorithm
PAPR	Peak-to-average Power Ratio
SOC	State-of-charge
PV	Photovoltaics
ETP	Equivalent Thermal parameter
DAP	Day-ahead price

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If it were not the help and support from my family, my advisor, professors from the College of Engineering and my lab mates, I would not be able to finish this thesis.

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My master program could have finished in three semesters but I decided to pursue a thesis which took me another year to write papers and do experiments. Fortunately, my family understand me and support me whole-heartedly and they always have the faith on me. Life has its ups and downs, but I know my family are my number one fans right there at my back.

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CHAPTER 1

INTRODUCTION

1.1 Brief Introduction of Smart Home

With the intensification of global warming due to greenhouse gas emissions, the more stringent regulations on emission and fuel economy, and the consideration of adverse consequences of conventional energy resources like thermal power stations, renewable energy resources, such as wind power and solar power, are increasing their penetration among power systems over the past decade. These power sources are clean energy that generates low-pollution electricity and allows diversity in the electricity supply. In addition, they can save a lot of cost for the system operators. Besides the growing number of renewable power resources, the market of electric vehicle (EV) is also developing rapidly since the beginning of 21th century which will increase the penetration of EV and surely increase the load pressure on the power system.

These concerns used to only relate to industry factories and commercial buildings where the energy consumption is relatively high. However, as more and more appliances are used daily inside houses, the total energy consumption of them will surely have an impact on the gird and therefore cannot be ignored.

Besides the EV charging mentioned beforehand, there are also a variety of smart appliances as the technology of home automation develops. These smart appliances often have better interface and can be customized according to user preference. Unlike conventional

appliances, these novel user-friendly appliances can upload their status information in real time and can be remotely controlled by custom in real time or by preset energy management programs. Hence, energy management mechanism for smart homes are needed by the end users and are attracting more attentions in recent years with novel artificial intelligent concept join in. It has also been often preferred by utility companies and system operators as it can schedule optimal power plan for each smart appliance and can save unnecessary wasted energy.

The concept of smart homes is basically based on the need for coordinating these smart appliances mentioned above. Smart homes are residential buildings equipped with devices that coordinate with each other using communication channels in order to achieve a common set of goals that benefit the end users. The goal that this paper covers in specific is the management of energy consumption [1-3] .

A well-established smart home system may consist of several systems that depend on the services that it supports. The size of the control system can range from a 30 mm microcontroller to a room-size mainframe computer depends on the size of the smart system. The fundamental subsystem among all smart home subsystems is the communication system because only by using the communication system to transfer data between installed smart meters and appliances can the status of each appliance been collected by the control system. After the exchange of information has down, all other smart home systems can been operated accordingly. Several kinds of hardware structures were proposed based on wireless sensor home area network using Zigbee technology[4].

Besides the communication system, there are other smart systems such as security system which includes cyber security like Akai and property security like ADT-monitored home security system.

1.2 Demand Response in Smart Home

As mentioned beforehand, electricity consumption in residential markets will undergo fundamental changes in the next decade due to the appearance of smart appliances and home automation. Since these appliances can be scheduled according to certain energy management algorithms, which means they can perform load shifting accordingly. This load shifting feature is also the key requirement for the demand response in optimization of smart home appliance.

Demand response (DR) is defined as changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity (price-responsive DR), or to incentive payments designed to induce lower electricity use at time of high wholesale market prices or when system reliability is jeopardized (curtailable DR)[5]. DR includes all intentional modifications to consumption patterns of electricity of end-use customers that are intended to alter the timing, level of instantaneous demand, or the total electricity consumption[6].

In smart home systems, the optimization of the energy management is most commonly performed based on the application of demand response. Under the demand response mechanism, energy consumers need some incentive to respond to load shifting request from system operators or from the power plant. There is always “reward” and “punishment” for demand of power in different time. This could be achieved by the price incentives i.e. offering lower net unit pricing in in exchange for reduce power consumption in peak periods. There could also be cashbacks when end users shift their demand to idle hours when power plants have spare

electric energy. On the punishment side, there could be mandatory load curtailment for users during high demand hours.

1.3 Related Works in Smart Community

Most of the previous works have discussed about demand response inside an independent smart home. The coordination involves four to five energy consumption models at most. However, as the number of smart home is increasing in a fast pace, researchers are facing problems in performing energy management on larger scale such as multiple smart homes and communities. In recent years, a few novel ideas have been proposed in community energy management system (CEMS).

In [7], an optimization of energy management is proposed for a community of 28 two story buildings with PV, wind power generation and battery bank. It proposed a GA to find the optimal solution of how much power should be imported from the grid. It also studied the reliability of renewable energy supply as well as taken the operation and maintenance cost of each distributed energy resources into consideration. However it neither mentioned the grid load curtailment situation nor consider the application of demand response to appliances as well as modeling of the appliances.

In [8] it presented negotiation linear temporal logic rules for the coordination of resource consumption within communities with the goal of minimizing the contracted power by community. The execution engines of the proposed rules are able to detect conflicts between rules and circular dependencies, and then it solves the problem by disabling the execution of rules with lower level of hierarchy. In [8], there are rules defined both at the community level and at the home level. In the SC [8] proposed, it modeled washing machine, lighting system,

microwave and dishwater at the home level. On the community level, it considered nominal power contracted by the community, margin power due to power control regulation standards, common services power consumption, self-generated power by community and the general consumption by each household inside the community. However, the proposed quota negotiation among neighbors in [8] is performed in the lower level of hierarchy which lowers the efficiency of optimization.

Authors in [9] developed a new renewable energy aware pricing scheme to minimize the total electricity bill among all customers in an SC. A discount factor is given to customers for the electricity bill reduction due to using renewable energy inside the community. This leads to competition among the customers for a better discount and lower electricity bill since the paper used decentralized energy management. The ideal of pricing the renewable energy is novel which customers can indeed reduce their electricity bill. It solves the situation when both power demand and renewable generation are high. Conventionally according to demand response mechanism, high power demand will lead to high electricity price which conventional controllers probably will not schedule the load during this time period. However the pricing scheme is more of a weight matrix than the real pricing, it does not directly provide the “price” to customers. In addition, the paper argues that in practice customers are independent decision makers and cannot be directly controlled by a centralized aggregator neglecting the fact that centralized controller schedule the power consumption plan within the range of satisfaction of the customers. It is also a pity that in the modeling of daily energy consumption of home appliances, [9] only considered the daily consumption and execution duration without discussion of the user preference and constraints for each appliances.

1.4 Proposed Smart Community

The vision of this paper is broader than only focusing on a single smart home, in fact it concerns a community consist of several smart homes and several other distributed energy resources (DER).

In the concept of SC proposed by this paper, an SC is a smart distribution system that consists of a group of smart homes which has been equipped with several smart appliances. In addition, the community will also install several PV panels and wind turbines and a sharing-based energy storage system (ESS). It can be regarded as a version of networked microgrid in grid-connected mode with centralized energy management system for coordinated operation of each appliance.

The distribution of the proposed SC power system is shown in Figure 1. All together four power sources, grid, ESS, Wind turbine and PV panels, supply the N smart homes inside the SC through converters and inverter first and then through bus lines. Since the loads studied in this thesis are conventionally AC loads, the bus line could be AC bus line. If it is a DC smart home, then it is also possible to set up DC bus line. The output power of PV panels and wind turbines has the highest priority to feed the bus line, and if the power generated is inadequate for the total load, or the electricity price is comparatively high at the time, the energy storage system can be discharged to a certain amount to feed the bus. If there is still insufficient power, or the electricity price is comparatively low at the time, a certain amount of power can be purchased from grid to feed the load or charge to the ESS.

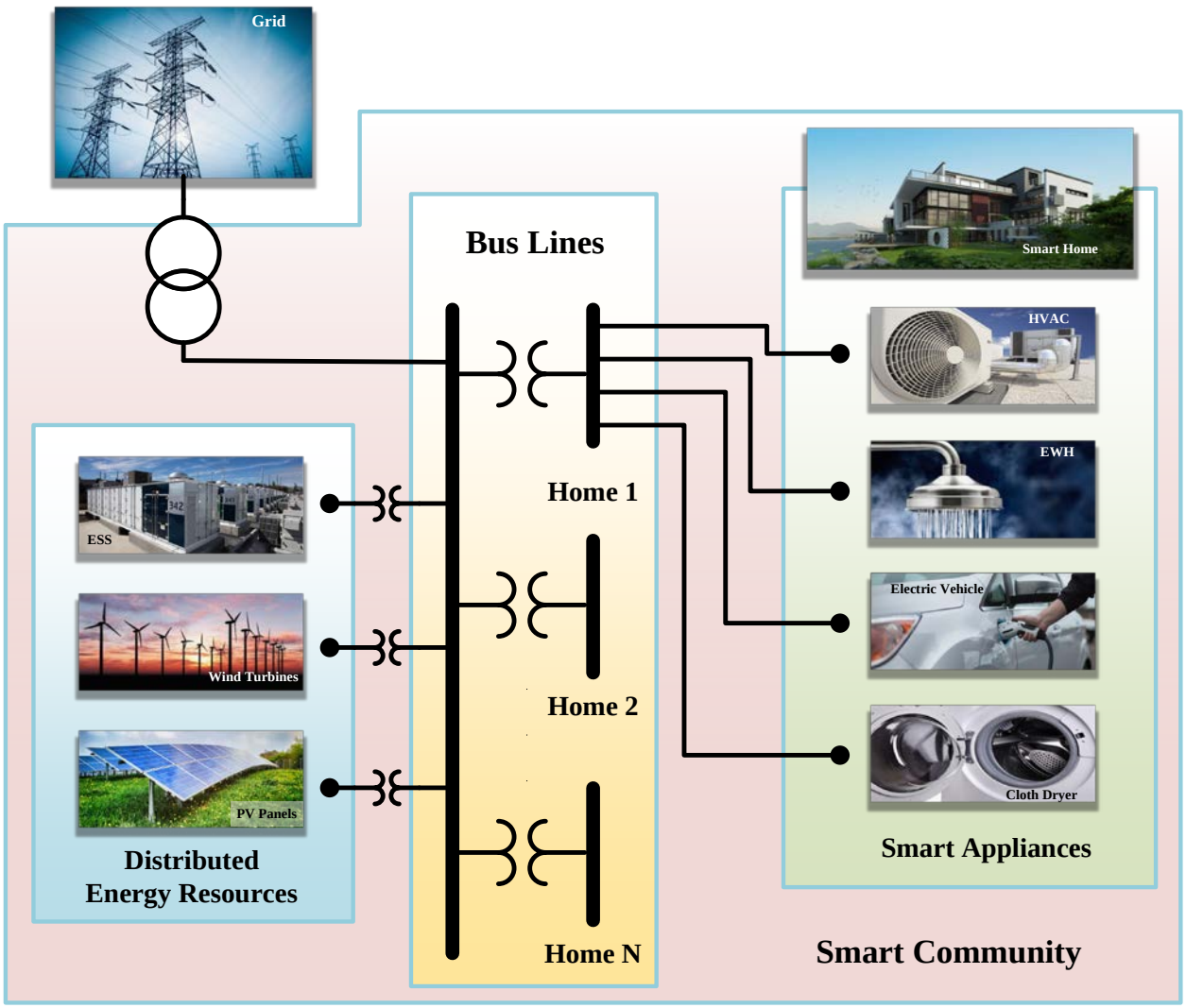


Figure 1: Smart Community distributed power system

1.5 Challenges

Researches are facing a lot of challenges towards the optimization of energy management in SC.

First, an accurate load forecast system is one of the prerequisite of energy management system. When the forecast is accurate enough, the reschedule in the second stage due to forecast

error will not cause impact on the overall energy optimization. The existing forecast methods will be reviewed in the second chapter.

Secondly, in the model of smart home, there are challenges in improving the accuracy of the model. The overall accuracy of the smart home modeling relates to the modeling of each appliance. There are different categories of appliances need to be taken into the overall smart home consideration. All these appliances need to have a proper mathematic model that depicts its energy consumption. Most of the existing mathematic energy consumption models are fixed models which do not change with changing environmental conditions. To improve the accuracy of the smart home model, learning-based modeling methods should be applied to build a dynamic model which can reduce the training error in long-time simulation and improve the modeling accuracy.

Thirdly, the increasing penetration of residential solar generation and other renewable energy resources impose challenges on the existing distribution strategy and the system operator[10]. In an SC with both dispatchable and renewable energy sources, there are challenges in designing an energy distribution strategy that both residents and system operators can have the maximum profit. In order to do so, the energy management mechanism needs to forecast the generation of renewable energy in order to pre-schedule the distribution of it. Also it needs a real-time make up control strategy if there are errors in the forecasting process. In smart communities that have ESSs, the charging and discharging of the ESS is also the duty of the energy distribution strategy. A price-sensitive algorithm is needed to calculate the amount of power from the grid.

Fourthly, such a community has a much larger size of smart home which makes the coordination of all entities not easy. When evaluating the complexity of the energy management

of SC, calculating the optimal energy plan that meet all kinds of requirement is equal to solving a high dimension non-linear function with a considerable amount of constraints where each dimension represent an entity. The higher the dimension the longer the computational time would take. Thus it imposes great challenge in shortening the computational time while given such a complicated equation.

1.6 Purpose of This Thesis

With regards of the above challenges, the thesis first proposes a demand response energy management strategy for the grid-connected SC with distributed energy resources. It is a centralized energy management system in specific which is brought up after studies of different energy management strategies. The management strategy can make day ahead schedule and send the control signal to each smart home based on forecasted load and weather information, utility curtailment condition and user priority settings.

Then the thesis proposed a novel learning-based energy consumption model for an SC under demand response mechanism. The mode consists of a certain size of smart homes all equipped with smart meters and typical controllable electric appliances. During the modeling of an SC, different thermodynamic models are studied; neural network modeling and several other modeling methods of residential appliance are tested and compared.

After that, the thesis proposed GA based optimal method to solve the energy cost function. For an SC, proper power solution should be scheduled to every entity to reach an overall lower cost for both residents and SC. The solution of the energy cost function will be adapted by the manager of SC i.e. the system operator.

1.7 Thesis Organization

This thesis is organized as follows. Chapter 2 gives a full analysis of the community energy management by studying different types of energy management methods as well as the impact of load shifting and the forecast system in community energy management. Chapter 3 introduces the entities and their models inside the proposed SC. Their working priorities and rules are also discussed in Chapter 3. The next chapter proposes a learning-based modeling method for the SC using neural network, whereas Chapter 5 builds the optimization problem for SC energy consumption and distribution uses GA based algorithm to find the optimal solution. Chapter 6 introduces the initial settings and analyzes the proposed energy management under different conditions. Finally, the conclusion of the thesis is provided in Chapter 7.

CHAPTER 2

ANALYSIS OF COMMUNITY ENERGY MANAGEMENT

2.1 Energy Management Strategy

An energy management system is essential for the operation of SC. The main responsibilities of an energy management system are to assign generation references to the grid and to distributed energy resources and manage controllable loads so as to control the power production and energy consumption in an SC.

There are many advantages of applying an energy system management to residential household. Compare with a household without smart home energy management system, the system which works with remote controllable smart appliances can save the manpower on turning on/off or plugging in/out each appliance, it can get the job done even nobody is at home. Moreover, the system can operate all appliances at the same time and at a macroscopic level. It means the system is price-sensitive, can operate household solar panel, wind turbine, and ESS. Even the utility assigns power curtailment to the house, the system can still get the most important work down according to preset priority. Last but not least, by using certain artificial intelligent algorithms, the system can provide an optimal control which reduces the energy consumption and cut down the electricity bill.

With different focus in the SC, the energy management system can be implemented in different ways. There are two parties in the SC, the residents, the system operator or the utility

company. The energy management strategy can be generally regarded as two types according to the two parties respectively, the decentralized energy management system and the centralized energy management system.

2.1.1 Centralized Energy Management System

Centralized energy management features a central controller that is provided with the relevant information about the microgrid, as well as the information from forecasting systems, in order to determine the dispatch of the resources according to the selected objectives[11].The modeling of the distribution system is usually non-linear equations, the solving of which could require considerable computational time due to the complexity of the model. Centralized controls only need one controller to cooperate all entities. All entities upload their status to the controller first, and it performs optimization based on the given information. There is no communication during the optimization process which saves the computational time. Besides, the controller can deal with power emergencies such as temporary power curtailment or grid failure from a Macro perspective.

Tsikalakis et al. [12] proposed a centralized control system for optimization of microgrids operation. The paper proposed a hierarchical control system that has three control levels, the local microsource controllers, the microgrid system central controller and the distribution management system. The microgrid system central controller is a similar concept compared with the energy management of the SC since they are both responsible for the maximization of the microgrid's value and the optimization of its operation. A comparison between centralized and decentralized for control of a scale of energy storage units was performed in [13] where the results are clear that the centralized control has allowed smaller ESS and has a much lower

lifetime cost. Olivares et al. [11] decomposed the centralized energy management into unit commitment and optimal power flow and applied it to the central of isolated microgrids. The proposed energy management is able to obtain solutions within the desired time spans where commercial solvers failed to obtain a solution, enabling the potential implementation of the energy management system in real-time, autonomous operation of isolated microgrids.

Besides the ability for solving large scale control problems, since there is only one controller that does all the optimization for energy management, the operation cost is much lower compares with decentralized control method. Also the maintenance cost will be lower correspondently.

2.1.2 Decentralized Energy Management System

The decentralized concept aims to achieve economical operation of a microgrid while providing the highest possible autonomy to the different entities. Decentralized energy management systems are based on optimization algorithms that offer autonomy to each entity to optimize its own objectives subject to its entity-specific set of constraints[14]. These algorithms often has two steps, each entity first solves its own optimization problem, after the local optimal solution is obtained, different entities will negotiate with each other until the optimal coordinated operation point is reached. Many studies have been made in the literature on the decentralized energy management.

However, there are several disadvantages about decentralized energy management system. First, in decentralized energy management system, each household, in the case of SC, must install a controller capable of solving optimization problem in advance because each household needs to optimize its own energy management decision according to its own

preference. When the size of the SC increases, the cost spend on these controllers increases. Besides, the cost on two-step negotiating with each other in a big network is time consuming. By given a certain converge criteria, it could take hours to reach an equilibrium point. Also there is not much difference between the final optimal solutions of the two types of management methods. In [15], a game-theoretic decentralized approach is proposed to optimize the scheduling of EV, comparing the final minimized cost of decentralized energy management with the decision of centralized management algorithm, the results are 1.3% different. In [9] it also approved that the optimal solution of decentralized smart home scheduling is equivalent to that of the centralized technique.

2.2 Proposed Smart Community Energy Management

In the SC proposed by this thesis, centralized control method is more suitable for energy management. In our design, the system operator coordinates every household at the same. The centralized control meets the requirement of system operator since it also cooperate all the entities at the top level. All households provide their preferences in advance and no negotiation is needed during coordination. These preferences include appliance shut down priority, thermostat setting, hot water usage and other usage patterns learned by the forecast system. The system operator can use all these information as constraints for the coordination. Also, instead of finding a convergence solution after optimization, the decision made by centralized control will be the final decision with no revise if there is no error in the forecasting process. Besides households, there is also an ESS in the system; it also needs a controller in the framework of decentralized control. Centralized control saves the work for each individual optimization of all distribution energy resources.

