RESIDENTIAL-LEVEL SMART DISTRIBUTION SYSTEMS WITH INTEGRATION OF DEMAND RESPONSE AND ELECTRIC VEHICLES USING AGGREGATORS

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The following faculty members have examined the final copy of this thesis for form and content, and recommend that it be accepted in partial fulfillment of the requirement for the degree of Master of Science with a major in Electrical Engineering.

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ABSTRACT

A new residential-level load management system in the presence of real-time pricing for future power systems with smart grid technologies and concepts was developed in this work. In the first part of this research, a new strategy combining demand response (DR) and vehicle-to-grid (V2G) application was designed. Since DR will inevitably affect a customer's comfort level and the V2G application will significantly degrade the life of a vehicle battery, it was hypothesized that the two together could compensate for their individual disadvantages. By reducing peak loading, a customer's comfort level and electric vehicle (EV) battery degradation are considered. Based on the first part of this work, a new control model was developed to reduce load-forecasting errors so that real-time demand would be as close as possible to the forecasting load. Currently, making a forecasted demand equal to a real-time demand is a very challenging task in power systems. Sometimes the unexpected load causes serious problems in power systems. From a technical perspective, overloading could affect the lifespan of infrastructures significantly at the distribution level. From an economical perspective, unexpected load demand could increase the market risks for utility companies, and eventually, the electricity bill of customers could be increased. If utility companies could offer an incentive model that customers could directly control, then this solution could help both utilities and customers reduce costs.

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LIST OF ABBREVIATIONS

AC	Air Conditioner
AMI	Advanced Metering Infrastructure
CF	Controllable Factor
DL	Demand Limit
DR	Demand Response
EL	Level of PEV Charge
EV	Electric Vehicle
EPRI	Electric Power Research Institute
EMS	Energy Management Systems
FREC	Federal Energy Regulatory Commission
G2V	Grid-to-Vehicle
HAN	Home Area Network
IPP	Independent Power Producer
OF	Oscillation Factor
OG&E	Oklahoma Gas and Electric
PEV	Plug-in Electric Vehicle
SOC	State of Charge
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home
WH	Water Heater

CHAPTER 1

INTRODUCTION

1.1 Motivation

"Smart grid" is a popular term used for the advancement of current power systems. One of the most practical smart grid technologies is demand response (DR). Several models have been developed in the literature. Many different DR strategies have been implemented into the current power girds. The best example is how Oklahoma Gas and Electric (OG&E) applied time-of-use program into their systems and benefited significantly [1].

In the work of Shao et al. [2], demand response strategies to a customer's comfort level were well developed. However, in this paper, the electric vehicle (EV) was only considered as a load for distribution systems. The vehicle-to-grid (V2G) concept is relatively new. During the V2G application, EVs would be considered as energy storage in order to support the demand response. However, battery and capacity degradation, which can result, are the most challenging factors and barriers to V2G [3]. Therefore, demand response and V2G could work together to compensate for each other's disadvantages and to improve their individual feasibility. This idea was the motivation for the first part of the work in this thesis.

Using the DR and V2G strategy, a model could be developed to reduce the error between forecasting load and real-time load. By applying this model, distribution companies could reduce the risk of buying energy from a spot market, which has extremely fluctuating prices. Also, they could delay infrastructure upgrades with direct load control to avoid overloading at the distribution level. Customers would benefit from this incentive program, depending on how much information they are willing to share with distribution companies. In order to make this model more efficient, aggregators would be utilized as a median party between distribution companies and customers.

By applying the first part of this work into a new model, it is possible to reduce the unexpected load demand without sacrificing significant comfort loss and help distribution companies avoid dramatic spot market risks.

1.2 Thesis Outline

This thesis is comprised of five chapters. Chapter 2 is a literature review of DR, EVs, and V2G. Chapter 3 presents the first part of this work, which is a peak-shaving strategy using a combination of DR and vehicle-to-home (V2H). Chapter 4 presents the new economic model at the distribution level in order to assist utility companies in obtaining a more accurate forecasting demand. Conclusions and future work are presented in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

In this chapter, DR, the V2G application, and power systems will be reviewed from different perspectives.

2.1 Demand Response

According to a Federal Energy Regulatory Commission (FREC) staff report [1], demand response is defined as "changes in electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized." In other words, DR is a way to manage power consumption based on the current situation of power grids to avoid overloading or unexpected power demand. This report also categorized DR into two types of programs: incentive-based and time-based, as shown in Table 2.1. In this thesis, because direct load control needs to be applied, only the incentive-based program is considered.

TABLE 2.1

DEMAND RESPONSE PROGRAM TYPES IN 2012 FERC SURVEY [1]

Incentive-Based Programs	Time-Based Programs
• Demand Bidding and Buyback • Direct Load Control • Emergency Demand Response • Interruptible Load • Load as Capacity Resource • Non-Spinning Reserves • Regulation Service • Spinning Reserves	• Critical Peak Pricing with Control • Critical Peak Pricing • Peak Time Rebate • Real-Time Pricing • Time-of-Use Pricing • System Peak Response Transmission Tariff

Currently, many studies have presented their own DR strategies. For example, Shao et al. developed an incentive DR strategy to avoid overloading on distribution transformers caused by EV charging. In their work, they considered customers' comfort losses when DR is applied. For

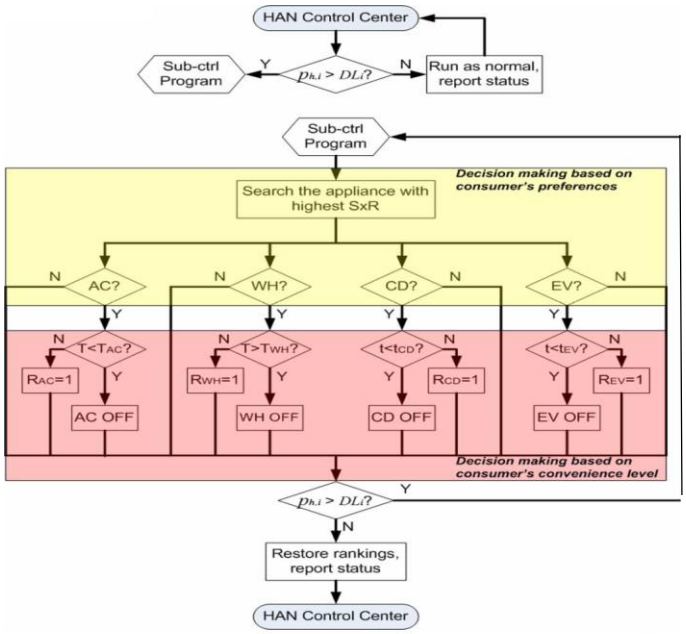
each household, once power consumption is higher than the demand limit (DL), the DR will start working. All loads are categorized into uncontrollable and controllable loads. Controllable loads are also ranked with different priorities, which could be controlled by a home area network (HAN) [2]. Each controllable load has different preference settings, as shown in Table 2.2.

TABLE 2.2

LOAD PRIORITY AND CONVENIENCE PREFERENCE [2]

Load Type	Load Priority	Convenience Preference
EV	1	Complete in 2.5 hours
Water Heater	2	Water temp >= 100°F
HVAC	3	Room temp < 82°F
Clothes Dryer	4	Complete in 2.5 hours

In this paper, EV charging has the highest priority among all controllable loads. Based on the working process of DR, the HAN control center will check the real-time power demand and DL. If the power consumption is higher than the DL, then the HAN control center will operate according to the flow chart shown in Figure 2.1.



Notes:
*AC = HVAC, WH = water heater, CD = clothes dryer, EV = electric vehicle.
* R is the set of rankings of all the controllable appliances. 1 is the highest. Consumers will pre-select the ranking of each controllable appliance and store them in the HAN control center.
* S is the set of status of all controllable appliances: 1 for ON and 0 for OFF.
* "Run as normal" means no central control, the appliances will run as needed.

Figure 2.1: HAN control flowchart [2]

As shown in Figure 2.1, if real-time power consumption is higher than the demand limit, then the working controllable loads with the highest ranking will be located. There are two values for S (the set of all controllable applicances): 1 for ON and 0 for OFF. If this controllable load could finish its work inside of the preference limit, then it will shut down temporarily until the real-time demand is less or equal to the DL.

2.2 EV and V2G Application

Currently, many auto manufactories have released EVs, such as the Nisan Leaf, Tesla, and Chevy Volt, to the auto market. With advancements in the grid-connected transportation industry and growing environmental concerns, personal EVs are becoming the most likely fleets to replace gasoline vehicles in the near future [3].

However, charging EVs could bring more pressure to power systems, especially on distribution systems. According to an Electric Power Research Institute (EPRI) report [4], there is only an 8% increase in electricity generation if 50% vehicles are replaced by EVs, but the distribution system will be affected significantly. Yilmaz et al. showed that the power consumption of typical EVs is more than two average household loads, which means it can cause undesirable peak demand and require more investment on the distribution system [3] .

