DISCRETE EVENT-DRIVEN APPROACH FOR ELECTRIC VEHICLE CHARGING AND UNCERTAINTY EVALUATION

A Thesis By

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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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DEDICATION

To my beloved parents, wife and daughters for their continuous love, support, and patience—without my extraordinary family this would not be possible—and to my father, I am doing this for you

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I would like to express my deepest and sincere gratitude to my advisor Dr. Visvakumar Aravinthan for his guidance and support throughout the entire graduate process, and especially for being a great mentor academically and personally. I am very thankful because you introduced me to research and encouraged me to do research.

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ABSTRACT

Reduction of greenhouse gas (GHG) emission is gaining momentum in recent years, and the transportation industry is one of the major contributors. Electric vehicles are proven to have very low greenhouse gas emissions in comparison to internal combustion engine (ICE) vehicles. In addition, the electrical vehicle (EV) market is growing rapidly, and the charging of EVs will affect the power grid because charging a single electric vehicle is estimated to consume as much power as an average household for an entire day.

This thesis modeled the charging of electric vehicles at the residential level and proposed different controller models for charging EVs in order to minimize the impact of their penetration. In addition, this thesis modeled and evaluated the uncertainty factor for load due to the EV penetration.

This work resulted in significant improvement to the charging process using the proposed controllers and a significant reduction in the uncertainty factor of load forecasting caused by EV charging on the secondary side distribution transformer and substation.

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LIST OF ABBREVIATIONS

BEV	Battery Electric Vehicle
DES	Discrete Event System
EV	Electric Vehicle
GHG	Greenhouse Gas
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
PHEV	Plug-in Hybrid Electric Vehicle
TOU	Time of Use
TSMC	Time Sequential Monte Carlo
V2G	Vehicle to Grid

CHAPTER 1

INTRODUCTION

Reduction of greenhouse gas (GHG) emissions is gaining momentum in recent years, and the transportation industry is one of its major contributors 0. On the other hand, electric vehicles (EVs) are proven to reduce GHG emission in comparison to conventional internal combustion engine (ICE) vehicles 0. In addition, the number of EVs is expected to grow in the near future due to the many benefits, which will be described in Section 1.2.

The impact of EV penetration (without controlling the charging of EVs) as will described in Section 2.2, is significant and could lead to damaging critical power grid equipment. With the smart grid initiative and discussion, the controllability of charging EVs is feasible. This mainly due to the communication infrastructure required for the smart grid.

Regardless, EVs reduce GHG emissions and reduce the dependency on the fossil fuel, EVs has the potential to increase the average energy and power consumption at residential level significantly. It is estimated that charging an EV using power grid to completely charge its battery is an equivalent of doubling the consumption of power of an average house [2], which means that the current power grid is not capable of supplying the additional demand caused by the penetration of EVs.

Based on survey results presented by Mohseni and Stevie [3], EVs will be in clusters, which would be in certain geographical area creating a locational importance of EVs charging. This is because people who tend to buy EVs usually prefer to live in certain neighborhoods, and according to the survey, these neighborhoods are usually upscale and already have a high demand profile compared to other neighborhoods.

Adding the demand of EVs to the equation would result in overloading and possibly damaging secondary distribution equipment, in the case of uncontrolled EV charging. Controlling EV charging at the residential level is needed, since the power grid will not be able to satisfy the demand of charging additional EVs during the peak time of power consumption (duration of time where the average power consumed by consumers is at its peak).

1.1 Electric Power Grid

The electric power grid is divided into three parts [4]:

- Generation
- Transmission
- Distribution

These parts are defined as follows [5]: The generation system is where the conversion from other forms of power sources (gas, coal, nuclear, wind, etc.) to electric power occurs. The transmission system is the connection between generation and distribution (delivering the power from generators to consumers). The distribution system is where the power generated from the generators and transmitted through the transmission system is distributed to consumers and is usually the most complex part of the electric power grid and causes 80% of power disturbances [6].

The electric power grid is a network of very complex connections among all three sectors (generation, transmission, and distribution). The complexity of a power grid comes from its massive size [5] [6]. Since, the power grid is complex and massive, any changes—even small changes—happening in one part of the power grid could lead to catastrophic failure in the entire system. This is why the penetration of EVs without controlling their charging is a concerning matter.