2.3 Load Shifting Effect of Demand Response

From the grid side, in order to meet all the energy demand from customers, the grid capacity needs to be designed to satisfy the peak power demand. In a typical household, the load will be much higher when customers are active at home. The main consumption time of conventional load pattern is between 7 am to 11 am and 6 pm to 12 am when people usually have showers[16]. When performing SC DSM, it is ideally to shift the load from formal peak hours to valley hours as much as possible in order to reduce the peaks. The valley hours corresponds to hours when appliances are idle and residents are usually inactive. The simulation in Chapter 6 will demonstrate the effect of load shifting.

The peak-to-average power ratio (PAPR) is a measure of the power waveform, showing the ratio of peak values to the average value. It is originally used for showing how extreme the peaks are in a waveform. However, it can also show the load peaks in a load pattern. It is calculated as:

$$\begin{aligned} \mathrm{PAPR}(Q_n) &\triangleq \frac{\max\limits_{0\le n\le N-1} |Q_n|^2}{P_{av}(Q_n)}, \\ P_{av}(Q_n) &= \frac{1}{N}\sum_{n=0}^{N-1} |Q_n|^2 \end{aligned} \tag{1}$$

where PAPR equals 1 indicates no peak which is the ideally desired goal in terms of DSM. The closer PAPR gets to 1, the less power loss will occur on the grid side. In [17, 18], distributed algorithm and game theory are proposed to reduce PAPR in DSM.

One of the main reasons that electric prices vary in a day is that in peak hours when total demand is high, more expensive generation sources are added to meet the increased demand[19]. For the proposed DSM under this pricing strategy, the shifting of load can reduce the peak hour

demand in the grid[20]. The new power solution will have a PAPR much closer to 1 due to the rearranging of the power consumption.

However, for renewable power resources like wind and solar power, the power generation itself already has a large PAPR due to its characteristic and the uncertainty of weather. Solar PV only generates power during daytime; wind turbine only generates power when it is windy. The system operator would require a DSM approach that can shift load pattern towards the overall power generation pattern considering renewable generations.

2.4 Forecast System

Forecast is a perquisite for solving the aforementioned energy management problem because many day-ahead information are needed for modeling and optimization. The forecast system proposed in this thesis consists of forecasting future load and also the availability of renewable energy resources inside the community. In this thesis, the system is designed to provide day-ahead forecast. Every day, the forecast system collects the data and provides prediction based on the historical data.

2.4.1 Resident Load forecasting

The load pattern for each household is unique due to varies factors[21]. It is a big challenge to precisely model and estimate energy consumption of the three categories of loads in a household. Actual energy consumption can be affected by occupant numbers, weather, seasons, etc., and can change over time. Because of this unique feature, it is necessary to develop a prediction mechanism for each individual household.

By using certain equivalent energy consumption models, the forecasting of load can be transformed to forecasting of load related information such as forecasting thermostat setting preference pattern for HVAC system, hot water consumption for EWH system, arriving and leaving time for EV system, etc.

Various techniques for power system load forecasting have been proposed in the last few decades and it has been developing from traditional regression and interpolation to novel artificial intelligence techniques and to a combination of several methods together. Analyzing the existing forecasting methods, there can be roughly divided into three categories[22].

The first one bases on classic statistic like regression model, which was trained to forecast daily energy consumption of a house based on the foundation of smart meter communication[23].

The second category involves time series model which include forecasting with seasonal naïve and seasonal decomposition in conjunction with exponential smoothing (STL and ETS) [24] or like [25] in which demonstrated short-term load forecasting and chose naïve seasonal model and to serve as benchmark which shows the possibility of using seasonal autoregressive integrated moving average models to deliver short-term energy forecasting.

The third category of forecast bases on artificial intelligence skills. In [26], a Bayesian updating approach is applied to learn the probability of customer hot water usage behavior at each hour, in which a large data set is needed to learn the model before using it. In [27], the author presented a forecasting method based on non-homogeneous Markov chains, where occupants change states within certain probabilities overtime. Support vector machine and artificial neural network methods were also been applied to forecast electricity loads for

individual houses[28]. The author in [29] also used a neural network to predict household heat demand in order to meet the demand. As shown above, developing a learning mechanism that can identify energy consumption model from historical data and update the model daily in real-time is critical for the model-based optimal demand response methods[30].

However when initially starting the DSM for an appliance, the forecast process starts with limited history data available for modeling with which the seasonal forecasting methods could have considerable error. Hence a forecast method that does not need long term historical data is preferred in the case of SC.

To overcome these challenges, [24] and [31] used models that have multi-function prediction. Inspired by these models, this paper used a time series decomposition forecasting methods, seasonal autoregressive integrated moving average (ARIMA) to forecast customer water demand pattern. The seasonal ARIMA(p,d,q)(P,D,Q)m model is a well-established modeling technique that combines autoregressive (AR) part, moving average (MA) part and integrated (I) part of a prediction progress where parameter p, d, and q are non-negative integers representing the order of the AR model, degree of difference and the order of the MA model. Comparatively, parameter P, D, and Q are seasonal AR, MA and I parts of the model. In addition, m refers to the number of periods in each season. Figure 2 shows the performance of five forecasting methods given the real public load forecasting data from Global Energy Forecasting Competition 2014 (GEFCom2014). It includes Seasonal mean method, MA method, ARIMA (3,1,1) with seasonal MA, ARIMA (1,1,1) $(1,0,2)_{24}$ and ARIMA (1,1,2) $(1,0,0)_{168}$. The fourth and fifth methods are chosen from the optimal methods in[24]. The red line is the target load data from GEFCom 2014[32], it has a two peaks in each 24 hour interval and also a long

term tide. All five forecast methods can follow the two peaks but they all have error to some extent in forecasting the long term load tide. The initial learning week is not shown in the figure.

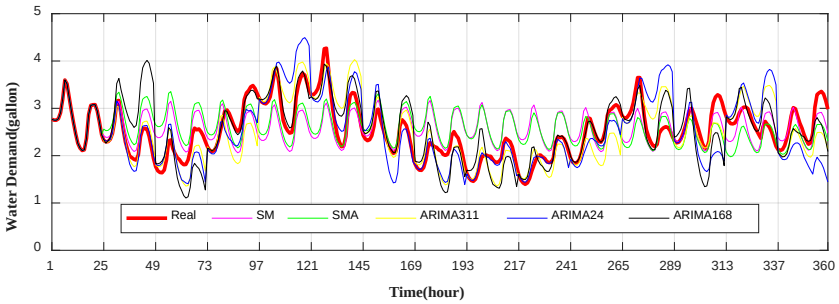


Figure 2: Forecast of water demand with different methods targeting data from GEFCom2014

In this paper, we use the most general practice to evaluate the performance of the forecast methods. We compare the normalized mean absolute error (nMAE), normalized root mean square error (nRMSE) and mean absolute scaled error (MASE) of different forecast methods. Mean absolute percentage error (MAPE) is unsuitable for hot water consumption due to the unstable of calculation [14]. Table 1 summarizes the performance of the above five methods. In Table 1, ARIMA (1,1,2) $(1,0,0)_{168}$ has the best performance in nMAE and MASE; ARIMA(3,1,1) with SMA24 perform better in nRMSE. ARIMA (1,1,2) $(1,0,0)_{168}$ is chosen as the optimal forecast method for the later optimization of this paper for all concerned. In order to have more accurate forecast model, different climate and economic scenarios [19] should also be put into consideration. Due to limitation of space, further discussion is not included.

Table 1. Model fitting results for EWH consumption

Method	Performance Measures		
	nMAE	nRMSE	MASE

Seasonal Mean	0.7502	0.9182	0.9743
MA_{24}	0.8213	0.9683	0.9638
ARIMA(3,1,1) with SMA_{24}	0.6045	0.7708	0.7851
$ARIMA(1,1,1)(1,0,2)_{24}$	0.6756	0.9571	0.8774
$ARIMA(1,1,2)(1,0,0)_{168}$	0.5815	0.8112	0.6824

2.4.2 Weather and Renewable Energy Source Forecasting

In order to determine the system marginal price of electricity, system operators are obligated to forecast the next-day electricity demand and generation. On a daily basis, the system operator need to know the possible amount of power available from renewable energy source that can be supplied next day.

There are many forecast models that only uses historical data of the power generation. These methods includes neural networks [33-35], wavelet analysis[36], evolutionary algorithms [37], fuzzy prediction interval model that incorporate an uncertainty presentation of future renewable resources including solar and wind generation [38] , etc.

However, renewable energy generations like solar and wind power are closely related to the weather. By collecting useful weather elements from available weather forecast web services, several methods are proposed to more accurately forecast these weather-related generations. These weather elements may include the temperature, humidity, precipitation probability, wind speed and direction, and sky condition, etc.

In [39], the authors use the information of cloud cover, season, precipitation probability and historical moving average insolation to predict a daily solar power generation. They also

compared their model, which is based on solar PV output formula, with existing regression models and artificial neural network models. The advantage of the model in [39] is maintaining a good performance given limited historical operational data.

Besides these researches, many companies in the nowadays market of energy services are providing predictions of renewable energy productions[40]. In this paper, we assume that we have the access to a short-term energy forecasting service since forecasting renewable energy generation is very mature and not the focus of this thesis. The service is assumed to provide accurate solar and wind power generation one day ahead of the operation day. Typical load patterns of PV and wind energy generation are shown in Figure 3[41] and Figure 4[42].

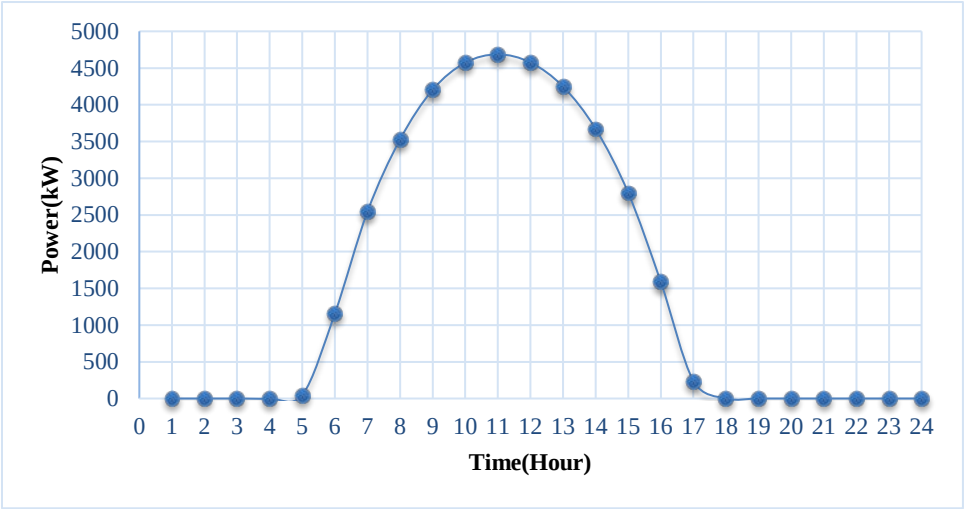


Figure 3: PV power generation of all sites on the campus of University of Queensland 10/01/2016

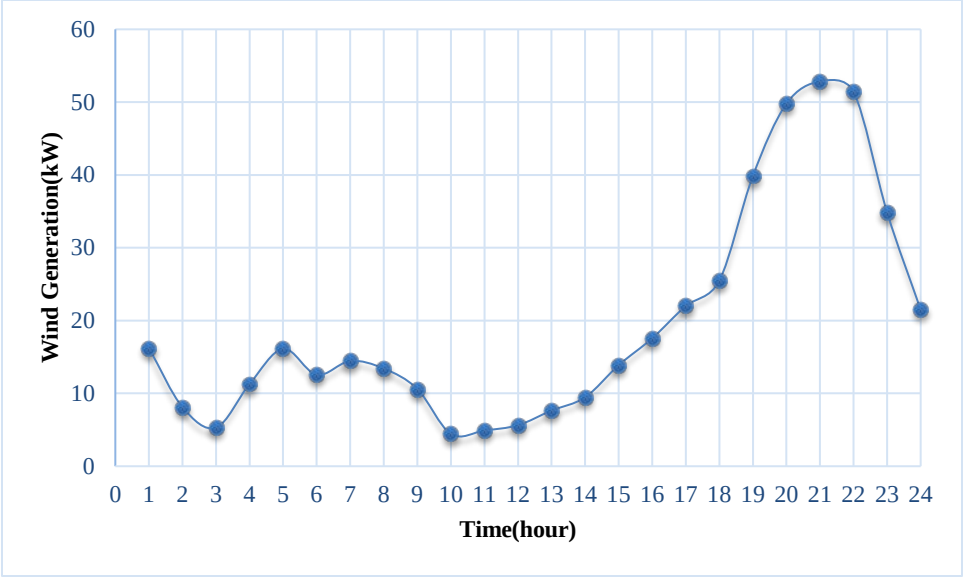


Figure 4: Wind generation from OeMAG, Germany, 10/01/2016

2.4.3 Electricity Price Forecasting

In most electric power systems, some or all consumers pay a fixed price per unit of electricity independent of the cost of production at the time of consumption. The consumer price may be established by the government or a regulator, and typically represents an average cost per unit of production over a given. Consumption therefore is not sensitive to the cost of production in the short term[43].

Many system operators include two electric energy markets that work together in a "multi-settlement" system. In these three cases, they provide either day-ahead market prices (DAP), real-time market prices (RTP) or settlement point prices (SPP).

The day-ahead energy market lets market participants commit to buy or sell wholesale electricity one day before the operating day, to help avoid price volatility. It matches willing buyers and sellers, subject to network security and other constraints, whereby energy is co-optimized with ancillary services and certain congestion revenue rights. It provides a platform to

hedge congestion costs in the day-ahead of the operation day, and instruments to mitigate the risk of price volatility in real time. This market produces one financial settlement[44].

The real-time energy market lets market participants buy and sell wholesale electricity during the course of the operating day. The real-time market balances the differences between day-ahead commitments and the actual real-time demand for and production of electricity. The real-time energy market produces a separate, second financial settlement. It establishes the real-time locational marginal price that is either paid or charged to participants in the day-ahead energy market for demand or generation that deviates from the day-ahead commitments[45].

In an idealistic fixed electricity price market, customers would use an appliance without the concern of time and price changing. However, in a price fluctuating market, which is the real situation, customers are encouraged to shift the working hours of appliances because consume electricity with low price will reduce their utility bills. The 24-hour electricity price can be provided by an electric utility one day ahead under a dynamic pricing program. The real-time electricity price and day-ahead price of an utility company can be found in [46], the company serves about 2.4 million customers in Illinois and Missouri. Figure 5 shows the 7-day electricity price posted on their website starting on Oct 1st 2016. In other cases that the electricity price is not available from the system operator, [47] proposed ARIMA model to forecast the day-ahead electricity price.

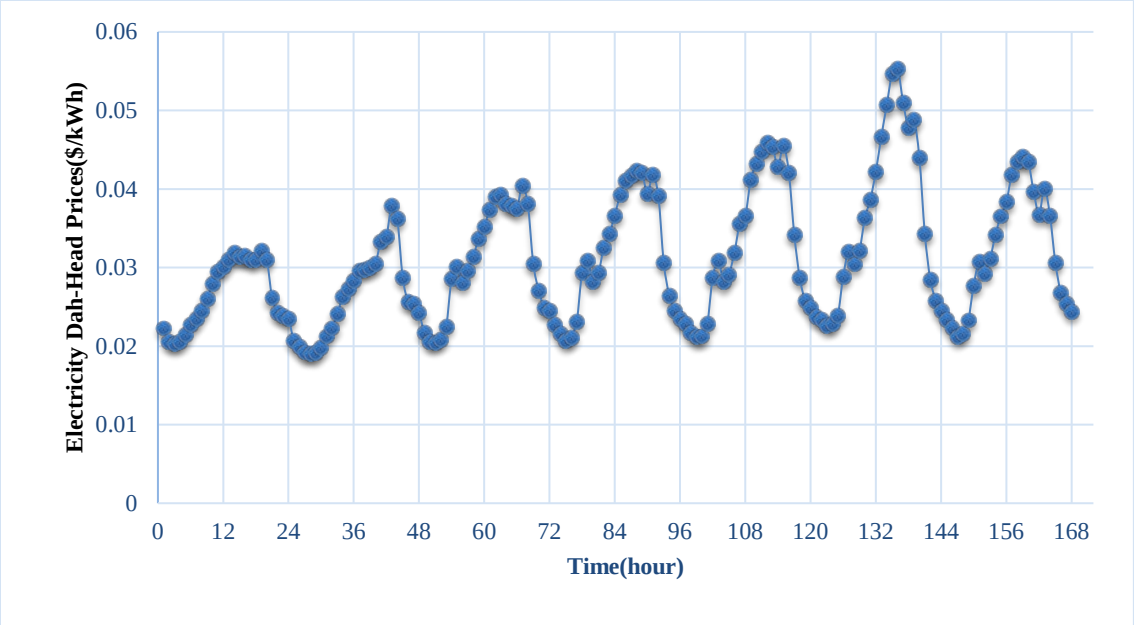


Figure 5: Day ahead pricing used for Ameren Illinois starting from 10/01/2016

With the day-ahead price, one can develop price sensitive energy management algorithm for SC to optimize the total cost by decreasing energy consumption during higher price hours and increasing energy consumption during lower price hours. This would help to cut down the electricity bill of the customer. In addition, some constraints should be considered to maintain the comfort experience of customer.

CHAPTER 3

ENTITIES INSIDE SMART COMMUNITY

3.1 Categories of Home Appliances

There are basically three categories of home appliances regarding their load characteristic and control strategy.

3.1.1 Base Load/ Fixed Load

The first type of appliances has what is called base load or fixed load. These appliances are the base need of the lives of the residents in the house because their delay of use or shut down is totally not acceptable by the residents. In addition, base load appliances make up the minimum load of a residential house because they are fixed and cannot be curtailed. One typical example of base load appliance is the lighting system in the house. Whenever illumination is needed in the house, the lighting fixtures have to be turned on either manually or by induction. Other appliances that attribute to base load include refrigerator, microwave oven, television, computers and electronics. The need for these appliances is either non-flexible or very hard to forecast so it will not be affected by demand response strategy. However, the load pattern of base load will be considered since the overall load pattern is one important factor in smart home demand response mechanism.

3.1.2 Deferrable Load

Deferrable load related to appliances that have fixed working cycles but the exact work timing is not that important. They can wait until the price of electricity is cheaper or power is available. These appliances such as dish washer or CD are designed to finish a certain job which is not very time sensitive because shifting the working time of these appliances under certain constraints can still meet the need of the customers. Different from smart load that will be introduced in the next paragraph, deferrable load only has limited possible load due to their working characteristic.

3.1.3 Smart Load

Appliances that relates to smart load, or shiftable load, do not have fixed load pattern. Instead, the load pattern is optimized by optimization algorithms that take the electricity price, the custom setting and the comfort of residents as factors. The aim of introducing smart load is to save the cost while maintaining everything the same for residents. These appliances include space heating, air conditioning, water heating and EV charging. In recent years, residential backup battery such as Powerwall[48] has also been categorized into smart load appliances.

3.2 Typical Home Appliances and Their Energy Consumption Model

When we considering the energy consumption, especially electricity consumption in a typical household in the United States, there are a large variety of appliances that use electricity to work. These appliances include HVACs, EWHs, lighting, cloth washers and dryers, dishwashers, refrigerators, electric stoves and etc[49]. In addition, in recent years, televisions and computers are upgrading to larger screen, faster CPUs and GPUs which will require higher

power rate to support. They will take up a considerable part of the total energy consumption in the near future.