Based on the recent literature, at the distribution level, increased penetration of EVs would accelerate the degradation of the DL components due to charging rates and uncertainty in the time of usage. Liu et al. showed that EV charging has adverse effects on power distribution systems, even considering diverse charging scenarios [5]. Figures 2.2 and 2.3 show how EV charging can affect transformers at the distribution level.

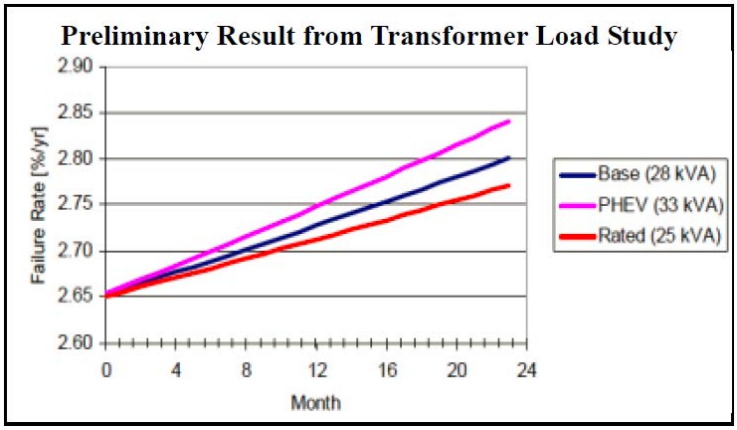


Figure 2.2 Transformer failure [5]

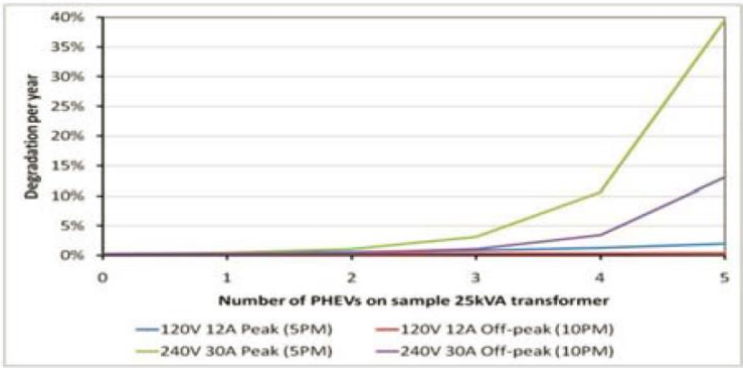


Figure 2.3: Transformer degradation [5]

Controlled charging strategies have the potential to minimize grid-level impacts [6]. Shao et al. used DR as a peak-shaving tool successfully to reduce the peak demand caused by EV charging, while also optimizing customers' convenience and comfort level [2].

The V2G concept is a way to discharge electric vehicles and supply energy from the EV back to the power grids. Yilmaz et al. reviewed V2G technology specifically from different perspectives [3]. To successfully implement the V2G approach, smart grid infrastructures are required. Control and communication devices between the grid operator and the EV need to be installed. Smart meters are also necessary for each household.

Yilmaz et al. showed that the V2G application could improve the reliability, efficiency, and stability of power grids, and they also pointed out that the biggest challenge for V2G application is the battery degradation of EVs. Battery lifespan will be affected by the charging and discharging frequency. Current battery technology is not able to provide economic power storage for electric vehicles; therefore, the V2G application will be much more challenging for power grid operators [3]. If battery degradation could be minimized, V2G could be more feasible.

2.3 Forecasting in Retail Market in Power Systems

Power system markets used to be a monopoly, which means that all energy generation and distribution were operated by the same company, whereby customers had no choice of purchasing energy from different companies. Figure 2.4 shows two different models of the vertical generation, transmission, and distribution monopoly. Part (a) shows that all generation, transmission, and distribution are one entity; there is no trading among them. Part (b) shows only generation and transmission as one entity; distribution companies must buy energy from wholesale transmission companies, and then they can sell the energy to customers [7].

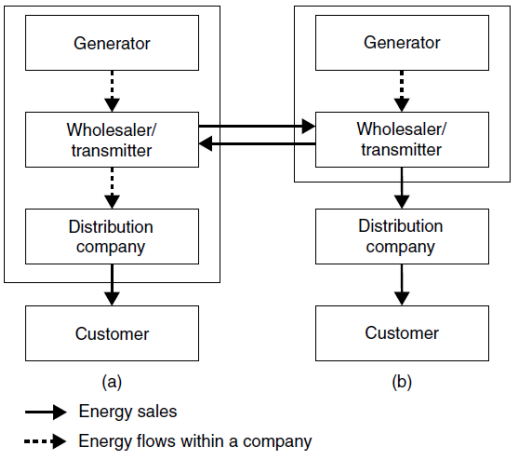


Figure 2.4: Monopoly Market [7]

Some economists think a monopoly causes unnecessary high costs to utilities and that the expense of unnecessary investments could be passed down to customers, eventually increasing

their utility bills. Therefore, a free electricity market has been proposed. Three different types of electricity markets are shown in Figures 2.5 and 2.6. Market (a), shown in Figure 2.5(a), shows that an independent power producer (IPP) could participate in the wholesale markets, and even distribution companies have their own generators and transmission systems. Market (b), shown in Figure 2.5, shows that all distribution companies must buy energy from the wholesale markets, which consists of all IPPs, and there is no longer a monopoly. Market (c), shown in Figure 2.6, shows that a large consumer could directly participate in a wholesale market without purchasing energy from the distribution companies.

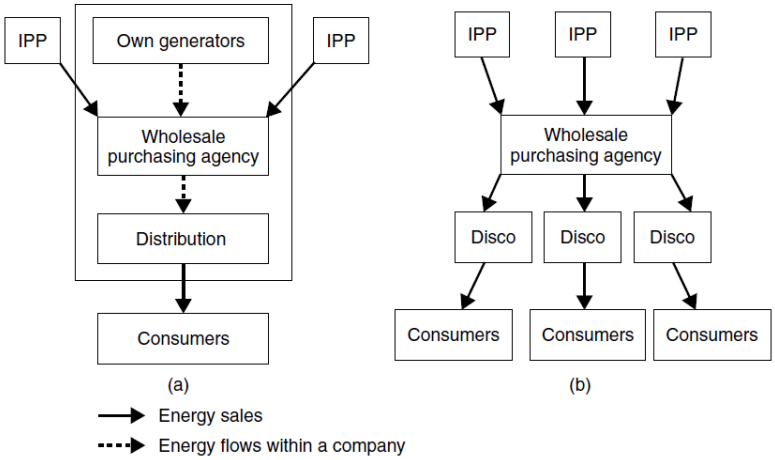


Figure 2.5: Power system markets (a) and (b) [7]

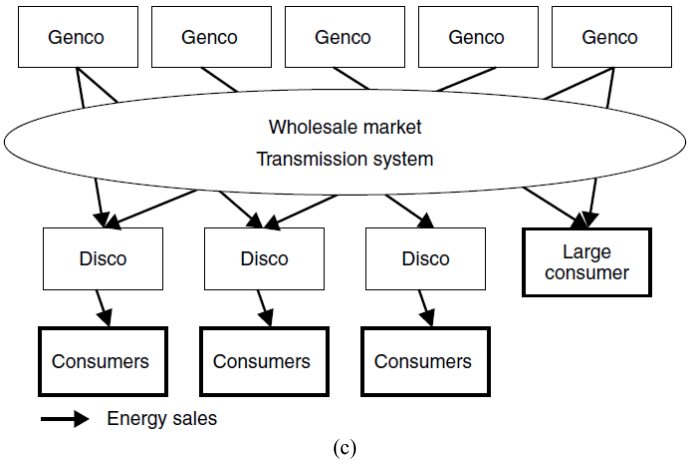


Figure 2.6: Power system market (c) [7]

In contrast, since electricity is different from other merchandise, currently it cannot be stored economically and must be consumed immediately when it is produced. Therefore, the power market moves much faster than any other market, which makes balancing the supply and demand more challenging. Most utility companies are retailers who must buy energy from wholesale markets with contracted prices. If the consumer's consumption is higher than the energy that retailers have purchased for that period, then the retailer must buy energy from the spot market that has extremely fluctuating prices. If they purchase more contracted energy than what they consume, then retailers must sell it back to the spot market. Thus, it is really necessary to forecast demand as accurately as possible. Today, with the most sophisticated forecasting methods, the hourly average accuracy could be achieved to 1.5–2%. If retailers could forecast their demand load accurately, they could benefit significantly [7].

2.4 Aggregator

Since more and more available smart grid technologies, such as DR, V2G, and grid-to-vehicle (G2V), are being released, a new agent is required for power systems to make it more efficient. An aggregator is an efficient way to manage power transactions between the grid side and demand side resources [8]. Moreno et al. proposed an aggregator framework for the micro-grid between a distribution operator and the demand side. An aggregator and EVs are used as a regulation service to help the distribution operator optimize the purchase of energy from the market. A distribution operator could have all the information showing the available energy from the storage during a day and adjust the power purchase, and the aggregator needs to be able to access all available EVs and obtain their state of charge (SOC), or available capacity [8]. Moreno et al. only consider the aggregator as part of a micro-grid, and only EVs are considered as controllable loads. Figure 2.7 shows a model of their work.