1.2 Electric Vehicles

Electric vehicles (EVs) are vehicle that uses electricity as main or one of the sources of energy to drive the vehicle [7]. There are three main types of EVs [8]:

- Battery electric vehicle (BEV) is an EV that runs entirely on battery and required charging from external power source.
- Plug-in hybrid electric vehicle (PHEV) is an EV that has two power sources, which are battery and conventional ICE. It runs on battery that charged using external power source and if needed it will use the ICE.
- Hybrid electric vehicle (HEV) it is similar to PHEV however, it does not charge the battery using external power source and it charges the battery by the energy generated by regenerative braking.

Three major concerns have been raised by Boulanger et al. [7] about EVs: the expensive initial cost of the battery used in EV vehicles and the high cost of the technology itself. Another concern is that EVs take longer to fully recharge, which may take hours, in comparison to conventional ICE vehicles, which take only minutes to fill the gas tank. Also, the driving range of an EV is a concern and is directly related to the previous problem whereby EV owners cannot recharge their vehicles fast enough to be able to drive them for long distances.

On the other hand, EVs have advantages, including reduction of GHG emissions in comparison to ICE vehicles 0 and lower operational cost (fuel cost) compared to ICE vehicles, if the cost of electricity is compared to the cost of fuel for the same driving distance [10].

The three standardized EV charging levels under standard SAE J1772 [9] are defined in Table 1.

TABLE 1

TYPES OF EV CHARGING LEVELS

Level	Setting	Supply Voltage (V AC)	Max. Current (A)
1	Residential	120	20
2	Residential	208-240	20
	Commercial	208-240	80
3	Commercial	208 or 480	400

The work in this thesis only considered EVs that require charging from an external power source (power grid) because the other types that do not require an external power source do not impact the power grid directly. In addition, residential charging Level 2 is considered in this work because commercial charging stations are built with the expectation that they would be able to accommodate a large number of EVs.

1.3 Discrete Event System

Discrete Event System (DES) is a system modeling and controlling method based on the idea of event-driven systems, whereby the events control the transition between states [11]. A typical DES consists of four main parts:

- Initial state (starting point of the model).
- Marked state/s (desired output from the controller).
- State/s that represent(s) behavior of the system.
- Event/s that cause(s) the transition from one state to another.

The visual representation of a DES is called an automaton where it has the state/s (initial, marked, other) with the connection/s (event/s) between states as shown in Figure 1.

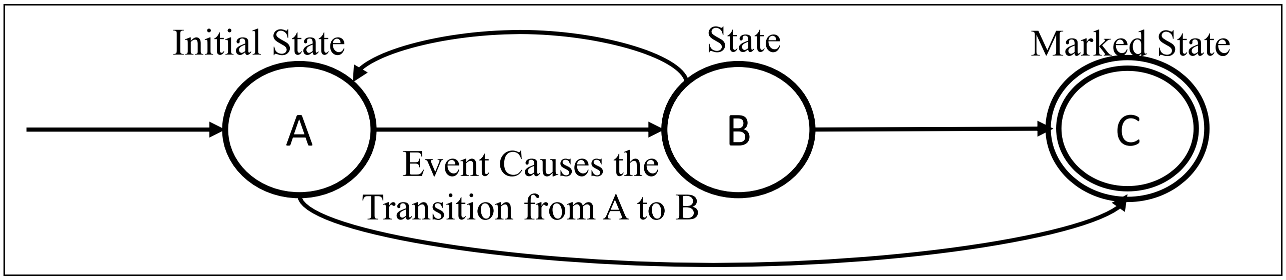

Figure 1. Typical automaton

A DES is used in this research because it is an event based modeling and controlling technique and the charging of an EV is event-based process. For example, the arrival of an EV at home for charging state would be considered as an event that triggers the controller to decide on charging the EV or not based on the predefined controller's parameters.

1.4 Time Sequential Monte Carlo Simulation

Time Sequential Monte Carlo Simulation (TSMC) is a common tool that is used to analyze systems when a deterministic system has stochastic inputs [12].