In the above section, these appliances are categorized into three categories of appliances from typical home appliances are chosen to be concerned in this thesis based on the total consumption percentage according to [50].In the survey conducted in [50], space heating took up 41% of the total energy used in homes while air conditioning took up 8%, water heating took up 20%, appliances and electronics took up 31%. In addition, among the many different appliances within residential end-user areas, thermostatically-controllable appliances (TCAs) including HVAC and EWH, refrigerators, etc., represent a considerable potential for demand response programs due to their rapid response and the fact that thermal inertia allows for a sustained interruption of their service without compromising the comfort of the end-user[51]. Hence, this thesis chooses HVAC and EWH as smart loads. In addition, since the EV penetration is increasing rapidly these years, plug in EV is also under consideration as smart load. CD is regarded as a typical deferrable load in this thesis. A community owned ESS is also taken into consideration. The detail modeling method of these loads are explained in the following paragraphs.

3.2.1 Heating, Ventilation, and Air Condition

According to the American Society of Heating, Refrigeration, and Air Conditioning Engineers (ASHRAE) [52], an HVAC system should “heat, cool, clean, ventilate, humidify and dehumidify as needed to provide health and HVAC comfort”. An HVAC system for residential house has a goal to provide thermal comfort and acceptable indoor air quality for the residents.

HVAC energy consumption as a function of time can be estimated using simplified first principles models such as an ETP since it is a typical TCA. This approach models the cooling and heating loads in a residence as a function of a few lumped parameters including effective envelope conductance, effective thermal mass, effective solar apertures, and coefficients of performance, weather, internal gains, and thermostat set points[53]. The HVAC energy consumption model can be represented as [30, 54-56]:

$$T_{\text{room}}^{i} = e^{-\Delta t/RC} T_{\text{room}}^{i-1} + \left(1 - e^{-\Delta t/RC}\right)\left(T_{o}^{i-1} + P_{\text{HVAC}}^{i-1} \cdot t \cdot R\right), \tag{2}$$

where,

T_{room}^{i} : average room temperature at hour *i* (°C);

T_{o}^{i} : average ambient temperature at hour *i* (°C);

C : equivalent heat capacity(J/°C);

R : equivalent thermal resistance(°C/W);

P_{HVAC}^{i} : HVAC heat rate during hour *i* (W);

Δt : time step.

With a proper P, the room temperature T_{room}^{i+1} should meet the thermostat setting in advance. In practical control of HVAC, since it is difficult to keep the room temperature at the exact thermostat setting temperature, a certain temperature deadband is set to 2°C or 4°C, to let the room temperature to fluctuate close enough to the thermostat setting[54].

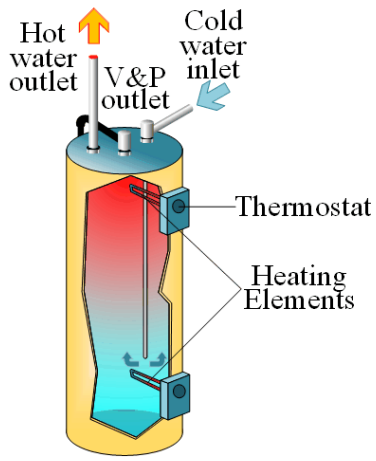
In conventional HVAC control, the thermostat setting is usually manually set at a fixed temperature by residents at their own comfort. Residents may change the setting due to changes in personal thermal comfort preferences or outdoor temperature. In a residential demand

response scheme, the thermal setting will be chosen differently in order to have a much lower cost while maintain the comfort of residents.

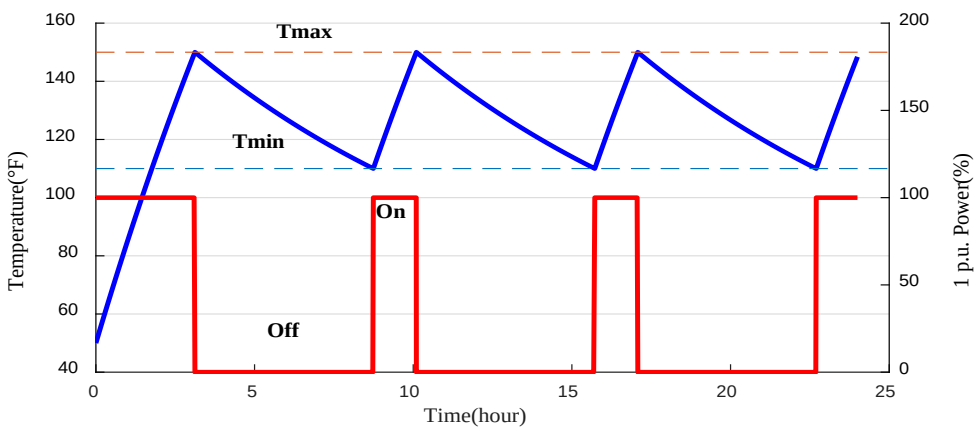
3.2.2 Electric Water Heater

A water heater typically uses gas or electricity to heat the water and to meet the demand of the household occupants. Most residential water heaters in North America have traditionally been the tank-type water heater. It consists of a cylindrical vessel or container that keeps water warm or hot to make the water be ready to use by occupants at any time. Typical sizes of residential water heaters can hold water ranging from 20 to 100 gallons. These water heaters may consume energy from electricity, natural gas, propane, heating oil, solar, or other energy sources. This paper focuses on EWHs, one of the most popular water heaters used in a common U.S. household.

The water tank of an EWH usually has one pipe on the bottom of the tank used to pump cold water into the tank and one pipe on the top of the tank used to lead hot water out from the tank as shown in Figure 6(a). There are commonly one or two heating elements inside the tank. A tanked EWH has the advantage of using electricity at a relatively slow rate compared to a tankless water heater because it can store the hot water in the tank for later use. The disadvantage is that in order to make the water in the tank hot and be ready to use at any time, the heating system of the EWH has to be turned on once in a while.



(a)



(b)

Figure 6: (a) Structure of electric water heater; (b) Traditional on/off control method illustration

For a tanked EWH with conventional control, the water is maintained at a constant temperature setting point due to the lack of knowledge of customer water usage behavior and comfort preference. Figure 6(b) illustrates traditional EWH on-off control method. In general, when water tank temperature reaches an upper limit, the heater turns off; when it reaches a lower bound the heater turns on. According to [57], the average heating time of a household EWH is around 2.6 hours per day. Since the conventional EWH cannot recognize high and low price

hours, there is a large room for improvement in control optimization. In addition, without the optimization, the tank size must be large enough because undersize tank may not meet the comfort requirement of a customer at peak usage hour.

The thermal dynamic model of an EWH was traditionally derived based on system energy balancing relation as shown in [58]. Basically, power enters an EWH and heats the heating elements and also heat the water in the tank; hot water flows out of the tank for the customer to use. In addition, thermal energy losses due to imperfect thermal insulation make up a part of the power consumption. The ETP modeling of EWH is a similar approach as HVAC. Hence, the ETP model of the EWH thermal system [59] can be represented as:

$$\frac{dT_{\text{tank}}}{dt} + \frac{\dot{m}c + hA}{Mc} T_{\text{tank}} = \frac{\dot{m}cT_{\text{input}} + hAT_{\text{amb}} + Q(t)}{Mc}, \tag{3}$$

which can be transformed into an approximate hourly model given that:

$$\frac{dT_{\text{tank}}}{dt} = \frac{\dot{m}_s cT_{\text{input}}^t + hAT_{\text{amb}}^t + Q_{\text{EWH}}^t}{Mc} - \frac{\dot{m}_s c + hA}{Mc} T_{\text{tank}}^t$$

$$\therefore \Delta T_{\text{tank}} = \int_0^{3600} \frac{dT_{\text{tank}}}{dt} dt = \frac{\dot{m}_h}{M} T_{\text{input}}^i + \frac{3600hA}{Mc} T_{\text{amb}}^i + \frac{3600P_{\text{EWH}}^i}{Mc} - \frac{\dot{m}_s c + hA}{Mc}\left(3600\left(T_{\text{tank}}^i + \frac{\Delta T_{\text{tank}}}{2}\right)\right)$$

$$\Rightarrow \Delta T_{\text{tank}} = \frac{\dot{m}_h}{M} T_{\text{input}}^i + \frac{3600hA}{Mc} T_{\text{amb}}^i + \frac{3600P_{\text{EWH}}^i}{Mc} - \frac{\dot{m}_h c + 3600hA}{Mc} T_{\text{tank}}^i - \frac{\dot{m}_h c + 3600hA}{2Mc} \Delta T_{\text{tank}}$$

$$\Rightarrow \left(1 + \frac{\dot{m}_h c + 3600hA}{2Mc}\right) \Delta T_{\text{tank}} = \frac{\dot{m}_h}{M} T_{\text{input}}^i + \frac{3600hA}{Mc} T_{\text{amb}}^i + \frac{3600P_{\text{EWH}}^i}{Mc} - \frac{\dot{m}_h c + 3600hA}{Mc} T_{\text{tank}}^i$$

$$\Rightarrow \Delta T_{\text{tank}} = \frac{2Mc}{2Mc + \dot{m}_h c + 3600hA} \cdot \left(\frac{\dot{m}_h}{M} T_{\text{input}}^i + \frac{3600hA}{Mc} T_{\text{amb}}^i + \frac{3600P_{\text{EWH}}^i}{Mc} - \frac{\dot{m}_h c + 3600hA}{Mc} T_{\text{tank}}^i\right)$$

$$\Rightarrow \Delta T_{\text{tank}} = \frac{2}{2Mc + \dot{m}_h c + 3600hA} \cdot \left(\dot{m}_h cT_{\text{input}}^i + 3600hAT_{\text{amb}}^i + 3600P_{\text{EWH}}^i - \left(\dot{m}_h c + 3600hA\right) T_{\text{tank}}^i\right),$$

the hourly thermodynamic model can be finally represented as:

$$T_{\text{tank}}^{i} = T_{\text{tank}}^{i-1} + \Delta T_{\text{tank}}$$

$$= \frac{2}{2Mc + \dot{m}_h c + 3600hA} \cdot \left(\dot{m}_h c T_{\text{input}}^{i-1} + 3600hAT_{\text{amb}}^{i-1} + 3600P_{\text{EWH}}^{i-1} - \left(\dot{m}_h c + 3600hA \right) T_{\text{tank}}^{i-1} \right) + T_{\text{tank}}^{i-1} \quad (4)$$

$$\Rightarrow T_{\text{tank}}^{i} = \frac{2}{2Mc + \dot{m}_h c + 3600hA} \cdot \left(\dot{m}_h c T_{\text{input}}^{i-1} + 3600hAT_{\text{amb}}^{i-1} + 3600P_{\text{EWH}}^{i-1} + 2McT_{\text{tank}}^{i-1} \right),$$

where,

M : mass of water in the tank (kg);

c : specific heat of water (J/kg°C);

$\dot{m}_s$ $\dot{m}_h$: average mass flow rate of a second/ an hour(kg);

h : heat transfer coefficient for convection to the ambient;

A : surface area of water tank/ heat transfer area (m^2);

T_{tank}^{i} : average temperature of the ideally homogeneous tank in hour i(°C);

T_{input}^{i} : average temperature of the input cold water in hour i (°C);

T_{amb}^{i} : average temperature of the environment in hour i (°C);

Q_{EWH}^{t} : total energy consumption of EWH in time t (J=W·s);

P_{EWH}^{i} : power of EWH heating element during hour i (W).

A new way of modeling the supply of hot water is proposed. We proposed the virtual concept of maximum hot water capability W_{max} (gallon) to represent the maximum hot water volume the water heater can provide. W_{max} is a function of T_{tank}, P and T_{base} in which T_{base} is the lowest temperature consumers can accept as usable hot water, it can be a variable due to seasonal changes. The whole tank of water is regarded as hot water when T_{tank} is above T_{base}, otherwise it is regarded as not usable cold water.

The W_{max} we proposed in the Supply-Consume model is a virtual water volume, instead of showing the real hot water volume inside the tank, it take into account the total volume of hot water in the coming hour. If W_{max} is larger than Wd, it means the scheduled P is a valid power consumption solution which meet the customer demand. This constraint of W_{max} larger than Wd will be used in later optimization constraint sets. In addition to W_{max}, we proposed a turn called equivalent hot water W_{eq} (gallon) to represent the actual hot water consumers can use given T_{tank} because when water from hot-water faucet is too hot consumers normally mix it with cold-water faucet water to get a moderate temperature.

Therefore, if T_{tank} is below T_{base}, the equivalent hot water volume W_{eq} is zero since nothing is usable; if T_{tank} is above T_{base}, W_{eq} would be larger than tank volume. It will consist of hot water stored in the tank mixed with the cold water from the cold-water faucet. The hotter the water in the tank, the larger the equivalent hot water volume W_{eq} will be. Take 110°F as the base temperature and 50°F as the cold-water faucet temperature for example, an adjustable coefficient (T_{tank} - 50)/60 should be applied to obtain the equivalent hot water volume W_{eq} shown as:

$$W_{\mathrm{eq}}{}^{i} = V_{\mathrm{tank}} K_e \frac{T_{\mathrm{tank}}^{i-1} - 50}{60}. \tag{5}$$

The equation is developed based on specific heat formula and the first law of thermodynamics. In (5), Ke is the efficiency of the tank heat preservation and it is usually set as 0.7 due to heat dissipation.

In addition to W_{eq}, W_{max} also includes Re which is the part of water heated up by heating elements. It is calculated based on empirical formula (6) provided by EWH company shown in[60].

$$R_e^{\ i} = \frac{P_{\mathrm{EWH}}^i \times 5.85 \times 70}{10^3 \times \Delta T^i} = \frac{P_{\mathrm{EWH}}^i}{\delta\left(T_{\mathrm{base}} - T_{\mathrm{tank}}^{i-1}\right)}. \tag{6}$$

In (5), ΔT is the temperature difference between T_{input}^i and T_{base}. δ is the empirical constant that equals 2.442. The volume of the water tank V_{tank} in this paper is sized as 50 gallons or 0.189271 m^3, a typical residential EWH tank size. The maximum heating element power rating is set as 4500W. In [61], the relationship between different water heater tank sizes and power rating was discussed among different households. This paper will focus only on optimal energy management of EWH.

As mentioned above, if T_{tank} is lower than T_{base}, W_{max} only depends on the newly heated water since the water in tank is not usable. In addition, since (5) is an empirical formula, it does not consider the situation that T_{tank} is very close to T_{base} hence we build a regression model replacing the recovery rate formula in order to avoid invalid results.

$$W_{\max}^i = C\left(T_{\mathrm{tank}}^{i-1}\right) V_{\mathrm{tank}} K_e \frac{T_{\mathrm{tank}}^{i-1} - T_{\mathrm{input}}^i}{T_{\mathrm{base}} - T_{\mathrm{input}}^i} + R_e\left(P_{\mathrm{EWH}}^i\right), \tag{7}$$

where, $$C\left(T_{\mathrm{tank}}^{i-1}\right) = \begin{cases} 1 & \text{if } T_{\mathrm{tank}}^{i-1} \geq T_{\mathrm{base}} \\ 0 & \text{otherwise} \end{cases}, \tag{8}$$

$$R_e\left(Q_{\mathrm{EWH}}^i\right) = \begin{cases} \dfrac{P_{\mathrm{EWH}}^i}{\delta\left(T_{\mathrm{base}} - T_{\mathrm{input}}^i\right)} & \text{if } T_{\mathrm{tank}}^{i-1} \geq T_{\mathrm{base}} \\ \dfrac{P_{\mathrm{EWH}}^i}{70\delta\left(T_{\mathrm{base}} - T_{\mathrm{tank}}^{i-1}\right)\left(T_{\mathrm{tank}}^{i-1} + 20\right)} & \text{otherwise} \end{cases}. \tag{9}$$

Thus, considering the above factors, W_{max} can be calculated using (7-9). The maximum capability of hot water we can have given different tank temperature and input power with T_{base} equals 110°F is shown in Figure 7.

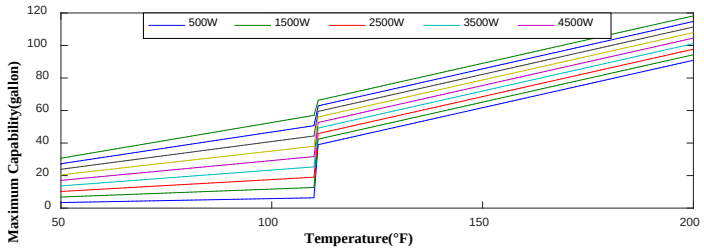


Figure 7: Maximum capability given different tank temperature and input power with base temperature set at 110 °F

We proposed Algorithm 1 to integrate equation (5) to (9). By using Algorithm 1 we can get the maximum capability W_{max} of each hour and use it as one of the constraints later in Chapter 5. In Algorithm 1, we have tank temperature T_{tank} in advance by using (4).

Algorithm 1: Calculating Maximum Capability of EWH

1: $T_{\text{tank}}^{0} = T_{\text{tank}}^{24}$ at the previous day
2: for n =1 to 24 do
3: $T_{\text{tank}}^{i} = \text{NARX}_{\text{EWH}}\left(T_{\text{tank}}^{i-1}, P_{\text{EWH}}^{i}, Wd^{i}, T_{\text{input}}^{i}, T_{\text{amb}}^{i}\right)$
4: if $T_{\text{tank}}^{i-1} \geq T_{\text{base}}$
5: $W_{\max}^{i} = V_{\text{tank}} K_{e} \dfrac{T_{\text{tank}}^{i-1} - T_{\text{input}}^{i}}{T_{\text{base}} - T_{\text{input}}^{i}} + \dfrac{P_{\text{EWH}}^{i}}{\delta\left(T_{\text{base}} - T_{\text{input}}^{i}\right)}$
6: else
7: $W_{\max}^{i} = \dfrac{P_{\text{EWH}}^{i}}{70\delta\left(T_{\text{base}} - T_{\text{tank}}^{i-1}\right)\left(T_{\text{tank}}^{i-1} + 20\right)}$
8: end if
9: end for

3.2.3 Electric Vehicle Load Model

The load model of EV only considered the basic charging scheme of the battery inside each EV that parked inside the SC. In[62], a fixed EV charging rate is considered according to the charging profile on the market. However, considering the In addition, this model considered a two level EV charging rate according to SAE J1772 standards[63]. The battery SOC is

calculated based on the relationship in [64] where three essential parameters are taken into consideration: the rated charging power, the plug-in time and the battery SOC. The energy management controls the EV charging by switching between the two levels of charging plus no charging idle status.