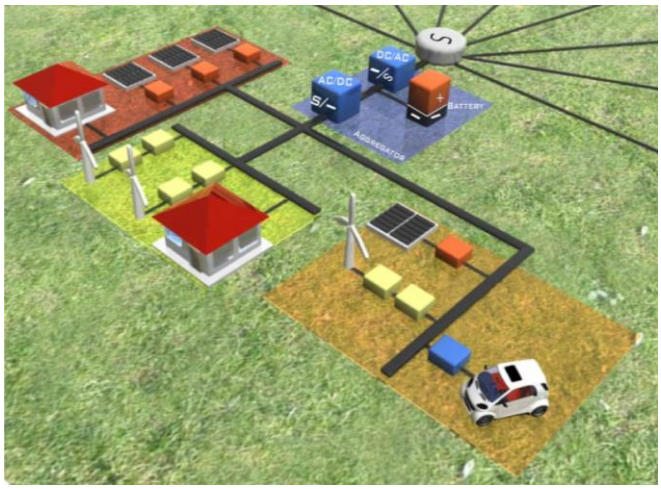


Figure 2.7: Micro-grid aggregation model [8]

In power systems, balancing generation and demand load is the key operation, also called the regulation service. Sun et al. presented the idea that the aggregator-EV system could be used as a regulation service tool using different distributed algorithms. Because the goal of the traditional regulation service is to use fast, responsive generators to adjust generation, which is also the most expensive way to provide regulation service, the aggregator-EV system could make regulation service more economic [9]. Figure 2.8 shows the aggregator-EV system, where both energy and information flow among the power grid, aggregator, and EVs. The aggregator is assumed to be nonprofit-driven—from the government or any other nonprofit third party. It combines all available EVs and uses them as available power storage, by charging and discharging, which can help balance generation and demand loads.

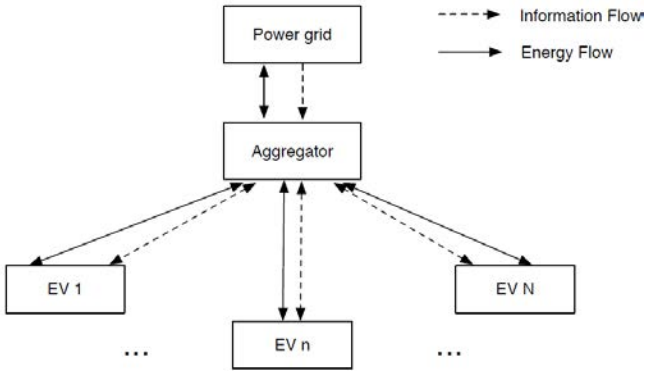


Figure 2.8: Aggregator-EV system [9]

In another paper, Gkatzikis et al. designed a hierarchical aggregation model in a smart grid demand response market. Here, there are numerous households under the electricity market, and each of them has a slight effect on the market; therefore, it is necessary to use an aggregator to combine the single houses to reduce the utility operation cost. As the third party, aggregators provide DR services to utility operators and receive monetary rewards based on how much money the utility can save from DR services. At the lower level, homeowners will receive incentive rewards based on their power consumption patterns. Since this model is a day-ahead market, the aggregator will receive the demand requirements from utility companies a day ahead, and then the aggregators negotiate with the customers. Homeowners modify their power consumption based on requirements from the aggregator. Figure 2.9 shows the framework of this aggregation model [10], briefly showing utilities, aggregators, and households. Ideally, they assume that customers would modify their power consumption patterns based on requirements from aggregators, and customers' comfort and convenience levels would not be considered at all. Therefore, the feasibility of this model is limited.

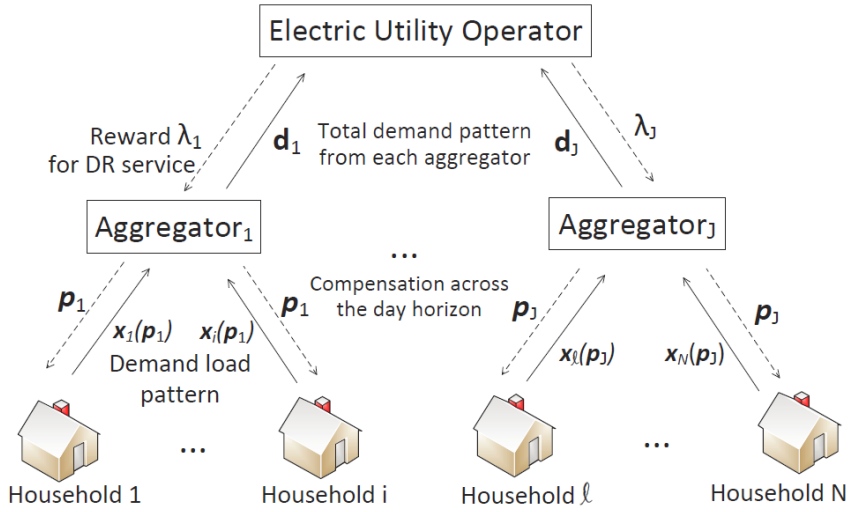


Figure 2.9: Structure of aggregation model [10]

CHAPTER 3

DEMAND RESPONSE AND V2H STRATEGIES

In this chapter, the strategies of demand response and V2H are presented specifically. The main goal of this work is to reduce peak load of a single-household load. The DR strategy in this paper is similar to the one proposed by Shao et al. with a maximum threshold [2]. A variable charging rate for plug-in electric vehicles (PEVs) based on customer preferences or available capacity of power demand is utilized in this work, in order to minimize the grid impact and enable all necessary appliances to operate while PEVs are charging. Finally, battery charging cycles affect the life of the battery [11]; therefore, this work minimizes the number of charging and discharging operations.

3.1 Infrastructures of DR and V2H

The necessary infrastructure for an active feedback-based demand-side response with PEVs that participate in the V2H is modeled based on the work of Wang and Wang [12] and Aravinthan et al. [13], as shown in Figure 3.1. This model considers each household separately.

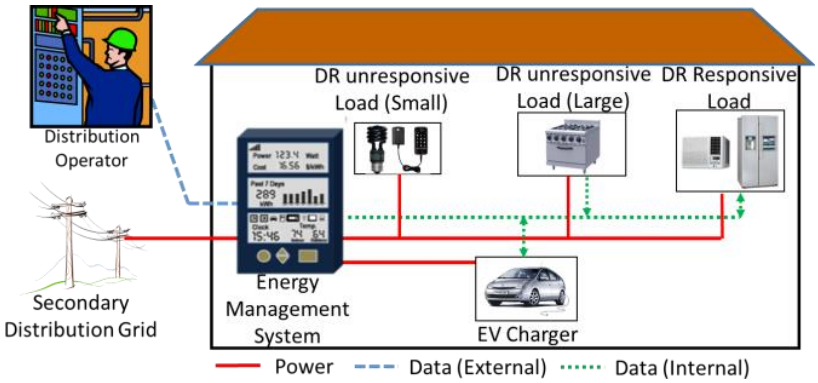


Figure 3.1: DR-based residential home in smart grid scenario [13]

Traditional residential loads need to be divided into three groups, some of which will not respond to price or any other control signal. For example, small loads like a phone charger will not

be controlled. Since their power requirement is small and portable, a data communication infrastructure will not be economical. This type of load is categorized as a "minor DR unresponsive load." Other loads such as a stove or oven consume a large amount of power; however, they are critical loads and will not be time shifted. Their usage information is important for a good DR implementation. For example, when an oven is being used, its temperature data will be sent to the controller.

The controller will be able to manage loads that can be time shifted optimally for maximum DR benefits. Therefore, one-directional communication is vital for this type of load, which is categorized as "critical DR unresponsive load." Finally, an appliance such as air-conditioner could be managed to minimize the peak consumption. This type of load needs to be controlled and is categorized as "DR responsive load." It is expected that with the penetration of smart appliances, both critical DR unresponsive load and DR responsive load will be addressed by an IPP [13]. Due to the charging and discharging options and extensive amount of data requirements, PEVs are considered a separate load group. This work focuses on V2H and uses a model that is similar to the paper proposed by Shao et al.[2], developing a peak-shaving application for a real-time application.

3.2 Process of DR and V2H

A PEV is considered as both energy source and controllable load, depending on the level of the state of charge and the residential demand. Due to the fact that battery degradation is a main concern for V2H applications, the beginning of charging and discharging must be limited, as explained in the literature [14] and as shown in Figure. 3.2.

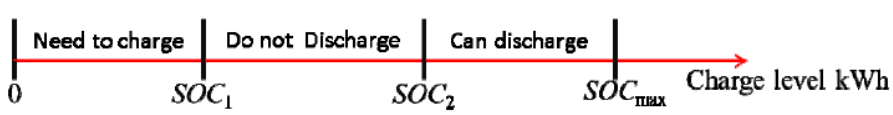


Figure 3.2: Battery charging and discharging strategy

SOC_1 is the level of battery charge below which the charging operation would be initiated. Once the charging operation is initiated, the battery will be charged to at least SOC_1, a safe level. $SOC2$ is the level of battery charge required to participate in the V2H model. If the charge drops below SOC_1, then battery discharging will be stopped. SOC_1 and SOC_2 are typically set by EV owners based on their preferences and traveling plans for the next day. In this paper, a single EV will be charged with either a dynamic charging rate or fixed rate, depending on the power demand and owner's traveling plans.