Figure 2 shows the Monte Carlo simulation process, where $a_1, a_2, a_3, \dots \dots, a_n$ are the random inputs to the system which could be any probability density function. Typically, historic data is used to model input probability distribution functions. y is the random output of the system.

Since TSMC uses the stochastic probability density input functions, the simulation has to be run for sufficient numbers of trials to have accurate estimation of the output. The decision of the accuracy of the estimation in TSMC is based on either a predefined number of runs (trials) or predefined error range.

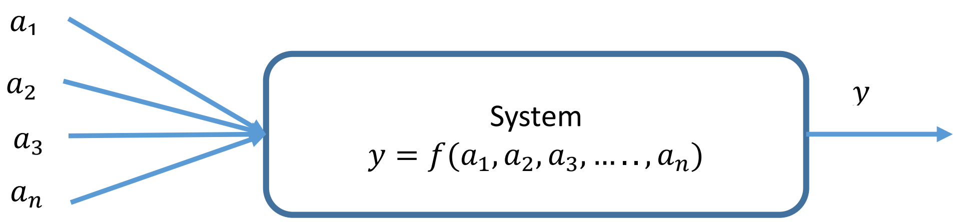

Figure 2. Monte Carlo process

TSMC is used in this work because TSMC has the ability to convert the randomness of the inputs' parameters of the simulation which are (arrival time of EVs, departure time of EVs, and state of charge left at the time of arrival) to acceptable (very small variation) estimated output if the simulation was done for a sufficient number of trials.

1.5 Contributions of This Work

EVs charging management is necessary for maintaining the reliability of the electric power grid. Many and different approaches were introduced by researchers to manage and control the charging process of EVs. However, not many took the approach of defining the charging process as an event as this research did to achieve the optimal controller.

The contributions of this work are summarized below:

- Developed a model for the charging process of EVs using DES and validated the accuracy of the model.
- Developed different DES control models that reduced the overall average power consumption caused by EVs charging.
- Developed a relationship for determining the uncertainty associated with EV charging at a given time.

Based on the proposed models the following analyzed:

- Reduction of the impact caused by EVs charging on the electric power grid.
- Reduction of the uncertainty factor.

1.6 Organization of the Thesis

Chapter 1 provides an introduction to this thesis. Chapter 2 summarizes previous studies related to this work, in order to justify the reasoning behind introducing these new techniques. Chapter 3 describes modeling EVs availability, charge left, and the uncertainty factor. Chapter 4 examines the proposed discrete event system models and their mathematical formulations. Chapter 5 presents the simulation approaches, numerical results, and analysis. Chapter 6 denotes the conclusion and discuss the future direction of this research.

CHAPTER 2

LITERATURE REVIEW

This chapter is introduces the different approaches and studies of modeling and controlling EVs charging in addition to studying the impact of EV penetration done by the researchers in this field. This chapter is divided in to two sections, which are impact of EVs penetration and EVs charging modeling and controlling.

2.1 EV Charging Modeling and Controlling

Luo and Chan [13] proposed a real-time scheduling of electric vehicle charging in low-voltage residential areas to minimize power losses and improve voltage levels. Voltage drop and power losses increased with the penetration of EVs charging at the residential-level feeder, and required coordinated and controlled charging to minimize impact on the distribution system.

Bhattarai et al. [14] built a smaller-scale smart power grid to test various smart grid applications such as demand response, real-time pricing, and congestion management. The coordination of EV penetration was simulated and controlled to find the optimal charging process. The limitation of the work is that it cannot be applied in the near future because of the limitation of the smart grid infrastructure due to lack of metering and communication infrastructures.

Ortega-Vazquez et al. [15] proposed an aggregator to oversee the charging and discharging of EVs and vehicle to grid (V2G) technology. The limitations of this work are that the aggregator cannot accurately or with bounded limited error predict the EV battery portfolio and the daily prediction of daily energy requirement of EVs. Another limitation is the assumption of EV capability of satisfying the energy requirement at each secluded period.