The model of the EV load model is presented as:

$$\begin{aligned} P_{\mathrm{EV}} &= S_{\mathrm{EV}} \circ \omega_{\mathrm{EV}} \cdot c_{\mathrm{EV}} \cdot P_{\mathrm{charge}} \\ SOC_{\mathrm{EV}}^{i} &= SOC_{\mathrm{EV}}^{i-1} + P_{\mathrm{EV}}^{i-1} / C_{\mathrm{EV}} \end{aligned} , \tag{10}$$

where,

P_{EV} : 1×24 matrix of EV charging power (kW);

S_{EV} : 1×24 matrix of EV connectivity status , 0 if EV is not physically connected to the outlet, and 1 if EV is connected;

ω_{EV}^{i} : 1×24 matrix of uncontrolled EV charging status in hour i which depends on the battery SOC as $\begin{cases} 0 & SOC_{\mathrm{EV}}^{i} \geq SOC_{\mathrm{EV\_max}} \\ 1 & SOC_{\mathrm{EV}}^{i} \leq SOC_{\mathrm{EV\_min}} \end{cases}$;

c_{EV} : 24×2 control matrix for EV, 0 = OFF, 1 = ON;

P_{charge} : 2×1 matrix containing two levels of charging power(kW);

SOC_{EV}^{i} : SOC of the EV at hour i;

C_{EV} : EV battery capacity (kWh);

$SOC_{\mathrm{EV\_min}}$: minimum SOC of the EV;

$SOC_{\mathrm{EV\_max}}$: maximum state of charging the EV.

3.2.4 Cloth Dryer

CD is considered as a typical deferrable load in the modeling of SC. In [65], the CD is considered to have two statuses, and a certain time interval is assigned for CD to finish the work. In [62] it included the motor part and the heating coils in the power consumption of a typical CD so it has three control conditions, off, motor on, and motor on with heating coils on. For more precise control of CD, [64] set the heating coils to have several levels of power. No time limit is assigned to the CD in the above works.

The model for CD in this paper combines the above works. The proposed model consists of both motor part and the heating coils which make the CD to have three statuses. The power of the heating coils is chosen as a fixed rate since major CDs in the market have fixed heating rate. Also, the total working timeof CD is constrained to a certain time interval. This makes the CD to have a limited number of load patterns.

This model of the CD can be modeled as:

$$P_{\mathrm{CD}} = N_{\mathrm{CD}} \cdot P_{\mathrm{level}}, \tag{11}$$

$$P_{\mathrm{level}} = \begin{bmatrix} P_m \\ P_h \end{bmatrix}, \quad N_{\mathrm{CD}} = \begin{bmatrix} n_m^1 & n_h^1 \\ \vdots & \vdots \\ n_m^{24} & n_h^{24} \end{bmatrix}, \tag{12}$$

where,

P_{CD} : 24×1 matrix, 24 hour CD power (kW);

P_m : CD motor rated power (kW) ;

P_h : CD heating rated power (kW) ;

N_{CD} : control signal matrix of CD;

n_m^i : control signal for motor at hour i, 0 = OFF, 1 = ON;

n_h^i : control signal for heating coil at hour i, 0 = OFF, 1 = ON.

3.3 Energy Storage System

In the structure of proposed SC, a community-shared ESS is equipped. Since the size of the SC could be very large, there will be a high acquisition, operation and maintenance costs to deploy residential ESS all alone. Thus a sharing-based ESS is applied in the system. Community-shared ESS is basically battery-based ESS, which means the working principle is similar to the charge and discharge of EV battery.

Different from individual ESS such as proposed in [66] in which the energy management of ESS is performed by decentralized control mechanism, a community-shared ESS is suitable for the proposed the proposed centralized energy management system. The capacity of the ESS proposed in this thesis is chosen based on the work in [67] where the relation between energy storage size and the customer class size is given a ratio of 0.2658.

The state of the charge of the ESS is modeled as:

$$P_{\mathrm{ESS}}^{i} \in \begin{cases} \left[\left(P_{\mathrm{PV}}^{i} + P_{\mathrm{Wind}}^{i} - P_{\mathrm{Load}}^{i}\right), P_{\mathrm{ESS\_max}}\right] & \text{if } P_{\mathrm{PV}}^{i} + P_{\mathrm{Wind}}^{i} \geq P_{\mathrm{Load}}^{i} \\ \left[-P_{\mathrm{ESS\_max}}, P_{\mathrm{ESS\_max}}\right] & \text{otherwise} \end{cases}, \tag{13}$$

$$\eta = \begin{cases} \eta_c & P_{\mathrm{ESS}}^{i} \geq 0 \\ \eta_{dc} & P_{\mathrm{ESS}}^{i} < 0 \end{cases}$$

where,

SOC_{ESS}^{i} : SOC of the ESS at hour *i*;

η_c : charging efficiency of the ESS (%);

η_{dc} : discharging efficiency of the ESS (%);

P_{ESS}^{i} : charging/discharging power of the ESS at hour *i* (kW);

C_{ESS} : Capacity of the ESS (kWh);

$SOC_{\mathrm{ESS\_min}}$: maximum SOC of the ESS;

$SOC_{\mathrm{ESS\_max}}$: minimum SOC of the ESS.

3.4 Priority of Load and DERs

In the frame of smart home energy management, many previous works has discussed about load curtailment based on demand limit signals sent by the utility provider to alleviate system constraint conditions. Under this condition, customer's priority-based load shedding was proposed since some of the appliances like EV, CD and ESS are interruptible loads. During the demand response energy management, the load with the lowest priority will be shed first if load curtailment happened. Besides, from the perspective of solving the multiple-constraint function for the SC which we will present later, in order to minimize multiple constraint functions, it is

desirable to convert the problem to one problem with only a single penalty function by using a weighting factor to indicate the importance of each constraint.

This priority-based load shedding was applied to the building energy management of EV and HVAC system in [68] where EV is given the lowest priority since discontinuity of EV charging will not have significant impact on the resident's satisfaction. [62] also set EV as the lowest priority whereas setting water heater, space cooling unit and clothes dryer as first, second and third priority for intelligent home energy management.

Under the concept of priority-based SC energy management, the resident of each house can customize their own load priority settings for their house. This feature will be reflected in the fitness calculation of the GA proposed in later Chapters.

In an SC that has distributed energy resources, it is also vital to discuss the priorities among all the DERs because the energy management needs to buy power from grid and distribute energy according to the priority setting in advance. The PV power generation and wind generation are assigned to loads in the first place because the more renewable energy used the less money the community will pay for buying power from the grid. If the renewable power generation is larger than the load demand in real time, it can be charged into the ESS for later usage. On the other hand, if the renewable power generation fall short of the load demand at the time, the energy management algorithm needs to decide the power from grid and the discharge power from ESS. From the view of ESS, when there is excess renewable, the controller needs to make decisions on how much renewable power to be charged into the ESS and how much gird power to be charged into the ESS with regard to the real time SOC of the ESS. When the renewable power generation cannot meet the load demand, the controller also needs to decide how much power to charge to the DC bus or if the electricity is comparatively cheap, how much

power to charge into the ESS. This priority characteristic will be included in the model in Chapter 4.

CHAPTER 4

LEARNING-BASED MODELING OF SMART COMMUNITY USING NEURAL NETWORK

The above presented ETP models for HVAC and EWH are models with fixed parameters. These fixed parameters represent the unique features of each appliance such as thermal resistance and heat transfer coefficient. However these features will not remain the same during the lifetime of the appliances. To make the modeling of these appliances more accurate, learning-based models are proposed by many works to keep up with the parameter changes in ETP models.

4.1 Learning-Based Method Analysis

A large number of different learning mechanisms have been applied in the pursuit of model accuracy. Xu et al.[69]presented a detailed study on the partial differential equation (PDE) physics-based model of an EWH. However, unlike a data driven or learning based model, the model presented in [69] cannot reflect EWH model variations caused by external conditions and over time. Besides the PDE model, a third-order polynomial linear regression function to build a data driven model for an HVAC system was proposed in [58]. However the linear regression method only performs a best fitting line or a best fitting plane, which could result in a considerable error when applied to EWH with highly nonlinear characteristics.

In the field of artificial intelligence, neural network has long been applied into the modeling of thermodynamic systems such as HVAC system since twenty years ago[70]. In [71],

it presented an artificial neural network for predicting domestic hot water characteristics but the model has a relatively high error rate. In [61], Gelažanskas et al. proposed a NARX model to compute short-term hot water usage forecasts tailored for particular house that also lacks the consideration of data driven. Zhang et al.[30] investigated both neural network based learning and regression-based learning in the modeling of HVAC, both models are capable of estimating HVAC energy consumption models as they are updated daily in order to accurately capture the thermal behavior of the house at different conditions. However, compare to time series neural network model, the one in [30] also has a considerable error. To overcome the challenge, a data-driven NARX model using neural network is proposed in this paper to learn the actual EWH model.

4.2 NARX Time Series Modeling

NARX is a recurrent dynamic network, with feedback connections enclosing several layers of the network, as a special case of the NARMAX(nonlinear autoregressive moving average model with exogenous inputs) model which does not include any noise-dependent model terms[72]. The defining equation for the NARX model is:

$$y(t) = f\left(y(t-1), y(t-2), \cdots, y(t-n_y), u(t-1), u(t-2), \cdots, u(t-n_u)\right), \tag{14}$$

where the next value of the dependent output signal $y(t)$ is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal. Besides the accurate performance of NARX mentioned in the previous works, this paper chose NARX model because both models similarity use previous model output data which is the same as the conventional HVAC and EWH models. We implement the NARX model by using a feedforward

neural network to approximate the model of both EWH and HVAC, the models of which are shown in Figure 8 and Figure 9.

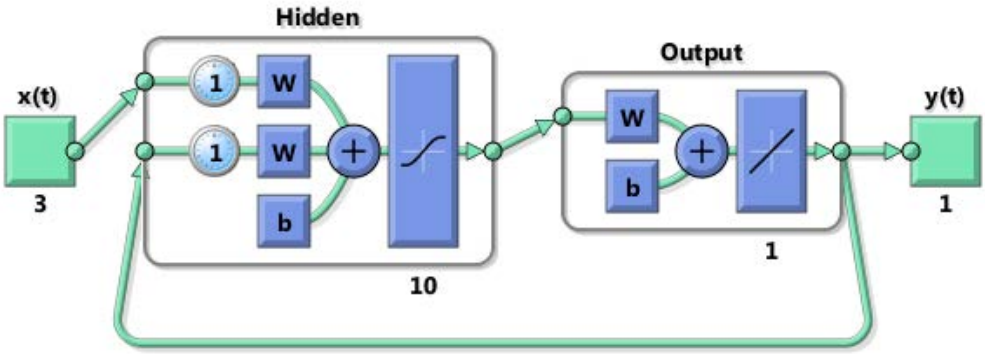


Figure 8: NARX model for HVAC

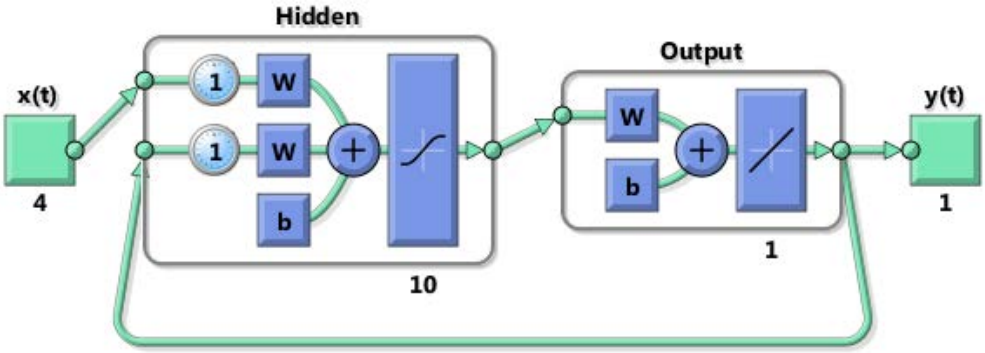


Figure 9: NARX model for EWH

4.3 Initial Training Data

4.3.1 Heating, Ventilation, and Air Condition

The desired NARX model for HVAC with its inputs and outputs given by its ETP model can be represented by:

$$\text{Input: } X = \begin{bmatrix} Q^i_{\text{HVAC}} \\ T^i_o \\ T^{i-1}_{\text{room}} \end{bmatrix} \qquad \text{Output: } Y = T^i_{\text{room}} = f(X), \tag{15}$$

where the training data for HVAC was collected by using building simulation software eQUEST as a virtual test bed to simulate home energy consumption done in the previous works done in the laboratory[30]. Using eQUEST software, a simulation of house model is built that is similar to a practical one. eQUEST uses standard commercial building materials defined in the software library and real-life weather and solar data available at [73]. For energy consumption simulation of a residential house, an architectural simulation model of the house was created based on the blueprint and construction materials used to build an actual house. The training data was generated given a generic floor plan for a two-story, 2,500 square foot house. The location for the model is Springfield, IL. Details about how to build a simulated house can be found in [26]. Table 2 shows the training and target data collected from eQUEST for a 24 hour simulation.

Table 2. HVAC Neural Network modeling input and target data (Note: $T_{(°C)} = (T_{(°F)} - 32) \times 5/9$, 1 gallon = 0.00378541 m^3)

Input			**Target**
Previous Room temperature (°F)	**Power input (kW)**	**Outdoor temperature (°F)**	**Room temperature (°F)**
71	0.671804	69	71
71	0.544518	68	71
71	0.446902	68	71

71	0.359103	67	71
71	0.290203	67	71
71	0.366046	66	71
71	1.51074	69	71
71	1.62282	71	71
71	1.61183	74	72
72	1.19441	77	73
73	1.00248	80	74
74	0.87479	83	75
75	0.82041	84	76
76	0.585663	84	78
78	0.300483	85	79
79	0.603441	84	78
78	1.27208	84	76
76	2.06905	83	75
75	1.4994	80	74
74	0.70461	78	75
75	1.69273	75	72
72	1.54755	75	71
71	1.23496	75	71
71	1.0778	75	71

4.3.2 Electric Water Heater

An overall EWH system, based on (3), was implemented using MATLAB Simulink and shown in Figure 10. The input settings of the system go to the thermal model as well as to the unit conversion block. The thermodynamic model is implanted in the thermal model. It calculates tank temperature based on electric power input, input cold water temperature, environment temperature, and mass flow rate. The maximum capability block calculates the maximum hot water volume ready to be used based on several input settings and tank temperature obtained from EWH Thermal block. Then, temperature of the EWH can be obtained by running the simulation model for 24 hours. By default, the initial EWH temperature is set as 10°C or 50°F. All the parameters are first converted to SI units before being applied to the EWH simulation model.

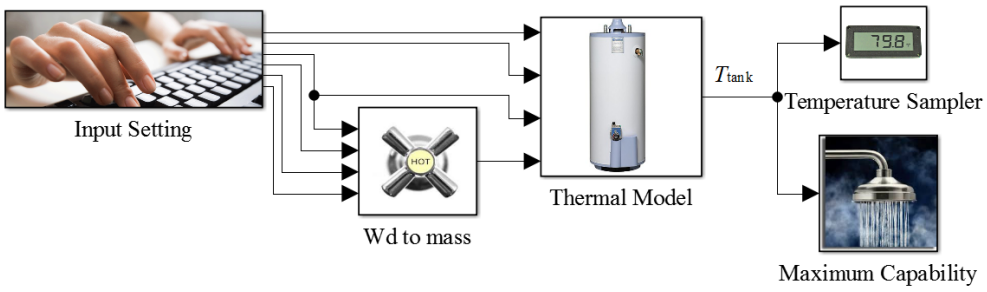


Figure 10: EWH simulation system in Simulink MATLAB

Energy consumption of an actual EWH is much more complicated because the parameters associated with the EWH model could be largely deviate from manufacturer's specified values and EWH heat transfer mechanism is more complicated than that represented in (3). In addition, the power efficiency of the water heater could change over time due to aging problems and change in environment conditions. As a result, developing a learning mechanism

that can update the EWH model on schedule and adapt changes in the parameters is critical for the optimal energy management of an EWH.

As mentioned above in Chapter 3.2, the output temperature of an EWH tank at hour *i*, T_{tank}^{i}, depends on the previous tank temperature T_{tank}^{i-1}, current power input P_{EWH}^{i}, water demand Wd^{i}, input cold water temperature T_{input}^{i} and ambient temperature T_{amb}^{i}. Based on this analysis, the EWH model with its inputs and outputs can be represented by:

$$\text{Input: } X = \begin{bmatrix} P_{\text{EWH}}^{i} \\ Wd^{i} \\ T_{\text{input}}^{i} \\ T_{\text{amb}}^{i} \\ T_{\text{tank}}^{i-1} \end{bmatrix} \qquad \text{Output: } Y = T_{\text{tank}}^{i} = f(X), \tag{16}$$

where the training target data for an adaptive EWH model was generated through the model shown in Figure 10. By providing random input power P_{EWH} within the rated power limit of 4500W, Wd, T_{input}^{i} and T_{amb}^{i} to the model, with a simulation time step of 1 second and simulation length for 24 hours, the output target temperature data is generated and collected.

Since the electricity price and weather forecast which obtained from electric utility company and U.S. national weather service were broadcasted in hours, in this paper we divided each day into 24 timeslots i.e. one hour for each time slot. Hence the proposed EWH model needs to be represented or generated based on hours, which means that all the input and output data of the EWH model should be represented in terms of hours. Therefore, after getting the raw data from the EWH simulation model shown in Chapter 3.2.2, the data need to be processed into hourly data. The temperature data are converted into hourly mean, EWH power input is

converted into hourly mean, and the water demand in each hour is the summation of total water demand in that hour. Table 3 shows a set of processed hourly data obtained from the MATLAB EWH simulation model.

Table 3. EWH Neural Network modeling input and target data

Input					Target
Previous Tank temperature (°F)	**Power input (W)**	**Water demand (gal)**	**Inlet water temperature (°F)**	**Ambient temperature (°F)**	**Outlet water temperature (°F)**
162.43	3643.5	1.17	48.80	51.64	179.81
179.81	789.5	3.18	48.50	51.61	171.01
171.01	276.4	1.78	48.53	48.33	160.50
160.50	1893.7	3.34	49.50	46.46	161.80
161.80	278.2	4.24	49.80	53.94	149.91
149.91	1655.4	2.70	50.65	51.85	151.20

4.4 Training HVAC and EWH NARX Model

The processed data for a period of one week is divided into training, validation and testing datasets with the ratio as 70%, 15% and 15%, respectively. The NARX training

performance evaluation is shown by Figure 11, which contains four subfigures for performance evaluation corresponding to training, validation, testing and overall datasets. Each subfigure shows in the output-target plane (1) the neural network output and target data pairs, (2) line regression of the output and target data relationship, (3) a line of Y (output) = T (target), and (4) an R value for measuring the goodness-of-fit. For the best training effect, the regressed line should overlap with the Y = T line and R value should be 1. As shown by Figure 11, the network was well trained.