Peak shaving is enabled by prioritizing the DR responsive load and PEV status (charging, idle, and discharging). The level of PEV charge (EL), SOC_1, SOC_2, required DR responsive load level ($Pc(t)$), and DR unresponsive load demand ($Pu(t)$) are used to determine different energy management schemes. An energy management system (EMS) equipped with an energy meter requires a communication infrastructure between the distribution operator and the household. Furthermore, a separate communication infrastructure between home appliances and EMS is necessary for internal communication. The scenarios that follow are considered for the model-based controller. Figure 3.3 shows all scenarios.

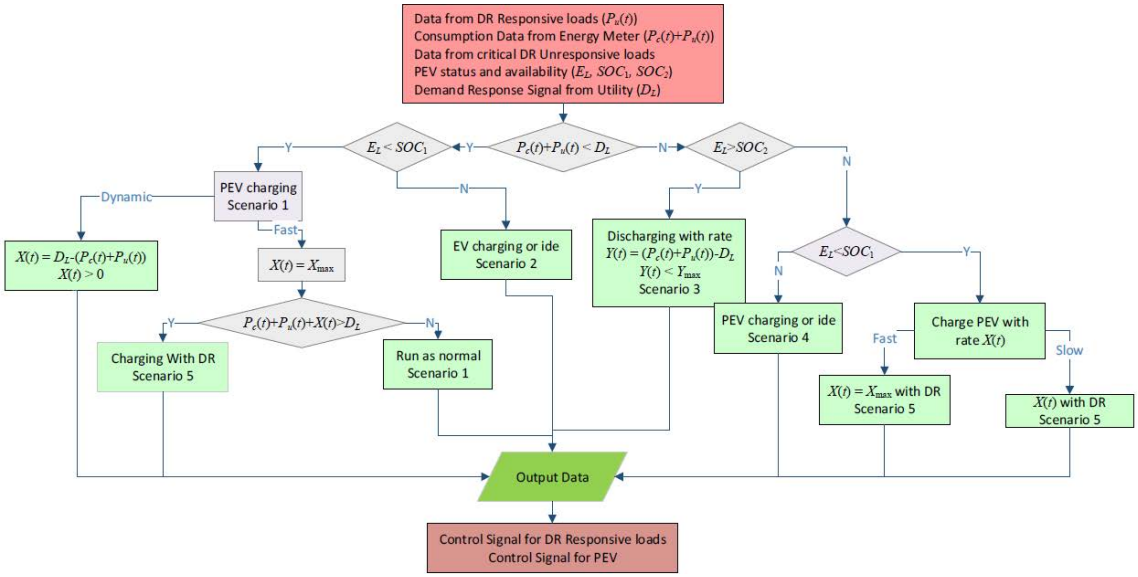


Figure 3.3: Energy management system control model

<u>Scenario 1</u>: $E_L < SOC_1$ and $P_c(t) + P_u(t) < D_L$

This scenario indicates that the PEV needs to be charged based on the owner's preferences. Under this scenario, the energy remaining in the battery is less than the safe level SOC_1, and the PEV needs to be charged immediately. The charging rate could be set to one of the two following modes by the PEV owners based on their preferences:

Mode 1 (rapid charge): If customers want their EVs to be charged to SOC_1 as soon as possible, then the rate of charging will be set to its maximum, $X(t) = X_{\max}$. During this time, if the following constraint is not satisfied, then the controller will proceed to Scenario 5:

$$P_c(t) + P_u(t) + X_{max} \leq D_L \tag{3.1}$$

Mode 2 (flexible charging rate): This rate is based on the following relationship:

$$X(t) = D_L - (P_c(t) + P_u(t)) \tag{3.2}$$

In this mode, $X(t)$ will be dynamic based on the current load profile as long as $X(t) \geq 0$. If $X(t)$ is less than 0, then the controller will proceed to Scenario 5.

<u>Scenario 2</u>: $SOC_1 < E_L < SOC_2$ and $P_c(t) + P_u(t) < D_L$

In this case, the current energy in the battery is between SOC_1 and SOC_2. At the same time, there is still available demand capacity to charge the EV. This indicates that the PEV could get charged with the dynamic charging rate until the state of charge reaches $SOC_{\max}$.

$$X(t) = D_L - (P_c(t) + P_u(t)) \tag{3.3}$$

Based on their traveling plans and expected household demand, the PEV owner could enable an idle mode if the remaining battery charge is between SOC_1 and SOC_2, in order to limit the battery degradation.

<u>Scenario 3</u>: $E_L \geq SOC_2$ and $P_c(t) + P_u(t) > D_L$

In this case, the current energy in the PEV battery is sufficient to operate in the discharging mode. Since the battery has enough charge, the total load of the house is considered without the PEV charging consumption. When the load is greater than D_L, the PEV battery would operate in the V2H mode to reduce the peak load. The PEV discharging rate is limited to a maximum value Y_{max}. The discharge rate during this scenario is defined as

$$Y(t) = \begin{cases} P_c(t) + P_u(t) - DL & \text{if } P_c(t) + P_u(t) - DL \leq Y_{\max} \\ Y_{\max} & \text{if } P_c(t) + P_u(t) - DL > Y_{\max} \end{cases} \tag{3.4}$$

Under the following condition, the DR will work along with the V2H mode to limit the power consumption below D_L:

$$P_c(t) + P_u(t)_{DL} > Y_{max}$$

The range between SOC_1 and SOC_2 is a really important factor to decide how long the V2H charge could last, which is also related to charging and discharging frequency.

<u>Scenario 4</u>: $\mathrm{SOC}_1 < E_L < SOC_2$ and $P_c(t) + P_u(t) > D_L$

In this case, the present battery energy is between SOC_1 and SOC_2, indicating that the PEV does not need to be charged immediately or discharged to support the DR. However, the total demand without connecting the PEV is greater than the demand limit (D_L). Therefore, a DR algorithm, similar to the one proposed by Shao et al., needs to be used during this period.

<u>Scenario 5</u>: $E_L < SOC_1$ and $P_c(t) + P_u(t) > D_L$

In this case, the current energy in the battery is less than the minimum setting SOC_1, which means the PEV needs to be charged to SOC_1 while running the DR. The PEV needs to be charged with the owner's desired charging rate $X(t)$ until the battery charge reaches SOC_1. This scenario also utilizes the same DR algorithm as used in Scenario 4.

This section presents a typical summer day in Wichita, KS, USA, to demonstrate the performance of the proposed method. Since Wichita has extremely high temperatures during the summer, a typical summer day is used to show the impact of demand response. The following subsections illustrate the proposed model along with data.

3.3 Results

3.3.1 Battery Profile

In this work, a Nissan Leaf automobile was chosen as the PEV to be used for the V2H application. This vehicle uses a 24 kWh lithium-ion battery. Based on the PEV project report [15], the average daily traveling distance of a Nissan Leaf about 26.7 miles. According to the Nissan Leaf's official website [16], the MPGe of Nissan Leaf is from 129 to 102, which is equal to 3.84 to 3.03 mile/kWh. Based on this information, the battery state of the charge profile is generated for a particular day in Kansas using Gridlab-D [17]. For this work, which is based on a typical weekday profile, it is assumed that the PEV leaves home at 7:30 a.m. and arrives home at 5:30 p.m., without charging during the working time. Figure. 3.4 shows the daily battery status for that particular day. As shown, at least 64% energy is left in the battery when the PEV arrives home, which means the vehicle only consumes 36% power of the battery daily.

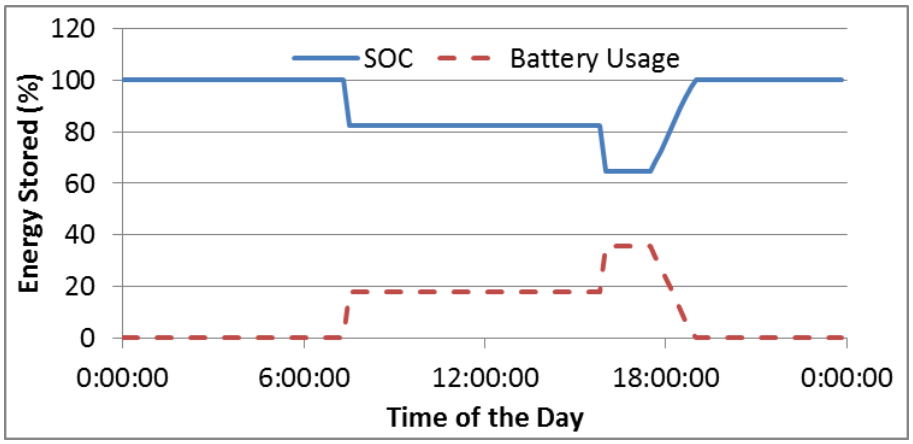


Figure. 3.4: SOC of random weekday in Wichita with charging at arrival

Based on this argument, the SOC_1 is set as 40% of the capacity, and SOC_2 is set as 50% of the capacity. Furthermore, based on the available PEV chargers, the maximum charging rate X_{max} is fixed at 6.6 kW, and the maximum discharging rate Y_{max} is taken as 2.0 kW.