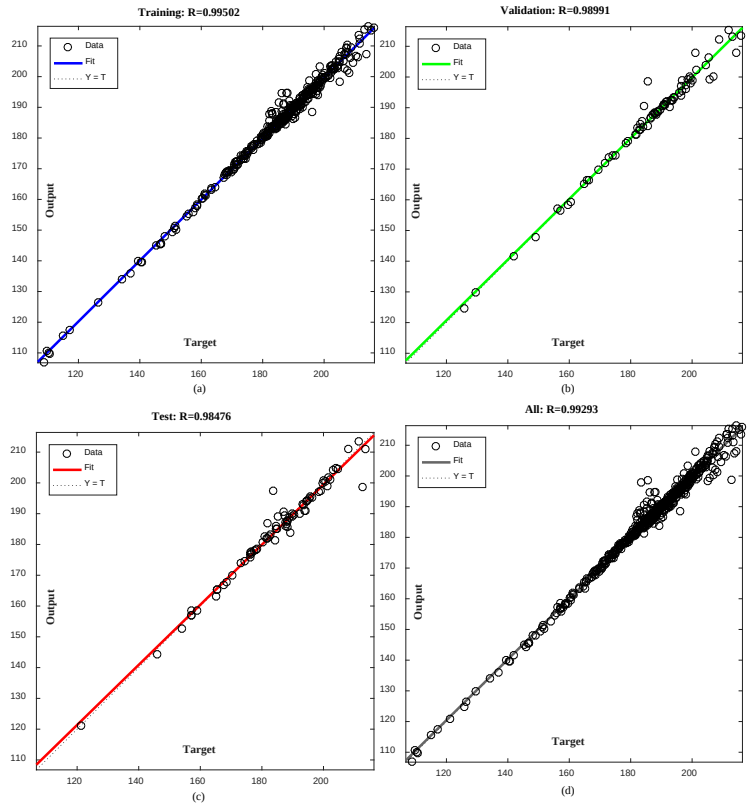


Figure 11: NARX training performance for (a) training dataset, (b) validation dataset, (c) test dataset and (d) overall dataset

After a training with satisfied goodness-to-fit performance, we use MATLAB to generate an m-file function that can be directly called by using MATLAB codes. The NARX neural network function $f(X) = \mathrm{NARX}(X)$ has the input X and output Y accordingly with (15) and

(16). By using the NARX(•) function, the room temperature and water temperature can be predicted recursively as:

$$\begin{cases} T_{\text{room}}^{i} = \text{NARX}_{\text{HVAC}}\left(T_{\text{room}}^{i-1}, P_{\text{HVAC}}^{i}, T_{o}^{i}\right) \\ T_{\text{tank}}^{i} = \text{NARX}_{\text{EWH}}\left(T_{\text{tank}}^{i-1}, P_{EWH}^{i}, Wd^{i}, T_{\text{input}}^{i}, T_{\text{amb}}^{i}\right) \end{cases}. \tag{17}$$

4.5 Model Updating Mechanism

The network training is updated every day with new data so as to make the trained network to be able to capture the energy consumption properties under different seasons, weathers and household conditions.

The proposed intelligent learning routine saves the real input and output of both HVAC and EWH models data from the installed smart meters everyday into the energy management system database. Before performing energy management for the next day, the training function will fetch the latest data from the database. In specific, the training of NARX models for HVAC and EWH uses the latest historical data of 7 days. The routine is shown in Figure 12.

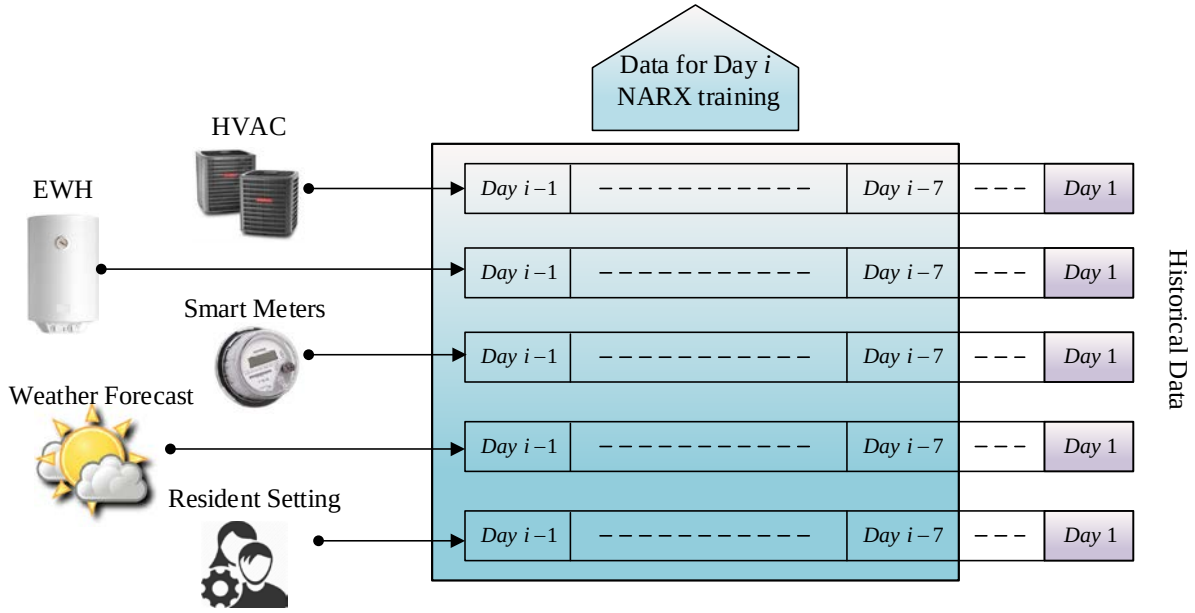


Figure 12: NARX model updating mechanism

CHAPTER 5

OPTIMIZATION OF SMART COMMUNITY ENERGY CONSUMPATION AND DISTRIBUTION

5.1 Cost function and Constraints

The N-house SC optimization for 24 hours of a day can be formulated as a multi-constraint nonlinear programming problem as in (18). The balance of the power is shown in the constraint in (19) where the power from grid equals to the total load plus the power from distributed energy resources. The rest of the constraints in (20) are comfort constraints, power limit constraints and SOC limit constraints.

$$\text{Minimize: } \text{Cost}(P_{\text{grid}}) = \sum_{i=1}^{24} \alpha^i \cdot P_{\text{grid}}^i \cdot t \tag{18}$$

$$\text{Subject to: } P_{\text{grid}}^i = \sum_{n=1}^{N} \left(P_{\text{HVAC}}^{i,n} + P_{\text{EWH}}^{i,n} + P_{\text{EV}}^{i,n} + P_{\text{CD}}^{i,n} \right) + P_{\text{ESS}}^i - P_{\text{PV}}^i - P_{\text{Wind}}^i \tag{19}$$

$$\begin{aligned}
&0 \le P_{\text{grid}}^i \le P_{\text{grid_limit}}^i && i = 1, \cdots, 24 \\
&T_{\text{room_min}}^{i,n} \le T_{\text{room}}^{i,n} \le T_{\text{room_max}}^{i,n} && i = 1, \cdots, 24 \\
&0 \le P_{\text{HVAC}}^{i,n} \le P_{\text{HVAC_Rated}} && i = 1, \cdots, 24 \\
&0 \le Wd^{i,n} \le W_{\max}^{i,n} && i = 1, \cdots, 24 \\
&0 \le P_{\text{EWH}}^{i,n} \le P_{\text{EWH_Rated}} && i = 1, \cdots, 24 \\
&-P_{\text{ESS_max}} \le P_{\text{ESS}}^i \le P_{\text{ESS_max}} && i = 1, \cdots, 24 \\
&SOC_{\text{EV_min}} < SOC_{\text{EV}}^{i,n} < SOC_{\text{EV_max}} && i = 1, \cdots, 24
\end{aligned} \tag{20}$$

$$SOC_{\text{ESS\_min}} \le SOC_{\text{ESS}}^{i} \le SOC_{\text{ESS\_max}} \qquad i = 1, \cdots, 24$$

where,

t : 1 hour time slot;

α^{i} : electricity price in hour *i*;

P_{grid}^{i} : SC overall load from the grid in hour *i*;

P_{PV}^{i} : the maximum possible power from PV panel in hour *i*;

P_{Wind}^{i} : the maximum power from wind turbine panel in hour *i*;

$P_{\text{grid\_limit}}^{i}$: SC grid inlet maximum power limit in hour *i*;

N : total number of smart homes inside the SC;

$P_{\text{HVAC}}^{i,n}$: HVAC power rate in house *n* in hour *i*;

$P_{\text{HVAC\_Rated}}$: HVAC rated power;

$P_{\text{EWH}}^{i,n}$: EWH power rate in house *n* in hour *i*;

$wd^{i,n}$: EWH water demand in house *n* in hour *i*;

$W_{\max}^{i,n}$: EWH maximum hot water capability in house *n* in hour *i*;

$P_{\text{EV}}^{i,n}$: EV charging power in house *n* in hour *i*;

$P_{\text{CD}}^{i,n}$: CD working power in house *n* in hour *i*;

P_{ESS}^{i} : ESS charging/discharging power in hour *i*;

$T_{\text{room}}^{i,n}$: room temperature in house *n* in hour *i*;

$T_{\text{room\_min}}^{i,n}$: minimum room temperature setting in house *n* in hour *i*;

$T_{\text{room\_max}}^{i,n}$: maximum room temperature setting in house *n* in hour *i*;

$SOC_{\text{EV}}^{i,n}$: SOC of EV in house *n* in hour *i*;

$SOC_{\text{EV\_min}}$: minimum SOC for EV;

$SOC_{\text{EV\_max}}$: maximum SOC for EV;

SOC_{ESS}^{i} : SOC of ESS in hour *i*;

$SOC_{\text{ESS\_min}}$: minimum SOC for ESS;

$SOC_{\text{ESS\_max}}$: maximum SOC for ESS;

However, if consider the distribution rules in specific, there are problems regarding to the distribution priority of distributed energy resources in (19). For example, if the renewable generation is abundant, and can support the all the loads plus give full charge to the ESS, then the P_{grid}^{i} will be negative which in our model is not possible because it is not allowed to send power back to the grid within the concern of this thesis. In addition, there is charging and discharging limit on the ESS, so the SC power system may not be able to make full use of the abundant renewable power generation. With all the above concerns, we make the rule that the renewable energy will first satisfy the need of residential loads first then can be charged into the ESS. The detailed distribution rules is added to the previous power balance equation (19). The (19) is revised as:

$$P_{\text{grid}}^{i} = \max\left(\left(\max\left(P_{\text{load-renew}}^{i}, 0\right) + P_{\text{grid2ESS}}^{i}\right), 0\right), \tag{21}$$

where,

$$\begin{aligned}
P_{\text{load-renew}}^{i} &= \max\left(P_{\text{load}}^{i} - \left(P_{\text{PV}}^{i} + P_{\text{Wind}}^{i}\right), 0\right) \\
P_{\text{load}}^{i} &= \sum_{n=1}^{N}\left(P_{\text{HVAC}}^{i,n} + P_{\text{EWH}}^{i,n} + P_{\text{EV}}^{i,n} + P_{\text{CD}}^{i,n}\right) \\
P_{\text{renew2ESS}}^{i} &= \min\left(\max\left(\left(\left(P_{\text{PV}}^{i} + P_{\text{Wind}}^{i}\right) - P_{\text{load}}^{i}\right), 0\right), P_{\text{ESS_max}}\right) \\
P_{\text{grid2ESS}}^{i} &= \max\left((P_{\text{ESS}}^{i} - P_{\text{renew2ESS}}^{i}), 0\right)
\end{aligned} \tag{22}$$

$P_{\text{load-renew}}^{i}$: the gap between load power and renewable power;

P_{load}^{i} : the overall load power for all smart homes;

$P_{\text{renew2ESS}}^{i}$: the power distribution from renewable to ESS;

P_{grid2ESS}^{i} : the power from grid to ESS.

There are some comments for the above cost function.

- It is a 24 hour energy cost model for an SC with N smart homes. Each house is assumed to have HVAC system, EWH, CD and to have EV charger installed. A community share-based ESS system, solar power source and wind power source are also modelled in the SC as mentioned beforehand.
- The cost model is based on the 24 hour SC energy consumption and the day-ahead electricity price. Each day is divided into 24 time slot, each slot represents one hour. Therefore, the energy management of the SC is based on hourly energy consumption control.
- Each smart home can have its unique HVAC and EWH learning-based model, own customer preference settings and own customer demand.

- This paper did not build learning-based model for CD, EV and ESS due to the fact that these three systems are neither thermodynamic models nor complicated multi-objective nonlinear models. And they do not change that much through seasons and different weather conditions. The difference between their simple energy consumption models and the ones that implemented by NARX models are negligible.

5.2 Optimization Method Analysis

After building the optimization problem in the above Chapter 5.1, we need a proper way to find the optimal solution for the problem considering both the accuracy of the solution, i.e., how close the solution is to the ideal global optimal solution, and the complexity of the method, i.e. how long the computational time will be.

In [26] it developed optimal DR algorithm based on the particle swam techniques that the fitness value of each candidate solution was transferred into their velocity and position based on both global best fitness position and local bet fitness position. But the candidate solution in the proposed model is for thermostat setting for HVAC instead of power rate of the HVAC. In [65] it applied fuzzy logic controller to determine the charging status of the battery preliminarily in the home energy management system which includes EWH, air condition, CD, EV, PV and battery. The electricity price and the SOC of the battery are considered as inputs of the fuzzy logic controller whereas the output is the power of the battery. It greatly improved the computation time however the results might not be the optimal value since there are only six linguistic possible outputs for the power of the battery, i.e. there are only six charging/discharging possibilities. In [74] it used Monte Carlo method minimize the distribution system losses where the Monte Carlo achieves the steady state solution around 400 runs. In addition, mixed-integer

linear programming (MILP) is also wildly used in the field of smart grid energy consumption optimization. In [75], a smart household that considering bi-directional EV and ESS is proposed where the authors used MILP framework-based modeling of a home energy management structure. In the category of evolutionary algorithm, in [76] it used immune clonal selection programming to determine the Pareto optimal temperature schedule solution for HVAC since it assumes there is not a single unique optimal solution. Based on the temperature setting, it then calculated the power consumption via thermal equation.

Since many of the above optimization methods are comparatively fully developed algorithms that were proposed and developed decades ago, there are many existing toolbox or open source code of them in software like MATLAB, GAMS, R, etc. Most of the works in smart home optimization are custom version of these open source works.

5.3 Genetic Algorithms Based Optimization

In our paper, we chose GA based optimization method to search for input power solution that has the minimum energy cost.

GA are optimization methods that are inspired by biological evolution. GA can encode a potential solution to a specific optimization problem on a simple chromosome-like data structure, and apply selection and recombination of genes to these chromosomes as to let the best candidate survive towards the desired optimal solutions. An implementation of GA begins with a population of typically random chromosomes. One then evaluates these structures and allocates reproductive opportunities in such a way that those chromosomes which represent a better solution to the target problem are given more chances to reproduce than those chromosomes which are poorer solutions[77]. The flow chart of a typical GA is shown in Figure 13. The fitness

of an individual is a metric that tells us how good each individual is as the solution to the given problem. Using a fitness function, individuals are assigned corresponding fitness values. The individuals with better fitness values are more likely to survive and reproduce[78].

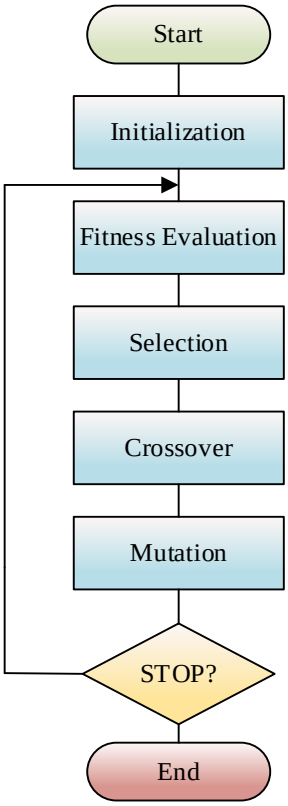


Figure 13: Flow chart of Genetic Algorithms

In our proposed GA, the fitness of each chromosome is initially calculated by the fitness function i.e. the cost function of the optimization problem. After that, the constraints of the optimization problem are taken into consideration as “antibody” or penalty which decreases the fitness of the chromosome if constraints are break. In this way, if a chromosome breaks the constraints, there will only be penalty added to the fitness instead of eliminate the candidate instantly. This feature turns all constraints into loose constraints that a final trimming algorithm is applied to trim the best fit candidate that might still break some constraints.

In calculating the fitness of each chromosome, a $5 \times N$ constraint matrix $\boldsymbol{w}$ is used to present the constraint status of all appliances inside the SC. The first $4 \times N$ shows the constraint penalty of the four appliances from the N households. The value of each element is the sum of all constraints penalties of the corresponding appliance and a value of 0 means the chromosome meet all constraint of that specific appliance. The $(5,1)$ element of $\boldsymbol{w}$ represents the constraint penalty of the ESS.

In addition, this paper uses $\boldsymbol{p}$, a $4 \times N$ matrix containing 1,2,3,4, to represent the load priority of each appliance in each smart home. The priority matrix is first multiplied with the penalty of each constraint then added to the original fitness. Besides, for appliances with relatively small constraint penalty like SOC mismatch for EVs and ESS, a proper coefficient c is chosen as the penalty coefficient. All the above constraint penalties are added to the original fitness value of each chromosome as the new fitness of each chromosome.

After getting the fitness of each chromosome, the GA routine that includes a sequence of operation in the order of diversity control, scaling, selection, death, mating and crossover, mutation, gene repair, migration, fitness evaluation, elitism and trim is performed in GOSET[78]. The algorithm execution of GOSET with a brief description of each execution is shown in Figure 14.

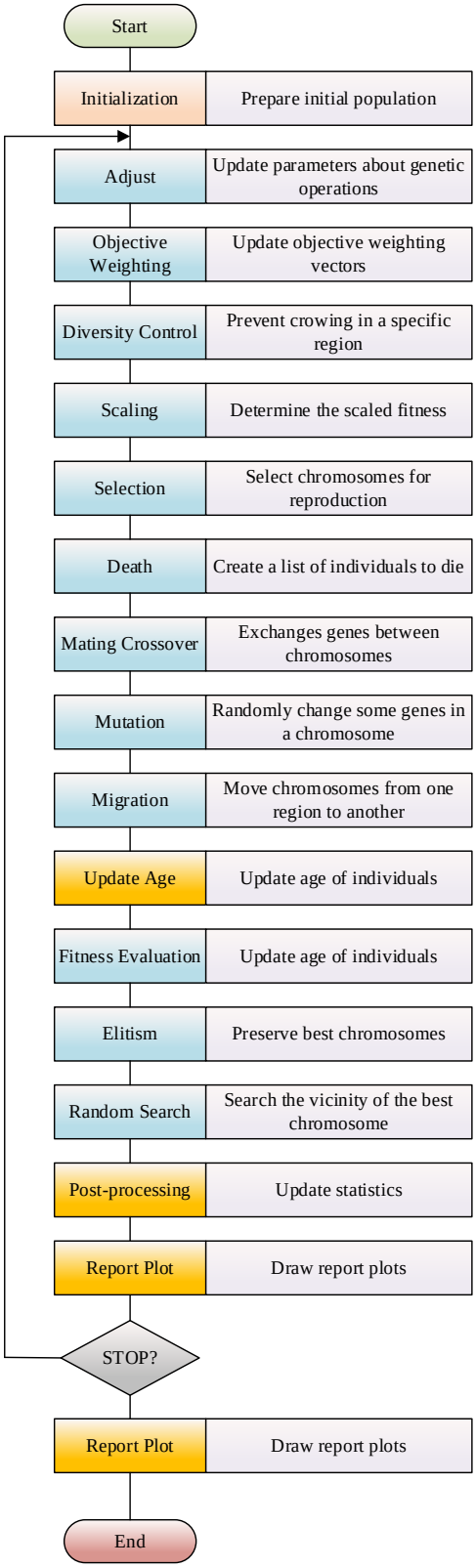


Figure 14: GOSET algorithm routine and its explanation

It is worth notice that GA does have an improved probability of finding a global optimum only in the presence of relative minima. This is because GA are fundamentally discrete variable method and they are essentially random search techniques which offer an improved prospect of finding the global optimum[79]. The detail of the proposed GA is explained in Algorithm 2.