3.3.2 Single-Household Load Profile without EV

Figure. 3.5 shows a single-household load profile without a PEV during a typical summer day in Wichita, Kansas. The midday peak (2–4 p.m.) occurs because of the increased air conditioning load due to the extremely hot weather. The evening peak (6–8 p.m.) occurs as a result of the typical evening household energy consumption after the consumer's last trip of the day.

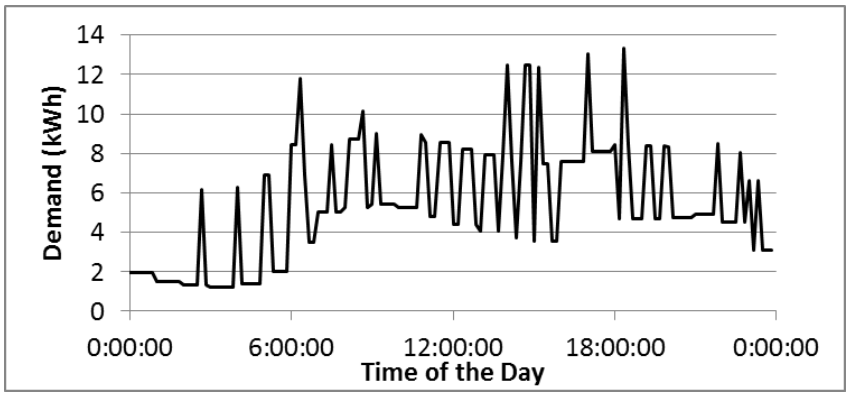


Figure. 3.5: Daily single-household load profile without PEV charging

3.3.3 Single-Household Load Profile with PEV Charging

For the same household demand, a PEV with the battery profile given in subsection 3.3.1 is added to study the impacts of the PEV on the system. PEV charging at arrival, all the other parameters, including appliance usage, is kept the same as in subsection 3.3.2. Results are plotted in Figure 3.6. Since the PEV charging rate is fixed as its maximum charging rate of 6.6 KW, the peak load increases significantly after the PEV arrives home. The zenith of the peak load value is almost 20 kW around 6:30 p.m.

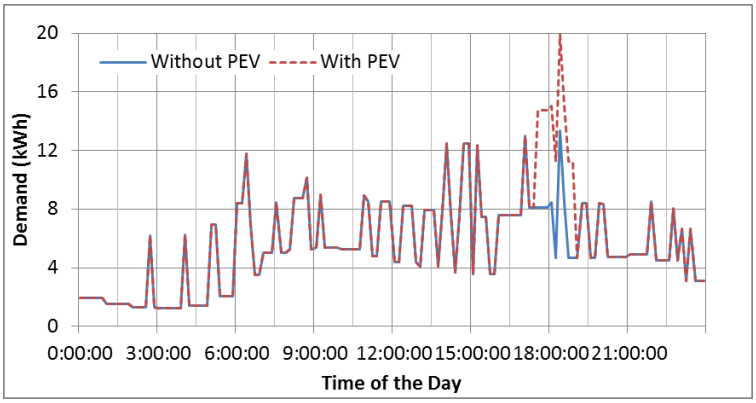


Figure. 3.6: Daily single-household load profile with and without PEV uncontrolled charging

3.3.4 Single-Household Load Profile with V2H and DR

This section analyses the validity of the peak-shaving strategy proposed in this work. In this part, for the same setup given in subsection 3.3.3, demand limit, D_L is fixed at 12.0 kW. Figure 3.7 shows a comparison between single-household load profiles before and after applying the EMS strategy proposed in this work. Since E_L is still greater than SOC_2 after discharging the PEV, the battery was not charged during this day.

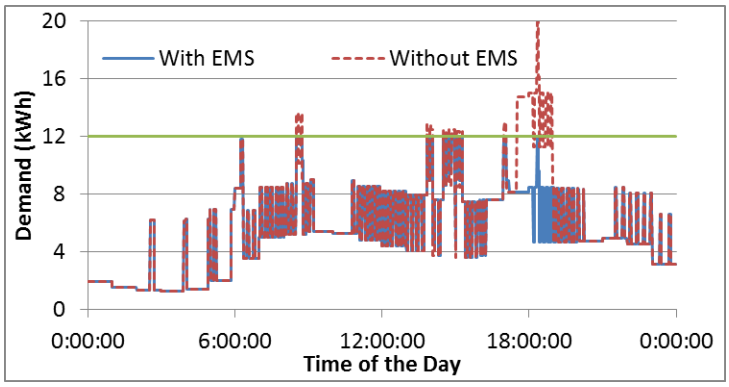


Figure. 3.7: Daily single-household load profile with V2H and DR without charging

3.3.5 Single-Household Load Profile with DR and V2H

Based on atmospheric conditions, several parameters could change daily: utility requirements, consumer driving pattern, and consumer preference. To study this variability a second setting was used with the following parameter: traveling distance of 48 miles; therefore,

only 8.64 kWh of energy is left in the battery (E_L = 0.36) when the PEV completes its last trip of the day. Figure. 3.8 shows the total household loading for both cases. From 5:30 p.m. to 6:19 p.m., according to the control model, $E_L < SOC_1$ and $P_c(t) + P_u(t) < D_L$; therefore, Scenario 1 is activated. From 6:19 p.m. to 6:23 p.m., $E_L \geq SOC_2$ and $P_c(t) + P_u(t) > D_L$; therefore, Scenario 1 is activated. After 6:23 p.m., since $SOC_1 < E_L < SOC_2$ and $P_c(t) + P_u(t) < D_L$, Scenario 1 is activated until $EL = SOC = 1$, or about 8:36 p.m..

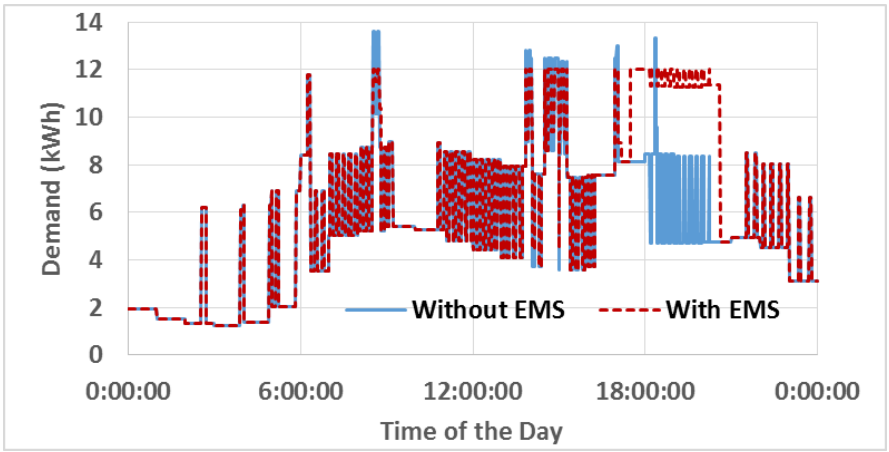


Figure. 3.8: Daily single-household load profile with V2H and DR

CHAPTER 4

ECONOMIC OPERATION MODEL AT DISTRIBUTION LEVEL

In this chapter, an economic model is proposed to help both utility companies and customers maximize their benefits. From a technical aspect, demand response and vehicle-to-grid are implemented as a single entity to compensate each other's disadvantages under an aggregator to reduce the peak loading, which is presented in Chapter 3. In such a case, the V2H model could minimize the negative impacts of DR, such as comfort and convenience losses, on customers, and DR could help the EV by reducing battery degradation caused by V2H. From an economical aspect, this model could help aggregators reduce the difference between forecasted load demand and real-time load demand so that risks on the energy market could be minimized significantly. From a customer's point of view, this model could help reduce utility bills without sacrificing comfort and convenience knowingly. For utility companies or system operators, this model could avoid system overloading and delay main infrastructure upgrades.

4.1 Framework

To implement the new economic model at the distribution level, smart grid technologies must be applied. Since demand limit $DL_A(t)$ for a particular neighborhood will be sent to the aggregator every day, two-way communication between utility companies and aggregators is necessary. To successfully implement V2H and DR to each single household by aggregators, every household needs to have an advanced metering infrastructure (AMI), controllable loads, and a controllable EV charging station. The framework for this new model is shown in Figure 4.1.