Algorithm 2: GA-based Smart Community Energy Consumption Optimization

---

Population initialization: generating a population of k chromosomes randomly

1: within the power range $Chr^j = \{Q_{SC}^1, Q_{SC}^2, ..., Q_{SC}^{24}\}$,

where $0 \le P_{grid}^i \le P_{grid\_limit}^i, i = 1, ..., 24, \ \ j = 1, ..., k.$

{Execute GA algorithm}

2: for i =1 to GA_{limit} do

3: Calculate $wd^{i,j}$ using ARIMA (1,1,2) $(1,0,0)_{168}$

4: Calculate $W_{max}^{i,j}$ using Algorithm 1, $i = 1, \ldots, 24, j = 1, \ldots, k$

{Calculating the fitness of each chromosome}

5: for j =1 to k do

6: Calculate constraint matrix $\boldsymbol{w}$

7: **if** $\boldsymbol{W} = 0_{6,N}$ then

8: $F(Chr^j) \leftarrow -\sum_{i=1}^{24} \alpha^i \cdot P_{grid}^i \cdot t$

9: **else**

10: $F(Chr^j) \leftarrow -\left(\boldsymbol{p} \cdot \boldsymbol{w} \cdot c + \sum_{i=1}^{24} \alpha^i \cdot P_{grid}^i \cdot t \right), \ j = 1, 2, ..., k$

```
        end if
      Call GA Routine according to [78]
      end for
  end for
Collect the best chromosome Chr_best, i.e., the best power input solution for the cost function in (7)
if w_best = 0_{6,N} then
      F_best ← p · Chr_best
  else
      Trim Chr_best, F_best ← p · Chr_best_trim
  end if
Output the best fitness value F_best, i.e., the minimum energy consumption cost for the SC
```

A demonstration of one smart home using GA based optimization is shown in Figure 15 where the standardized 24 hour energy consumption of EWH, HVAC, EV and ESS are shown in corresponding areas in the upper figure. However, there are only two parameters for CD, the first one is the start time and the second one is the load pattern type. The optimization can be virtually seen through the lower figure as the fitness of each generation approved gradually. The simulation is set to stop at the fiftieth generation. The blue, green and red line refers to the best fitness, median fitness and mean fitness respectively. As seen from the lower fitness figure, the

best fitness has already reaches its stabilized value long before the end of the simulation, it means 50 generation is enough for a single smart home optimization. For a bigger scale SC, the generation setting will be increased to 100 to 200 as the case may be.

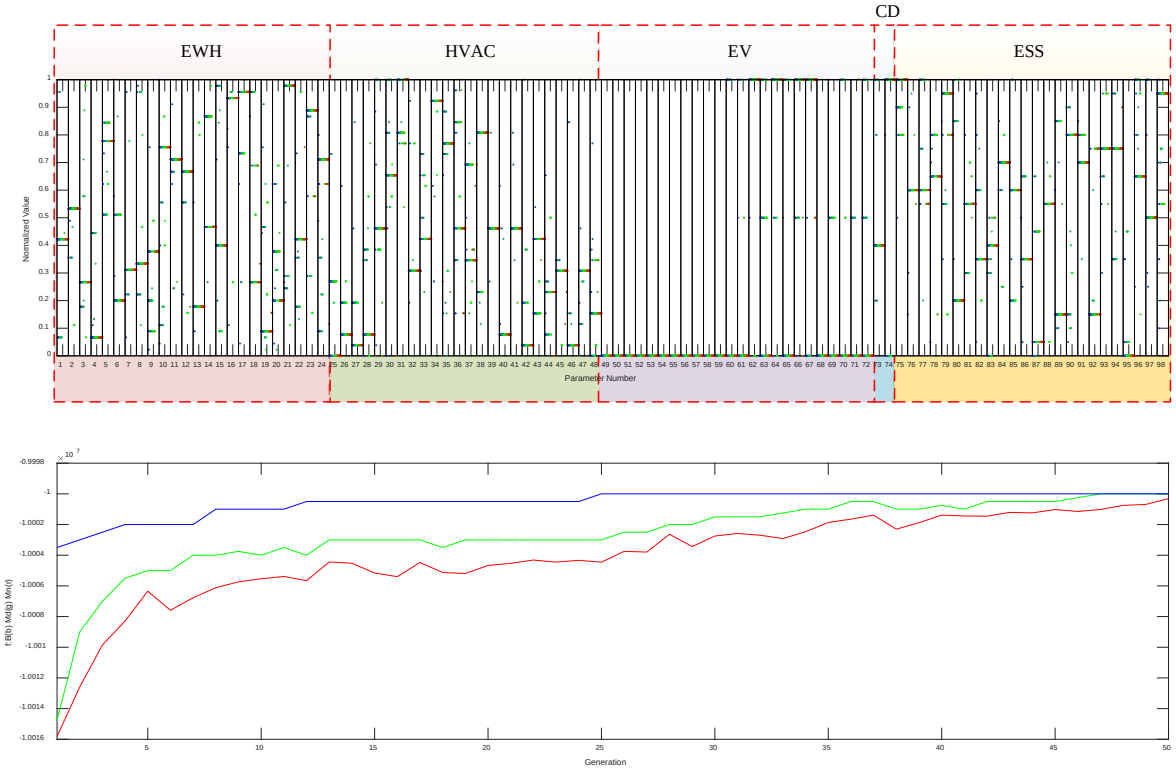


Figure 15: Genetic Algorithm optimization demonstration

CHAPTER 6

SIMULATION STUDY AND RESULTS

This Chapter presents a study of the proposed learning-based demand response on SC by using the genetic algorithm developed in Chapter 5, which requires forecasted weather and electricity price data in 24-hour ahead. The weather forecast is available from National Weather Service and the 24-hour electricity price can be provided by an electric utility one day ahead as discussed in Chapter 2.3.3. The experiment is implemented on the MATLAB 2016a and it is performed on a Windows 7 Professional Dell Precision T3600 PC installed with Intel Xeon E5-1620 and 16 GB memory.

6.1 Initial Setting

The maximum power from the grid is initially set as 20 kW. The load curtailment will be added to the grid under different scenes in later simulation.

The priority matrix for the SC is randomly generated for each house that imitates the different preference of each individual household.

The traditionally thermostat for HVAC is set at 71°F or 72°F for a typical house in the United States. In our simulation, the comfort temperature range for HVAC is set between 71 °F to 79 °F based on the “nine-point” thermostat setting in [26]. The maximum power of the HVAC is set as 7 kW.

The maximum power of the EWH is set as 4.5 kW. For the comfort hot water temperature T_{base}, this paper does not take full consideration of the Legionnairs' disease due to which that the Occupational and Safety & Health Administration(OSHA) of the United States Department of Labor requires a minimum domestic water heater maintenance water temperature of 140°F and 122°F for water at the faucet[80]. The comfort hot water temperature for the proposed EWH is set as 110°F considering the combination of both hot water and cold water and the tank is considered ideally brand new and bacteria free. The size of the EWH tank is set as 50 gallons.

The capacity of all EVs inside SC is set as 60 kWh for laboratory implementation. The time range of the EVs that park at home is set from 6 pm to 7:30 am in the next day morning. The initial SOC of the EV that arrives at home is set as 0.35. The maximum SOC of the EV is set as 0.95 where the minimum SOC of the EV is set as 0.3. The final SOC of the EV before leaving the house is required to be no less than 0.9. Since under the proposed energy management, the EV will not discharge to the network, so the minimum SOC will not be violated at any circumstances. The charging rate of the EVs is designed as a bi-level EV charging scheme with the power of 3.3kW or 6.6kW respectively.

The maximum turned on time for CD is set as 3 hours. The working range of the CD is limited within 6 pm to 1 am and it refers to timeslots from 11 to 18.

The charging efficiency of the ESS is considered as 0.95[81] whereas the discharging efficiency is set as 0.9[82]. The capacity of the ESS is set as 100 kWh. Initial SOC for ESS is set as 0.35[82]. Maximum and minimum SOC are set as 0.95 and 0.3 correspondently. The maximum charging/ discharging power of the ESS is set as 10 kW.

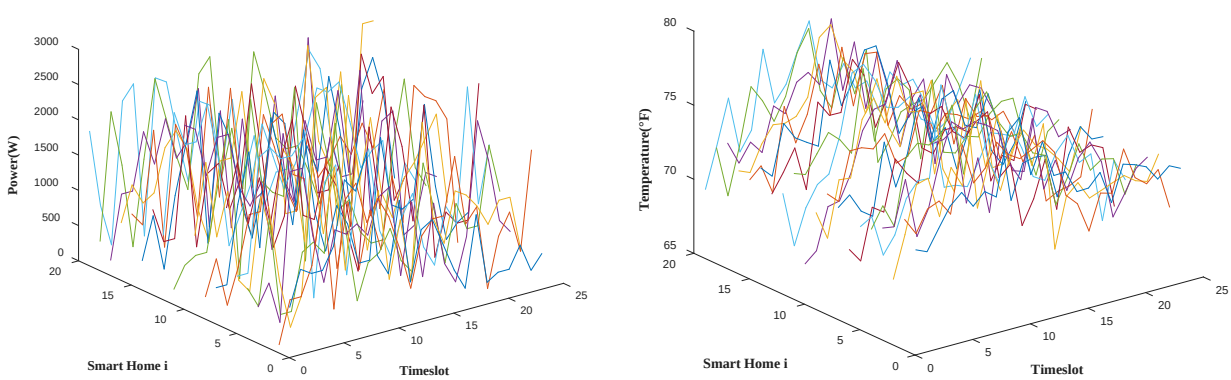
The day ahead forecast of the PV power generation is obtained from [41].

6.2 Simulation Analysis of Different Conditions

The simulation of the SC energy management optimization was conducted under several different scenes representing different real life situations that the power system might face. Besides that, simulations with different parameters are performed to analyze the effect of these parameters on the optimization result.

6.2.1 Smart Home Simulation Results

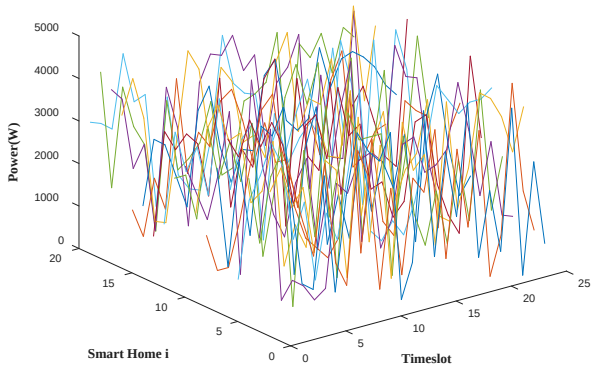
The HVAC simulation of a 20 household SC is shown in Figure 16. In fact, almost every HVAC simulation looks similar with Figure 16. In (a), there is the energy consumption of 20 HVAC systems over a day whereas the 24 room temperature is shown in (b). Since the comfort zone is from 71 to 79 Fahrenheit, in most of the timeslots, the room temperature is maintained inside this temperature range. However, if there exist mandatory load curtailment and it cannot be compensated by load shifting, the temperature will fell out of the comfort zone.



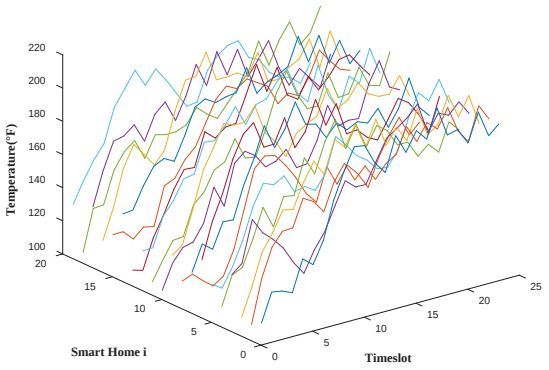
(a) (b)

Figure 16: (a) HVAC energy consumption and (b) room temperature

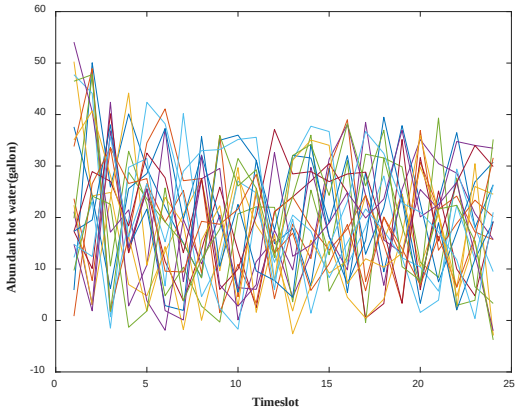
The energy consumption, tank output temperature and abundant hot water of the 20 EWHs inside the SC is shown in Figure 17. The power consumption solution in Figure 17(a) is similar with HVAC in a way that it looks like random assigned solutions. However, as we check its tank temperature in Figure 17(b) and Figure 17(c), the tank temperature are maintained in the working temperature above 110 Fahrenheit whereas there is always abundant hot water. The abundant hot water is the maximum capability minus the actual water demand which depicts whether the EWHs will satisfy their customers. The results of EWHs energy consumption simulations show that at most of the timeslots for most of the users, the energy management for EWHs assigns proper power rate for it, and they surely satisfy their user's need. However, at some hours when load curtail happened, there might be a tiny hot water shortage of at most 5 gallons as shown in Figure 17(c). It really depends on the load priority setting of the users.



(a)



(b)



(c)

Figure 17: (a) EWH energy consumption; (b) tank temperature and (c) abundant hot water

The load pattern of CDs for 20 houses is shown in Figure 18. The performance of CDs does not need further calculations since they have limited load patterns and limited working range, in another word every solution locates inside the constraint. However, since they are not that flexible, the coordinating of CDs will not contribute a lot to the optimization. In this specific simulation shown in Figure 18, there are two load patterns with a maximum working period of 3 hours. There is no load curtailment seen on the energy consumption.

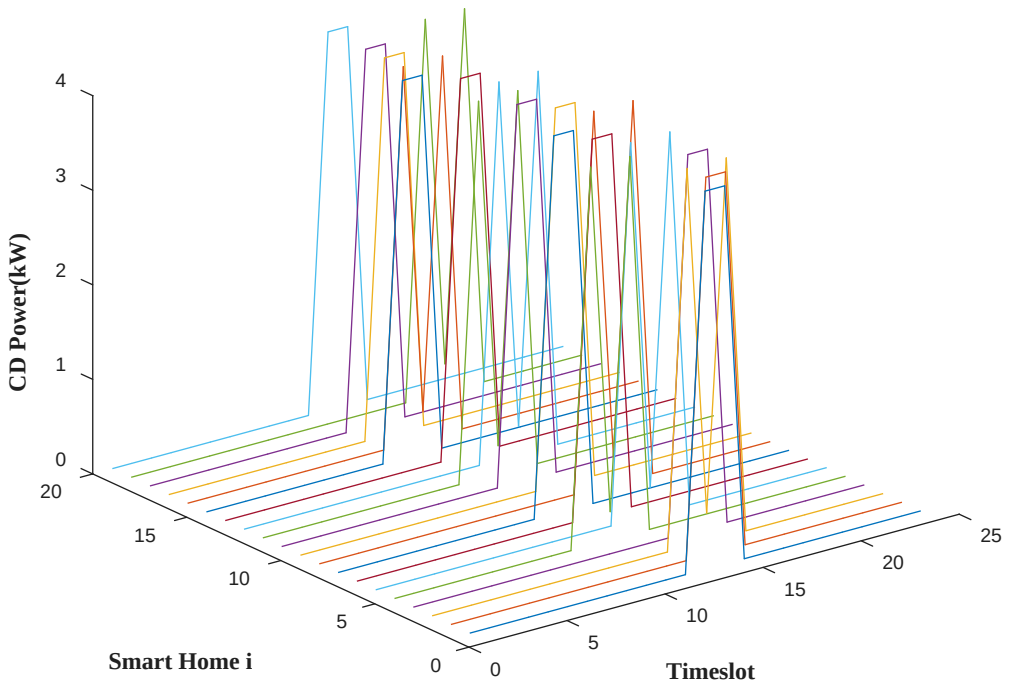
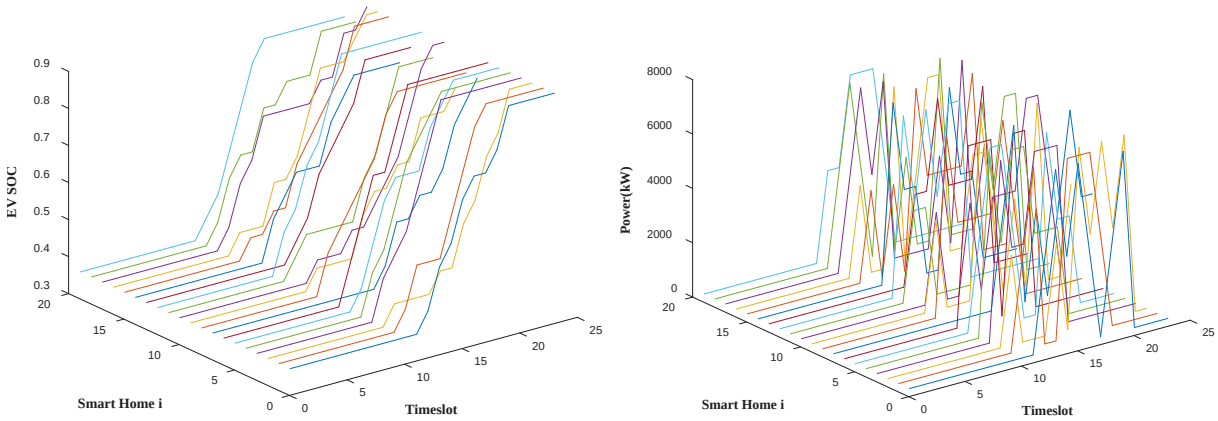


Figure 18: Load status for 20 CDs inside the Smart Community



(a) (b)

Figure 19: (a) SOC of 20 EVs, (b) Charging power of 20 EVs

6.2.2 Smart Community Scale Comparision

The first set of simulations involves an SC with different scale. A size of 2, 5, 10, 15, 20 and 25 houses inside the SC was simulated with no limitation on grid power, fixed size of ESS, fixed power rate of PV and wind turbine.

The overall power flow of the SC is shown in Figure 20. In the figure, the purple line is the maximum possible solar power and the green line is the maximum possible wind power. The blue line represents P_{load} , the red line represents $P_{\text{load-renew}}$ and the yellow line is P_{grid} .

With a small scale of 1 or 2 smart homes, there is almost no power coming from the grid because the renewable energy resources can already satisfy the need. As the scale of the SC rises, the residential load also rises. Figure 20(c) clearly demonstrates the effect of the renewable power. Even though the original residential load has a peak of over 50 kW, with the help of the renewable power sources and the abundant renewable energy stored in the ESS in low demand timeslots, the final power sent from the grid is much lower and the peak is greatly shaved. In (d), (e) and (f), the residential load exceed the renewable power generation. As a result of power shortage, P_{grid} increases. It is worth notice that the difference between $P_{\text{load-renew}}$ and P_{grid} is due to the effect of the ESS. In all three conditions, the ESS helps to shave the load peaks to a certain degree. However, in the last condition (f) with 25 homes, the effect of the DERs is much smaller than previous small scale SCs. Unlike in previous conditions, in (f) the P_{load} , P_{grid} and $P_{\text{load-renew}}$ has very similar load patterns. From the comparison of the scale of SC, it is clear that the DERs have performed certain demand response operation. In addition, we come to notice that a proper scale of the renewable power source is also very important in the operation of energy management.