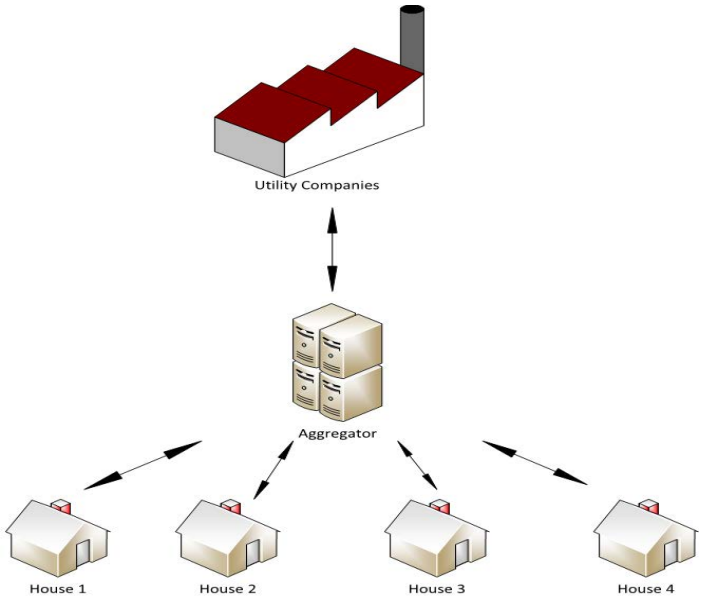


Figure 4.1: Framework of new model

4.2 Process

In this study, aggregators are considered as an aggregated isolated control center between utility companies and customers. All information and data will be sent from both utilities and customers to aggregators. Utility companies will send forecasted demand $DL_A(t)$ a day ahead of time.

To forecast demand at time period t to different households is a challenging task because a single-household load profile is extremely fluctuating. Therefore, the predicted demand will be assigned to aggregators. A new concept called the oscillation factor will be applied in this process and is defined in equation (4.1). The goal of this process is to minimize the difference between forecasting demand and real-time demand. To do this, aggregators must have direct control over all controllable appliances. A controllable factor (CF) for each household at time t is defined as their willingness to participate in the demand response scheme. The more that CF customers are willing to share, the more incentives they will receive.

$$\min_{P_i(t)} \quad OF = \left(\frac{\sum_{i=1}^{N} P_i(t) - DL_A(t)}{DL_A(t)} \right)^2 \tag{4.1}$$

The power demand of each household at a given time $DL_i(t)$ depends on several factors: daily routine, house size, and number of individuals living in the household, etc. To appropriately apply V2H and/or DR to different households under the same aggregator, it is necessary to normalize their demand limitation. In this paper, $R_i(t)$ in equation (4.2) is used as the number indicating the ratio between real-time power consumption and demand limit at time period t.

$$R_i(t) = \frac{P_i(t)}{DL_i(t)} \tag{4.2}$$

Based on the demand response model developed in previous work [18], if $P_A(t) > DL_A(t)$, then the aggregator will find the maximum $R_i(t)$ and apply V2H and/or DR to reduce the power consumption until the oscillation factor (OF) value is acceptable. If $P_A(t) < DL_A(t)$, then the aggregator would activate G2V and/or find the maximum CF, and run the appropriate controllable loads at time *t* until OF is acceptable.

All data from the utility company and customers will be collected by the aggregator of a particular neighbourhood. Forecasted demand for that particular neighbourhood at the time interval *t* for the second day will be sent to the aggregator a day ahead. In order to minimize the difference between the forecasted demand and real-time demand, the aggregator must follow the process shown in Figure 4.2.

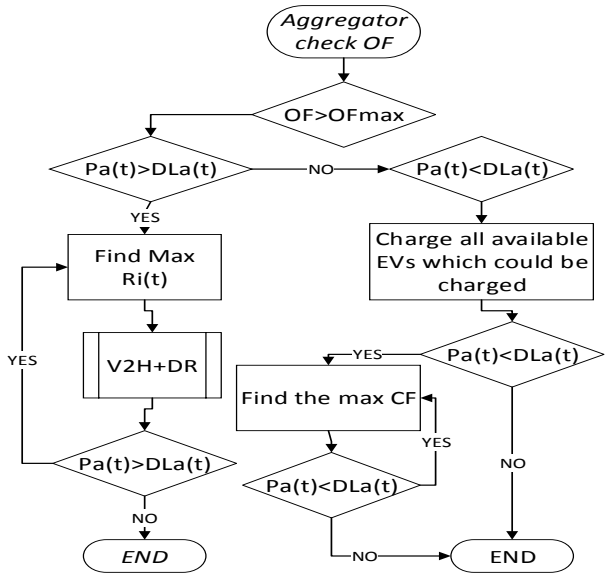


Figure 4.2: Flow chart of aggregator process

If the aggregator determines that the OF exceeds the OF_{max}, then the aggregator will take steps as follows:

- Step 1: The aggregator will check the OF based on the forecasted demand and real-time demand. If the OF exceeds the acceptable range OF_{max}, then the aggregator will check whether the real-time demand $P_A(t)$ is greater or less than the forecasted demand $DL_A(t)$.
- Step 2: If $P_A(t) > DL_A(t)$, then the aggregator will locate the household that has the maximum $R_i(t)$. Once Max $\{ R_i(t) \}$ is located, the aggregator will apply V2H and/or DR based on the algorithms proposed in previous work [18] to make $R_i(t) \leqslant 1$ until $OF \leqslant OF_{max}$.
- Step 3: If $P_A(t) < DL_A(t)$, the aggregator will check all available EVs, apply G2V in this neighborhood, and ensure that $OF \leq OF_{max}$.
- Step 4: If $P_A(t) < DL_A(t)$ after applying G2V, the aggregator will find the household that has the highest CF in order to operate appropriate controllable loads for it based on the customers' presetting. After applying DR to the most flexible household, if $P_A(t)$ is still less

than $DL_A(t)$, then the aggregator will apply DR to the second household that has the second highest CF until $OF \leq OF_{max}$.

Table 3 shows the ranking of controllable loads as a single-household example. Here, the water heater (WH) is the most flexible controllable load, whereby the customer could set the maximum acceptable temperature during DR application. During the critical time, aggregator will start operating the water heater to the maximum acceptable temperature. If $P_A(t)$ is still less than $DL_A(t)$, then the air conditioner (AC) will be turned on automatically. In this paper, the specific ranking lists are not analyzed.

TABLE 4.1

RANKING OF CONTROLLABLE LOADS

Ranking	**Controllable Loads**	**Flexibility**
1	WH	Water temperature ≤150°F
2	AC	Room temperature ≥70°F

4.3 Results

Simulations were run for 10, 30, 50, and 100 houses, and daily power consumption and oscillation factors for different households were plotted. Forecasting demand $DL_A(t)$ was assumed, based on real-time power consumption. However, forecasted demand could be set by power system utility companies in the real world. Since the current forecasting technique could make the hourly accuracy for large number of households close to 1.5–2% [7], forecasting demands were assumed based on this range. Also, OF_{max} was assumed to be 3×10^{-4} in this study and is shown as a red line in the graphs that follow.

4.3.1 10 Households

At the residential level, current forecasting techniques are not able to forecast demand load with 1.5–2% accuracy for a small number of households. Therefore, for the 10-household simulation, the forecasting accuracy was assumed to be 10–15%. Figures 4.3 to 4.5 show the power demand of 10, 30 and 100 households, respectively, in a summer day with different accuracy.

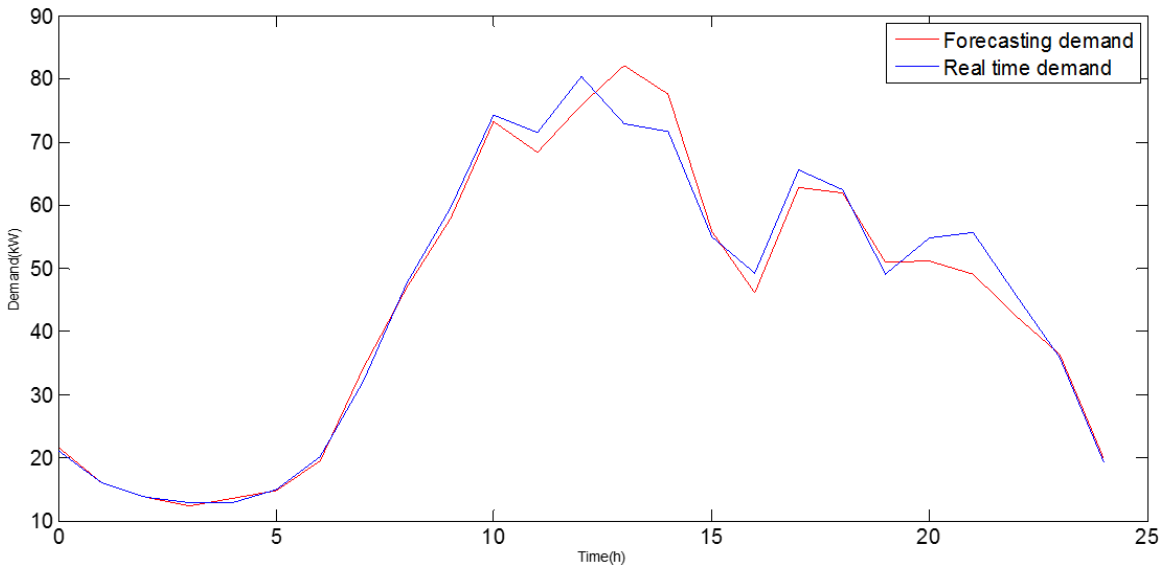


Figure 4.3: 10-house demand in a summer day

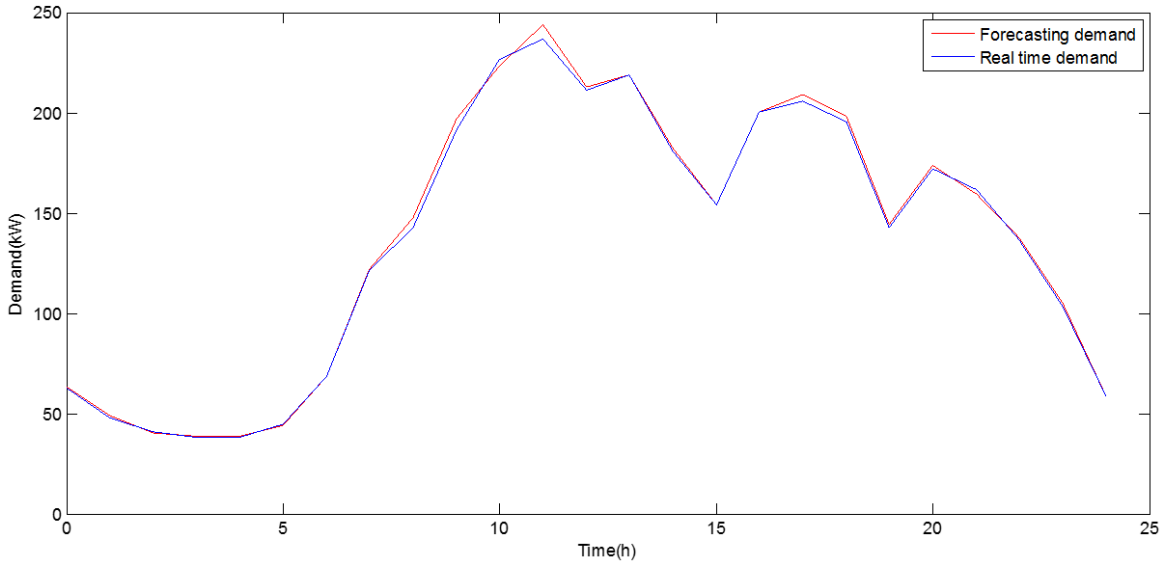


Figure 4.4: 30-house demand in a summer day

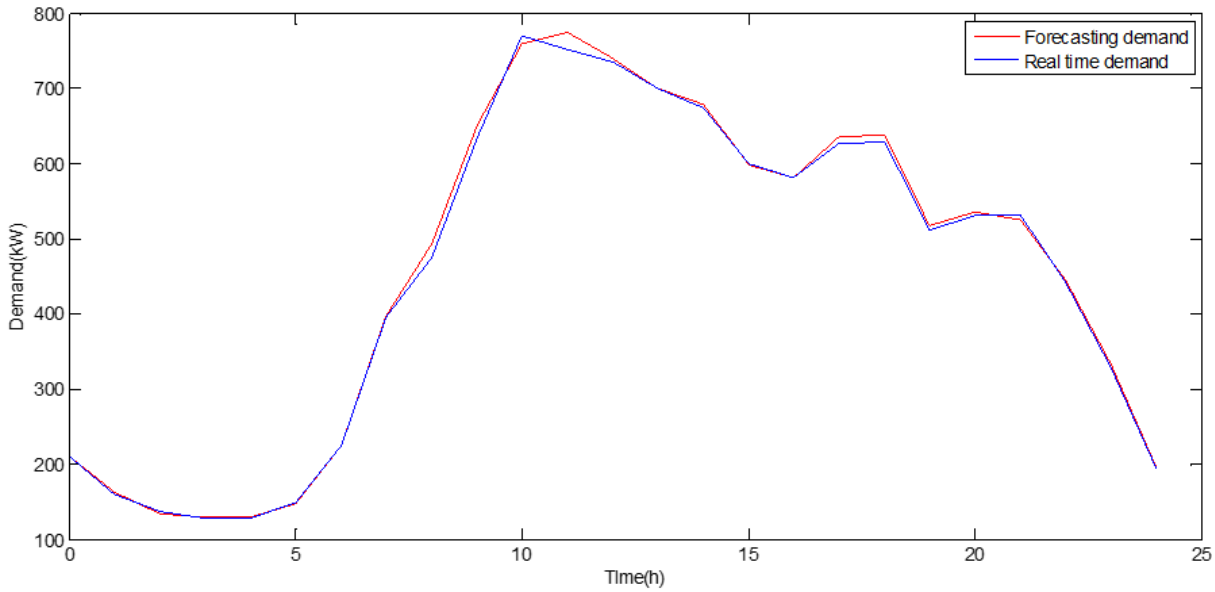


Figure 4.5: 100-house demand in a summer day

Figure 4.6 shows the oscillation factor before and after applying the demand response. For a small number of households, OFs are much higher than the maximum. To reduce the difference, DR, V2H, and G2V must be applied frequently. Therefore, it is necessary to implement the aggregator with a large number of households in order to make this model more efficient and feasible.