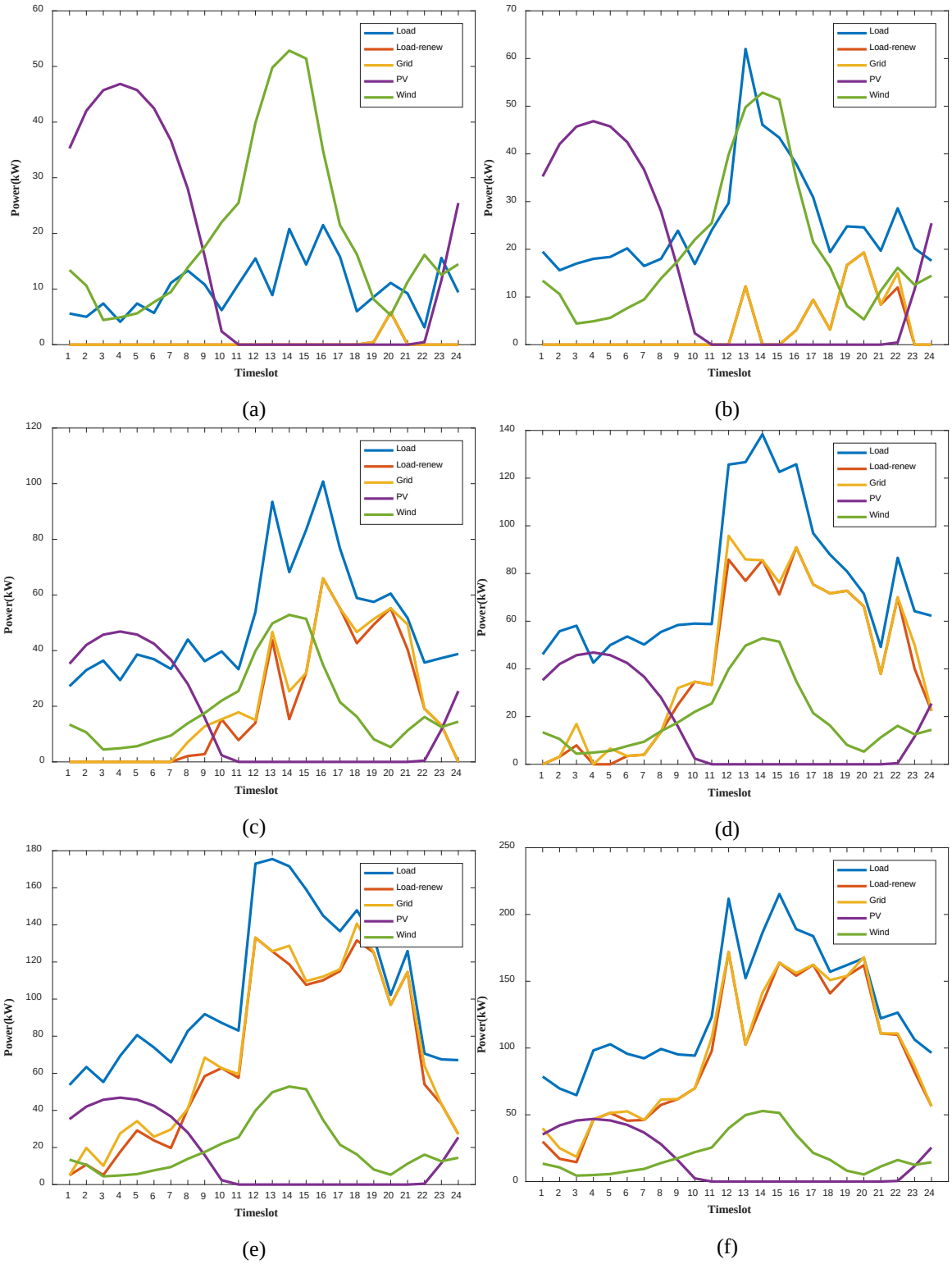

Load
Load-renew
Grid
PV
Wind
Power(kW)
Timeslot
(a)
(b)
(c)
(d)
(e)
(f)

Figure 20: Smart Community overall power flow with a smart home (a) size of 2, (b) size of 5, (c) size of 10, (d) size of 15, (e) size of 20, (f) size of 25

6.2.3 Total Load Curtailment on The Smart Community

The above 6 simulations are based on the conditions that does not have load curtailment. The last one with 25 homes has an original load peak of more than 200kW. In this set of simulation, different load curtailment are applied to the simulation with a fixed SC scale of 20 houses and fixed renewable generation same as in the previous simulation.

Figure 21 shows the power flow of the SC with a load curtail of 110 kW. Compare with Figure 20(e), the original peak load in Figure 20(e) is reduced from 130 kW to below the limit of 110 kW. The effect of the ESS is worth noticing that in timeslot 17, it helped to make the power from grid lower than the load curtailment limit.

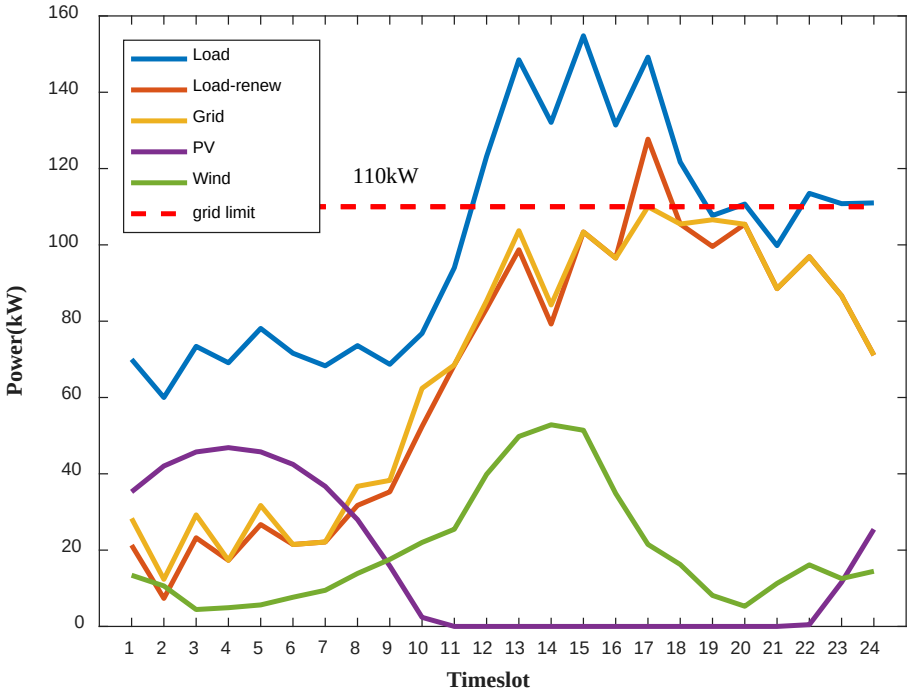


Figure 21: 110 kW grid load curtailment

Figure 22 shows the power flow condition an 80 kW load curtailment limit. From the figure, we can see there are power failure somewhere inside the SC in timeslot 12, 14-22, because the difference between $P_{\text{load-renew}}$ and P_{grid} is larger than the maximum discharging power of ESS. It is clear that with such a low load curtailment, not all the smart appliances can meet the demand of the customers. They will be turned off according to the load priorities. Under severe conditions like in Figure 21, there will be a clear load peak shaving phenomenon shown on the grid inletting power rate. In this case, a lot of the appliances will face power shortage.

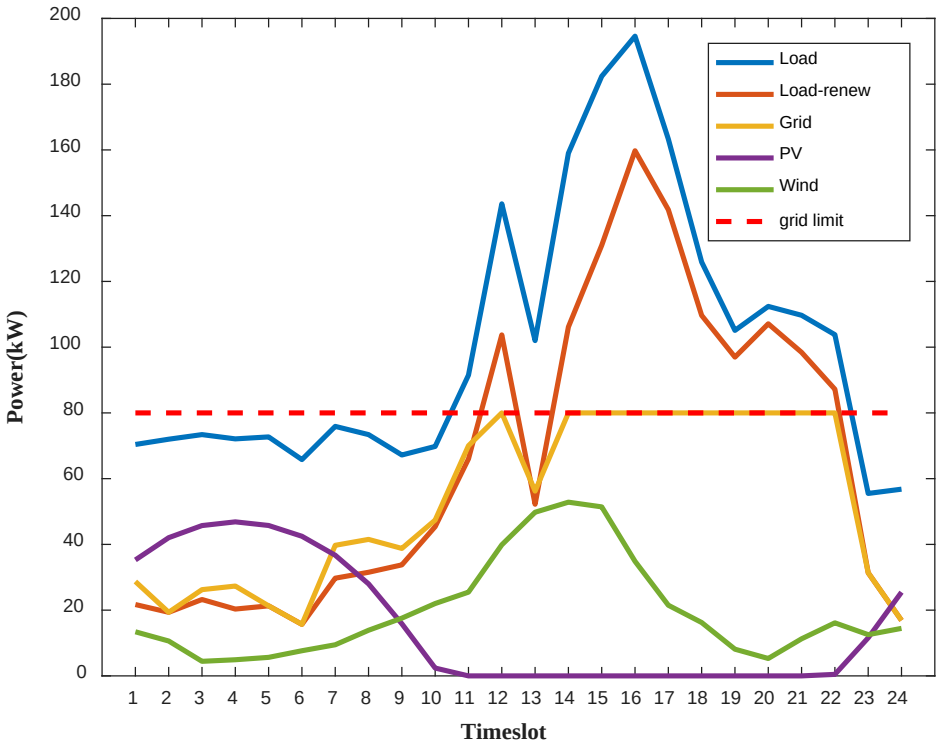
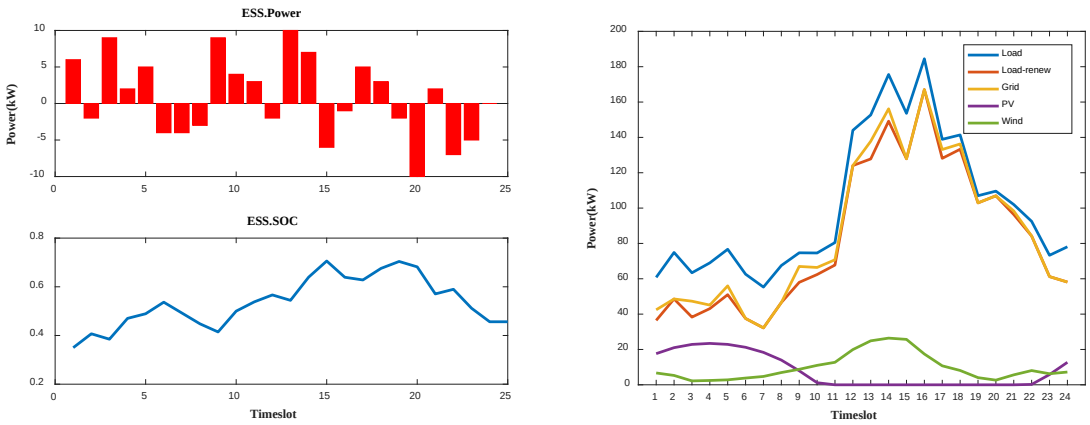


Figure 22: 80 kW severe grid load curtailment

6.2.4 The Effect of Renewable Generation

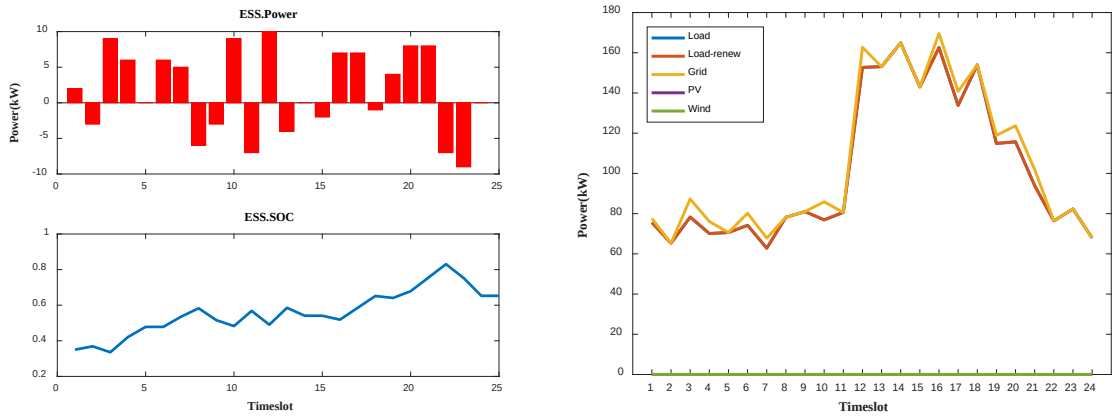
Figure 20(e), Figure 23 and Figure 24 show a comparison between an SC with renewable power resources, with half its size and without it. It is a 20 household SC and all other simulation setting are the same.

From the comparison, it is clear that the less renewable power generated, the more power needed from the grid. It seems that the larger the renewable power rate, the more money will be saved. However, as shown in Figure 20(a) and (b), if the renewable power rate does not have a proper size, there will be a lot of renewable energy wasted. In addition, the ESS status is enclosed in the figures. They charge at more timeslots and do not have certain reaction towards the change in renewable power generation.



(a) (b)

Figure 23: (a) ESS charging and SOC status, (b) Overall power flow with half the renewable resource generation



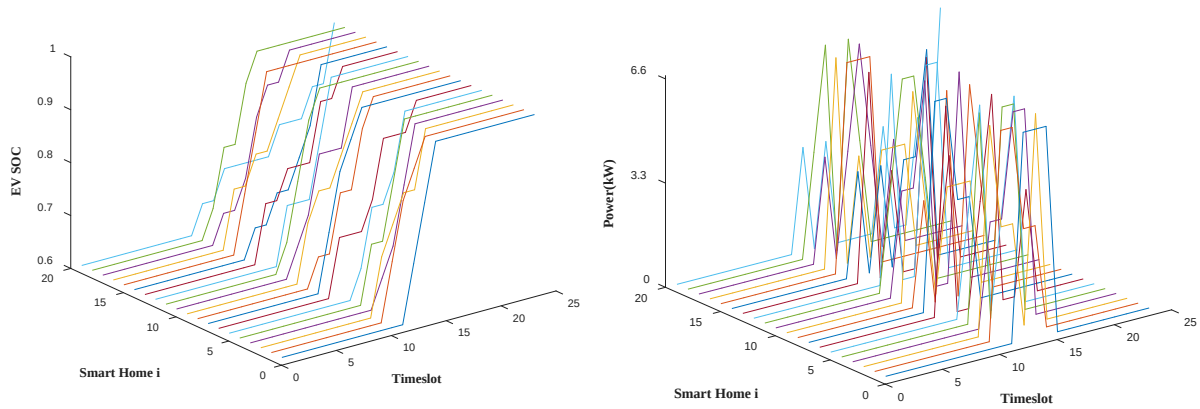
(a) (b)

Figure 24: (a) ESS charging and SOC status, (b) Overall power flow with no renewable resource generation

6.2.5 Different Initial SOC for EV and ESS

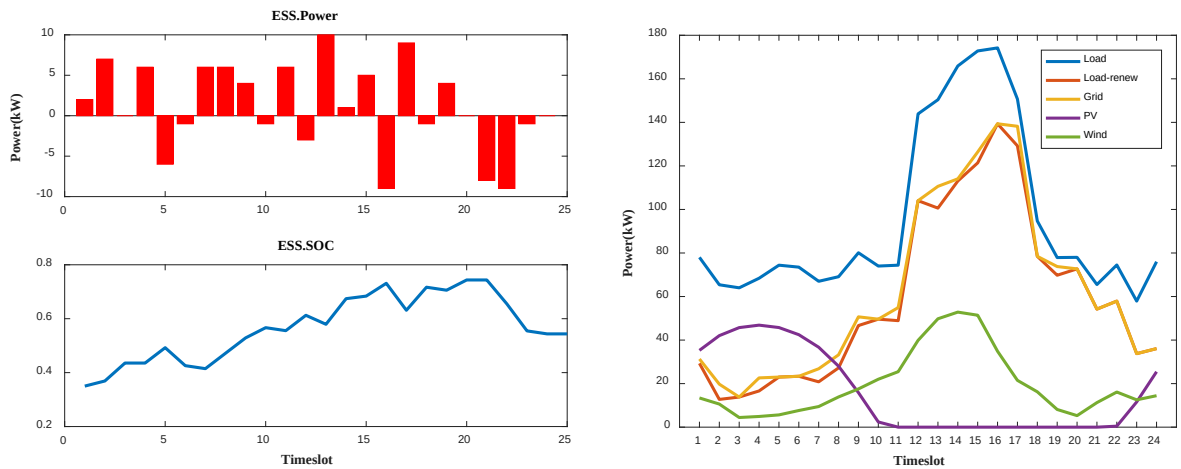
Simulations with different initial SOC for both EVs and ESS are tested. All of the simulations in this subsection uses fixed SC size of 20 and fixed renewable power generation as in subsection 2 and is compared with the simulation in Figure 20(e).

Figure 25 shows the EVs' SOC status with 0.6 initial SOC and their 24 hour power solution. It is obvious that EVs with higher initial SOC will finish charging four to five hours earlier than EVs with initial SOC of 0.35 shown in Figure 19(a). Figure 26 provides the ESS status and overall power flow of the SC for reference. However, no further conclusion has been obtained from Figure 26.