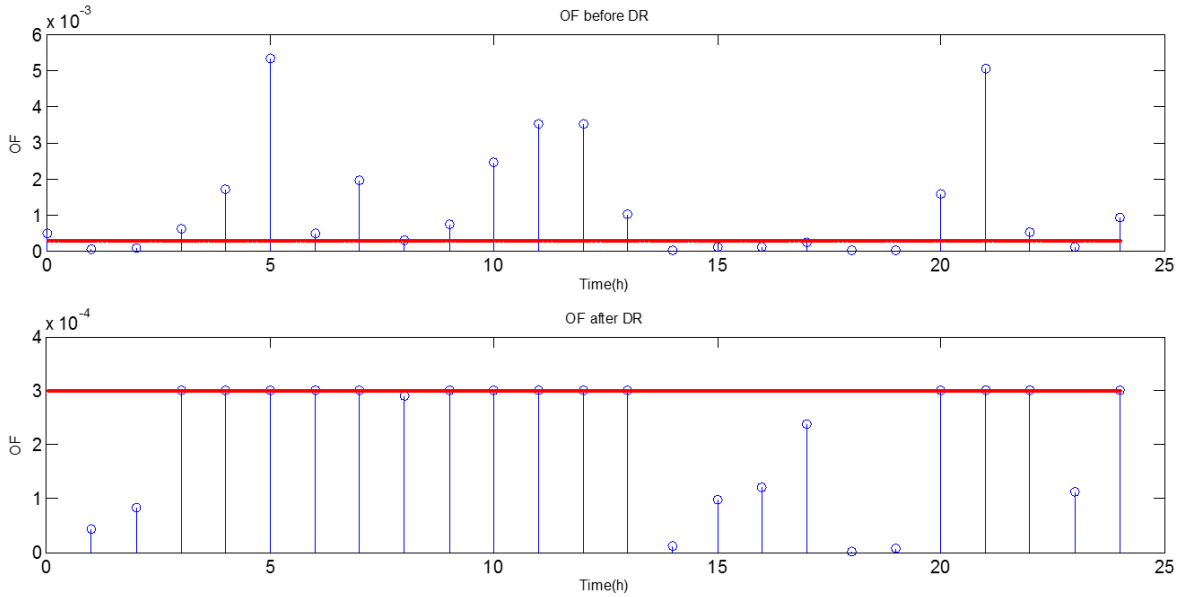


Figure 4.6: Daily oscillation factors for 10 households before and after DR

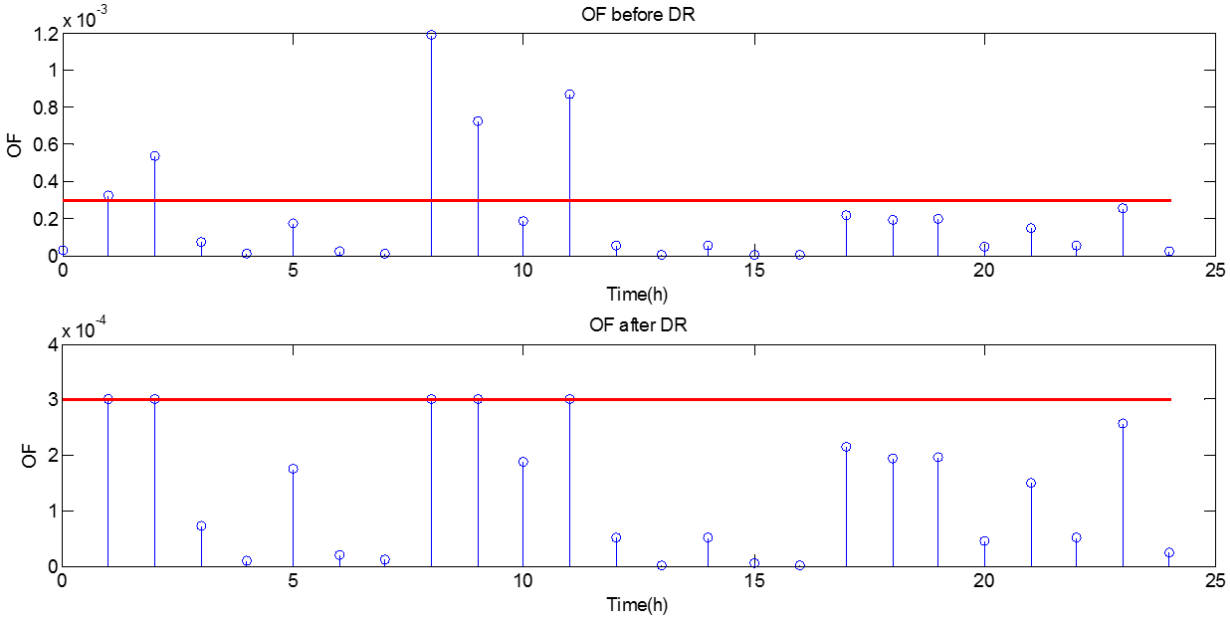


Figure 4.7: Daily oscillation factors for 30 households before and after DR

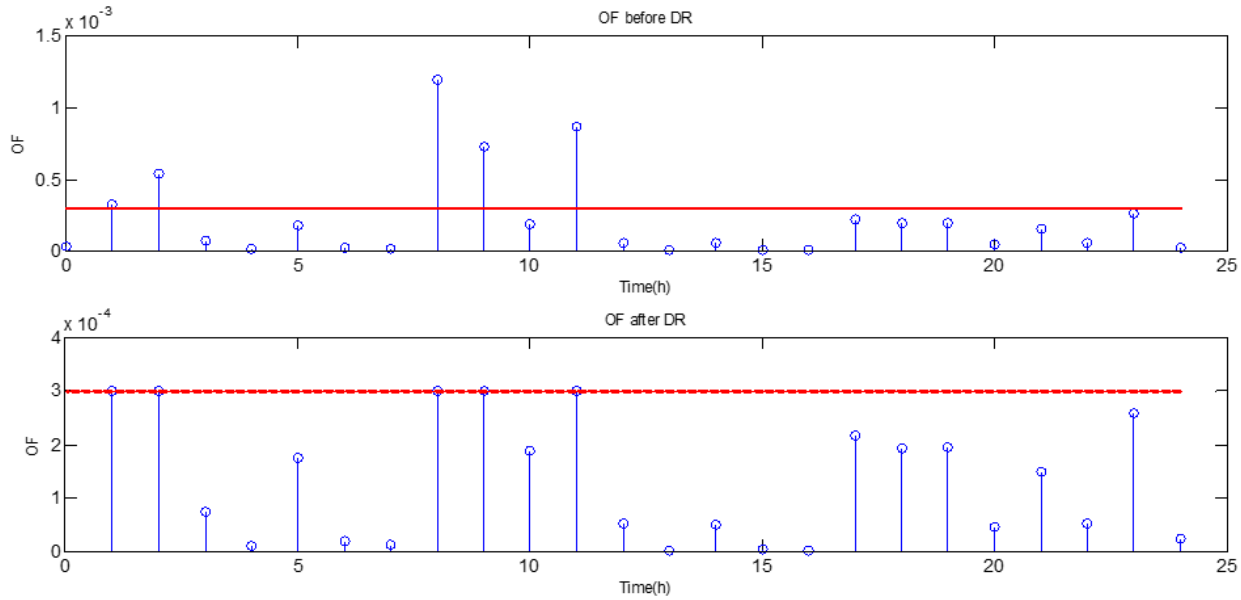


Figure 4.8: Daily oscillation factors for 100 households before and after DR

Comparing Figures 4.6 to 4.8 clearly show OFs close to the maximum, which means more households with higher demand could make this model more efficient and feasible. When the aggregator receives the signal that $OF > OF_{max}$, it checks the power consumption with the forecasted demand and directly sends a control signal to the controllable loads based on the scheme

mentioned earlier. Figures 4.6 to 4.8 show that after applying DR, V2H, and G2V, the oscillation factor would be close to the maximum, which means that by applying this model, real-time demand will be close to the forecasting demand.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

5.1 Conclusion

In this report, two smart grid results were presented. As two new technologies that have been studied for a while in power systems, both demand response and vehicle-to-grid have many advantages to making the power systems more efficient, reliable, and stable; therefore, numerous studies have been undertaken to analyze and develop them. Nevertheless, due to the fact that DR and V2G applications have unavoidable disadvantages, such as customer comfort and cost issues, in this thesis, they were combined as one entity to help each other compensate for the disadvantages. By applying this technology, the customer comfort level can be maximized, and the battery degradation of electric vehicles caused by charging and discharging can be minimized.

In the second part of this work, DR and V2H were applied as an entity for each household, and a new model was developed to help utility companies forecast the demand load more accurately using a direct load-control strategy. The problem for direct load control is that utility companies are challenged to control all household appliances at the same time. So, in this work, an aggregator was used to make this work more feasible. With the new model, the difference between forecasted demand and real-time demand should be minimized significantly.

5.2 Future Work

In this thesis, only 10, 30, and 100 households were simulated. Here, the control factor for each household at time t was assumed to be 1, which means all customers are willing to participate in this program, and all controllable loads, including electric vehicles in each house, are fully controllable by the aggregator. However, in future work to make this model more feasible, the following are suggested:

- Consider different CFs and different EV brands and penetration with a different number of households.
- Evaluate the economic value of this model with the power system market.
- Consider renewable energy resources, such as solar, wind, and hydro power, in this model.

REFERENCES

REFERENCES

[1] "Assessment of demand response and advanced metering," Federal Energy Regulatory Commission, Feb. 2011, URL: http://www.ferc.gov/legal/staff-reports/2010-dr-report.pdf [cited May 16, 2013]

[2] S. Shao, M. Pipattanasomporn, and S. Rahman, "Demand response as a load shaping tool in an intelligent grid with electric vehicles," *IEEE Trans. Smart Grid*, to be published.

[3] M. Yilmaz and P. Krein, "Review of the impact of vehicle-to-grid technologies on distribution systems and utility interfaces," *IEEE Trans. Power Electronics*, vol. 28, no. 12, Dec. 2013, pp. 5673–5689.

[4] M. Duvall and E. Knipping, "Environmental assessment of plug-in hybrid electric vehicles," Nationwide Greenhouse Gas Emissions, EPRI and NRDC, Final Report, 2007, pp. 1–56.

[5] R. Liu, L. Dow, and E. Liu, "A survey of PEV impacts on electric utilities," in *Proc. IEEE 2nd PES Innovative Smart Grid Technology Conference*, Jan. 2011, pp. 1–8.

[6] C. Roe et al., "Power system level impacts of PHEVs," in *Proc. 42nd HI Int. Conf. Syst. Sci.*, 2009, pp. 1–10.

[7] Daniel Kirschen and Goran Strbac, "Introduction" and "Markets for electrical energy," in *Fundamentals of Power System Economics*, J. Wiley & Sons, Chichester, UK, 2004.

[8] R. Moreno et al., "A framework for energy aggregator model," in *Power Electronics and Power Quality Applications (PEPQA)*, Bogota, Columbia, July 6–7, 2013.

[9] S. Sun et al., "Distributed regulation allocation with aggregator coordinated electric vehicles," in *Smart Grid Communications IEEE Int. Conf.,* Vancouver, BC, Oct. 21–24, 2013, pp. 13–18.

[10] L. Gkatzikis et al., "The role of aggregators in smart grid demand response markets," *IEEE J. Select. Areas Commun.*, vol., 31, July 2013, pp. 1247–1257.

[11] A. Hoke et al., "Maximizing lithium ion vehicle battery life through optimized partial charging," *2013 IEEE PES Innovative Smart Grid Technologies (ISGT)*, Feb. 24–27, 2013, pp. 1–5.

[12] Z. Wang and S.Wang, "Grid power peak shaving and valley filling using vehicle-to-grid systems," *IEEE Trans. Power Delivery*, vol. 28, no. 3, July 2013, pp. 1822–1829,.

[13] V. Aravinthan, V. Namboodiri, S. Sunku, and W. Jewell, "Wireless AMI application and security for controlled home area networks," *In Proc. 2011 IEEE PES General Meeting*, Detroit, MI, 2011.

[14] C. Jin, J. Tang, and P. Ghosh, "Optimizing electric vehicle charging: A customer's perspective," *IEEE Transactions on Vehicular Technology*, early access article 2013, p. 99.

[15] S. Schey, "Q2 report 2013 EV project," Phoenix, AZ, URL: www.theevproject.com/cms-assets/documents/127233-901153.q2-2013-rpt.pdf [cited July 22, 2013].

[16] Nissan Leaf, URL: http://www.nissanusa.com/electriccars/leaf/versionspecs/ [cited May 16, 2013].

[17] GridLab-D, URL: http://www.gridlabd.org/ [cited August 20, 2013].

[18] L. Zhao and V. Aravinthan. "Strategies of residential peak shaving with integration of demand response and V2H," *Proc. 5th IEEE PES Asia Pacific Power and Energy Conf.*, Hong Kong, 2013.