(a) (b)

Figure 25: (a) EV SOC status and (b) EV power with initial EV SOC = 0.6

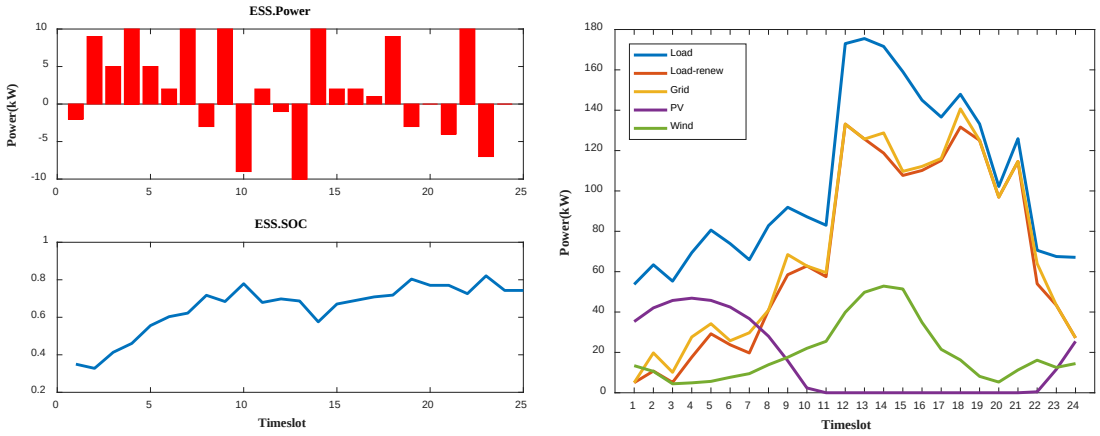


(a) (b)

Figure 26: (a) ESS charging and SOC status, (b) Overall power flow with initial EV SOC = 0.6

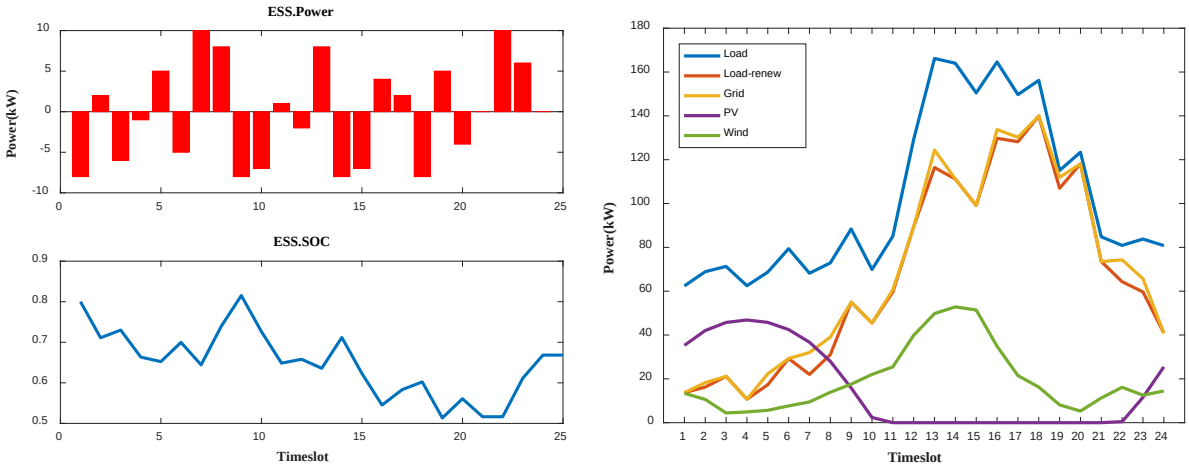
Figure 27 and 28 show the comparision between an initila ESS SOC of 0.35 and 0.8. From the charging/discharging status of the ESS shown in red bars, we can clearly see that with higher initial SOC, the ESS tends to discharge in more timeslots than with lower initial SOC. It shows that the proposed GA method can find a certain smart way to make use of the enrgy inside the ESS or find the right time to perform energy storage. In addition, it is interesting to find out

that the final SOC of the two different conditions tends to converge to the same final SOC of around 0.7. The reason for this phenomenon still needs further research on the GA.



(a) (b)

Figure 27: (a) ESS charging and SOC status, (b) Overall power flow with initial ESS SOC = 0.35



(a) (b)

Figure 28: (a) ESS charging and SOC status, (b) Overall power flow with initial ESS SOC = 0.8

6.2.6 Different DAP

A simulation with different DAP pattern is presented in Figure 29 and 30. In this DAP pattern, the highest price is set on timeslot 17. It should be noticed that this DAP pattern is made up just to test the ability of the proposed energy management. Compare with Figure 20(e), the power coming from grid reduces from around 120 kW to 110 kW in peak hours from timeslot 12 to time slot 19. The reason that there is not that much load shifting is due to the fact that the working range of CD is limited between timeslot 11 to 17. And in addition, the EVs are designed to arrive at timeslot 12 (7 pm) which will put a lot of load pressure on the power system. However, it is clear that in the DAP peak price hours, the ESS stops buying power from the grid.

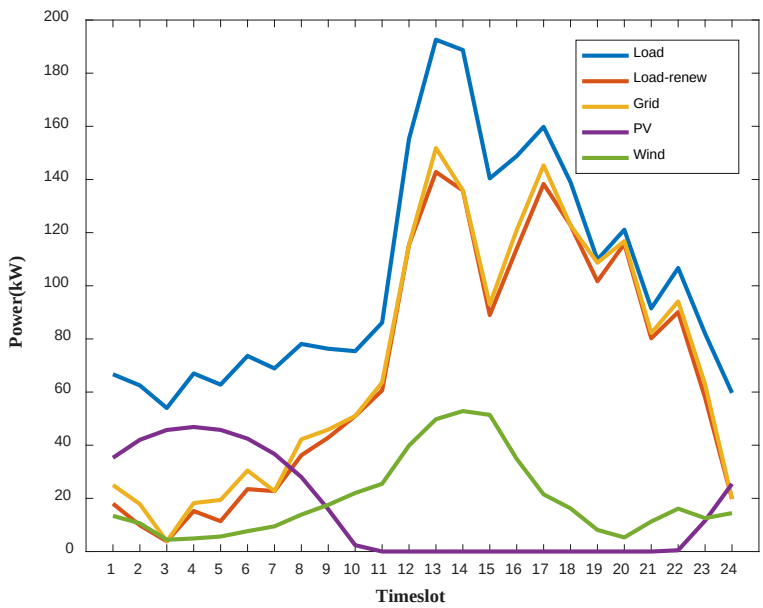


Figure 29: Overall power flow under different DAP

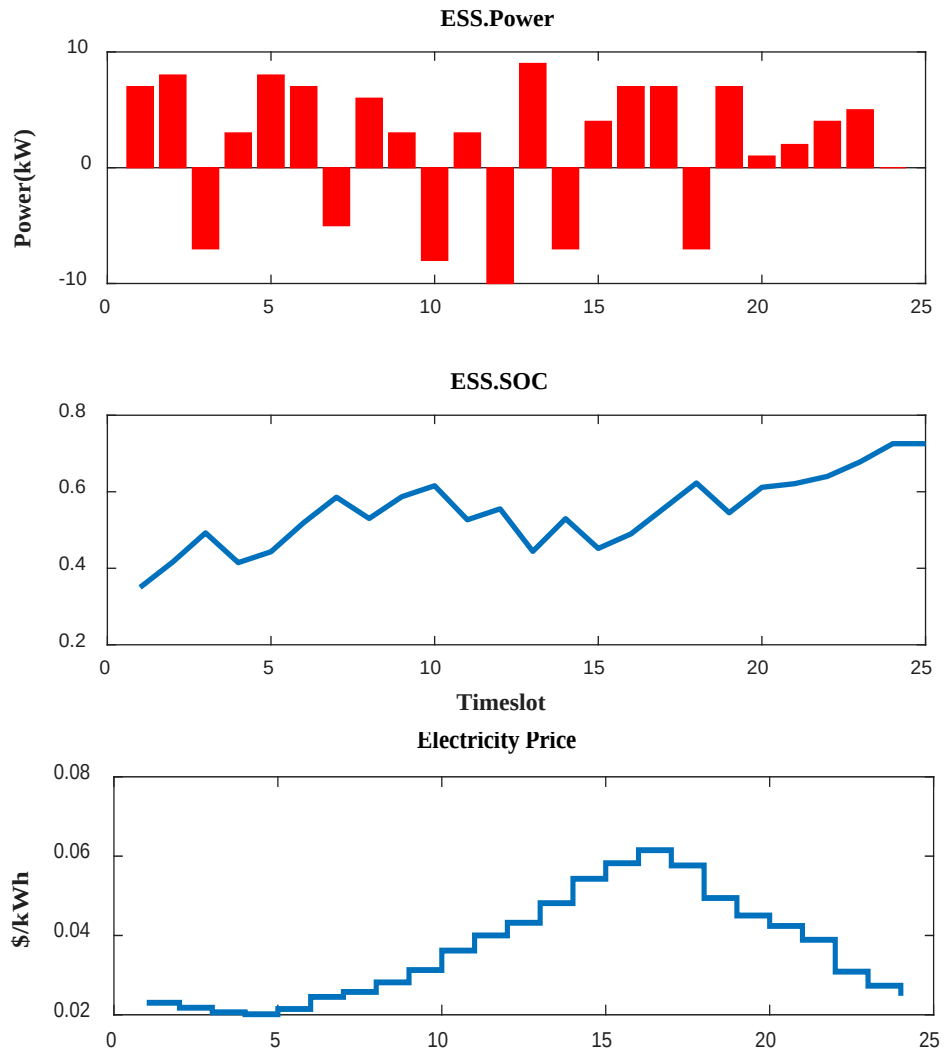
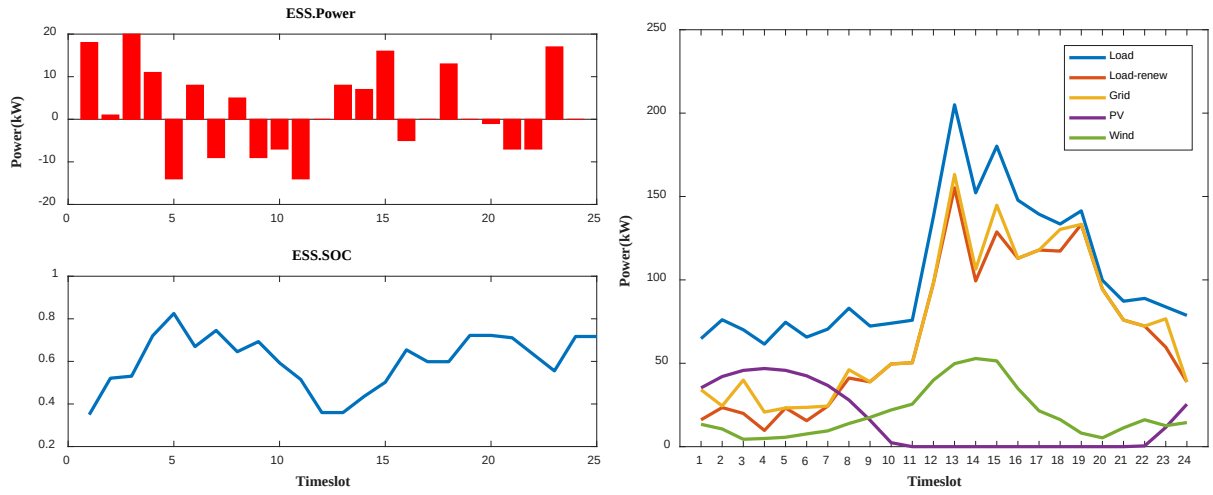


Figure 30: ESS charging and SOC status plus the electricity price

6.2.7 Different ESS Charging/Discharging Rate

The maximum charging and discharging rate is changed to ±20kW for the ESS. The ESS status and the overall power flow is shown in Figure 31. However, even with a larger charging and discharging rate, the ESS does not show an active effect on load shifting or peak shaving in the overall power flow diagram. It is probably due to the weight setting problem in the multi-objective GA. Since different weight is multiplied to different penalties, the algorithm is weight

sensitive. This “no action” of the ESS probably depicts the inaccuracy in setting up the weight matrix for all constraints.



(a) (b)

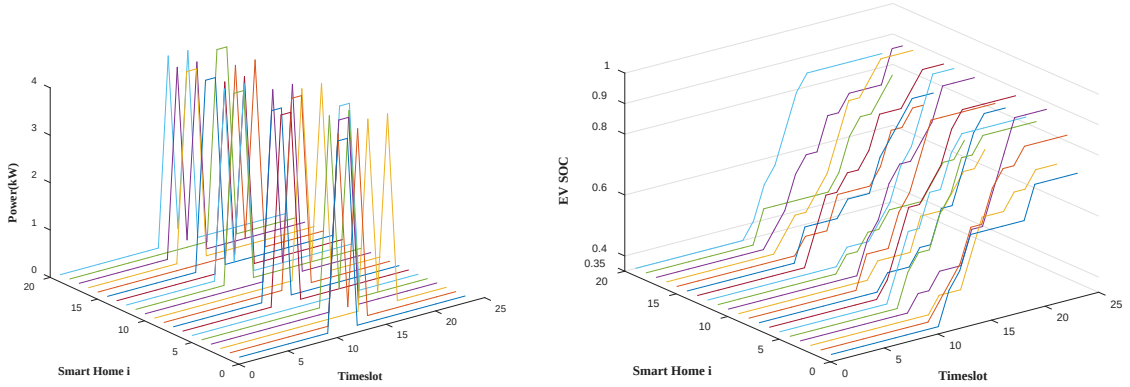
Figure 31: (a) ESS charging and SOC status, (b) Overall power flow in Smart Community

6.2.8 An Example of Invalid Solution

In an example of invalid solution when facing severe power failure, results are shown in Figure 32 and Figure 33. In Figure 32(a), the working range of all CDs are stretched to as wide as possible from timeslot 11 to timeslot 18. In addition, more load pattern two is used since it reduces the chance to create load peaks. In Figure 32(b), most of the final SOC of EVS does not reach the expected leaving SOC which is between 0.9 and 0.95 due to the power failure.

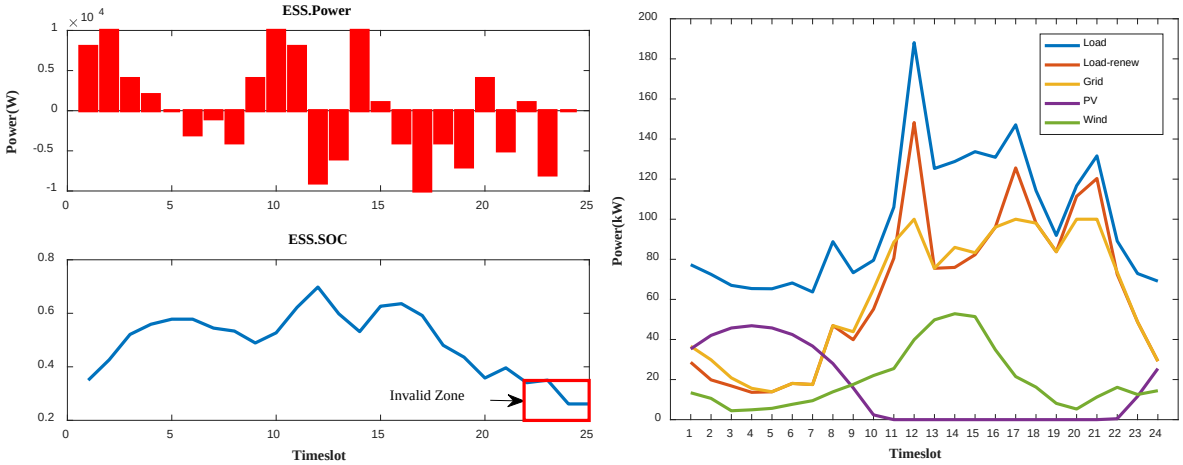
In Figure 33(a), the SOC of the ESS drops under 0.3 which is the minimum limit for ESS. It makes the simulation become invalid simulation. It is due to the soft constraint characteristic of GA. Further trimming of the ESS power solution can be applied to overcome this issue. If it is an invalid solution, no matter how small the fitness of the solution is, the optimization needs to

start over again. Figure 33(b) shows the places that power failure happened. By comparing $P_{\text{load-renew}}$ and P_{grid}, we can find out that in timeslot 12, 17, 20 and 21, mandatory load curtail, or power failure occurred.



(a) (b)

Figure 32: (a)The load status of CDs, (b) The SOC of EVs



(a) (b)

Figure 33: (a) ESS charging and SOC status, (b) Overall power flow in Smart Community

6.2.9 Economic Summary

The economic summary of different conditions using 20 homes is shown in Table 4. All these conditions have the same DAP and same EV initial SOC as 0.35, same ESS initial SOC as 0.35. In the table, Q_{grid} is the total energy bought from the grid. Besides total energy and cost, the average EV SOC when they are leaving the house is also considered as well as the final ESS SOC. In addition, the status of applying mandatory load curtailment is also shown in the table. For reference, the average electricity price is 0.0364 $/kWh.

In Table 4, the best performance of each item is bold. Among the ones that does not have mandatory load curtailment, the condition that with no load curtailment and with renewable energy resources has the best performance i.e. lowest cost and highest final ESS SOC. However, among all the simulation conditions, there is not one condition that has two best performance. It is also worth noticing that "110 kW load curtailment with renewable" has the lowest PAPR which is reasonable due to the mandatory peak shaving.

Table 4. Economic summary of different conditions using 20 homes

Condition	Q_{grid} **(kWh)**	**Cost($)**	**Average unit price ($/kWh)**	**Average EV Leaving SOC**	**Final ESS SOC**	**Mandatory Load Curtailment**	**PAPR**
No limit w/ renewable	1721	58.79	0.0341	0.8725	**0.7432**	**No**	2.8
No limit w/o renewable	**2510**	88.42	0.0352	0.8752	0.6528	**No**	2.35
110 kW limit w/	1612	52.83	**0.0328**	0.8230	0.2564	Yes	2.1

renewable					(invalid)		
100 kW limit w/ renewable	1530	50.94	0.0333	0.8367	0.5216	Yes	2.0
80 kW limit w/ renewable	1281	**43.80**	0.0342	NA	NA	Yes	1.8
110 kW limit w/o renewable	2169	30.11	0.0354	0.8587	0.399	Yes	**1.44**
No limit w/ ½ renewable	2164	74.1976	0.0343	0.8780	0.7169	**No**	3.6
110 kW limit w/ ½ renewable	1861	53.0211	0.0348	0.8285	0.3169	YES	1.9145
20 kw ESS charge/discharge	1740	57.64	0.0331	**0.8780**	0.7169	Yes	3.732

CHAPTER 7

CONCLUSION AND FUTURE WORK

Under a day-ahead, dynamic electricity price framework there is a huge potential to save the cost of the residential appliances. In addition, as the penetration of smart houses and the installment of renewable energy resources increases, the need for community-level energy management system is more urgent. The main goal of this thesis is to design an energy management system that can properly manage the operation of all entities inside an ideally SC at the lowest cost.

First, the paper reviewed the previous works in designing the two categories of energy management strategies and proposed a centralized energy management for the SC that has smart homes, share-based ESS, PV panels and wind turbine inside.

Secondly, this paper analyzed several forecasting method on residential hot water consumption pattern and developed a seasonal ARIMA model for DSM. The accuracy of the forecasting is closely related to the optimization of energy solution and the satisfaction of the user's experience.

Thirdly, each of the entity inside the SC, including HVAC, EH, EV, CD and ESS, was studied and then modeled based on models from previous works, its thermodynamic model and its power consumption characteristics.

Fourthly, this paper proposed and tested data driven NARX models of HVAC and EWH. The aim of developing learning-based model is to obtain an accurate model that can be adaptive to seasonal change, climate change and resident changes. The training, validation and testing performance of NARX shows the accuracy of the proposed NARX models and they are capable of being used in the framework of demand response optimization.

Finally, a GA-based algorithm is developed to find the optimal power solution for managing SC energy consumption and renewable sources with minimum cost. The simulation results show that the proposed mechanism can properly perform optimal community energy management in many different ways regarding all the different appliances. However, under certain load curtailment, there will be mandatary load curtailment and it will affect the comfort of certain lower priority smart appliances.

To put all in a nutshell, this paper considered the comfort of HVAC and EWH, the working of CD, the leaving SOC of the EVs from the residents' perspective and see the total SC energy consumption, total electricity cost, electricity unit price, final SOC of ESS, and the PAPR of the power of grid from the stand point of the system operator. Both of them formed the overall analysis of the SC.

Future work may include continuous optimization of consecutive hours instead of 24-hour frame, detailed compensating methods for prediction error and new applications of the proposed mechanism for multiple grid and for other systems like smart building and smart city. Besides, there could also apply learning-based modeling method to EV and CD. In addition, the whole smart home can be modeled as one single NARX model for the convenience of optimization. For the GA, right now the computational time is still considerable. Hence, the efficiency of the algorithm can have further improvement in future works.

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