Shao et al. [9] proposed a load-shaping demand response for EVs and household appliances. The weakness of their work is the assumption that the demand limit of each house is fixed at a certain value.

Steen et al. [16] proposed a demographical data collection scenario where they control the charging of EVs based on the data collected. However, the drawback here is the extensive data needed for the proposed method to work, including consumer willingness to participate in providing the data.

Cao et al. [17] proposed a time of use (TOU) electricity pricing to optimize the charging of EVs. The drawback of this work is that the TOU pricing they used is constant through large periods and does not take into consideration the rapid changes in power demand.

Stüd i et al. [18] developed a Markov chain-based control scheme to manage EV charging. An automaton was developed to represent the behavior of EVs that would manage the charging of EVs based on the system congestion signal by switching ON/OFF the charging of an EV. The decision of whether or not to charge an EV was based on the capacity of the grid and the power consumption of each EV. Gaming theory was used to manage the charging decision of multiple EVs.

2.2 Impact of EV Penetration

Argade et al. [19] studied the impact of EV charging on the loss of life of distribution-level components, focusing on the residential level. This research also provided a probabilistic function representing the arrival time of EVs and the state of charge at that time. Their work studied the impact of EV charging but did not propose changing the management approach in order to reduce the impact of EV charging.

Hilshey et al. [20] studied the impact of EV penetration and wind energy generation systems impact on the reliability of the power system in addition to the cost of power consumption from consumer side. Impacts of both (EVs and Wind generation) were reduced and the fluctuation of power generation form wind generators are minimized by using EVs as storage units.

Wu et al. [21] studied the impact of EVs penetration and wind energy generation systems impact on the reliability of the power system in addition to the cost of power consumption from consumer side. Impacts of both (EVs and Wind generation) were reduced and the fluctuation of power generation form wind generators are minimized by using EVs as storage units.

Verzijlbergh et al. [22] studied the impact of uncontrolled and controlled EV charging on the power grid distribution components and found that in uncontrolled charging the impact of overloading the components (need replacement) is almost doubled in comparison to controlled charging. In addition, the controlled charging reduced the energy losses by about 20% comparing to uncontrolled charging.

Kazerooni and Kar [23] studied the effects of EV charging on the ageing of distribution transformers with large-scale application of EVs. The ability of the current system to accommodate the large-scale penetration of EVs studied and founded to be that the current system as is cannot accommodate large-scale EV penetration.

2.3 Uncertainty Modeling

Xu et al. [24] studied wind power output uncertainty effects on minimizing the electricity payment cost. The work showed that the randomness of wind power output is the major contributors to uncertainty of cost minimization. They have developed a probabilistic approach that would help consumers predicting the electricity cost based on the random behavior of wind power. The drawback of the work is that they, did not quantify uncertainty factor and did show how their proposed approach of minimizing the cost reduced the uncertainty factor.

Sankararaman et al. [25] studied the uncertainty quantification in remaining useful life estimate of components used in engineering applications to assets decision-making risk management. They suggested that there are four major contributors to uncertainty in any system which are:

- Present uncertainty (being able to estimate the current condition accurately).
- Future uncertainty is the most contributor to uncertainty because future is unknown and difficult to predict.
- Modeling uncertainty is based physics and it cannot predict the true response of the system to operation conditions.
- The combined contribution for all mentioned above uncertainty factors is difficult to predict.

Tabone and Callaway [26] showed that the usage of photovoltaic generation as distributed generation would increase the uncertainty of the power output of the system because photovoltaic generation output is difficult to predict. The difficulty of prediction the output of photovoltaic generation comes from the large number of factors that paly major role in the photovoltaic generation power output such as weather. In addition, they developed relationship to quantify uncertainty factor for a single photovoltaic. Furthermore, they developed relationship to quantify the uncertainty factor for the whole photovoltaic system taking in consideration the correlation between all photovoltaic generation units.

CHAPTER 3

EV AVAILABILITY AND UNCERTAINTY MODELING

In this chapter, the probabilistic distribution functions for the parameters of the controller are founded. The arrival time of EVs at home, departure time of EVs, and charge left in the battery of EVs at the time of arrival were fitted into the appropriate probability density functions.

In addition, the uncertainty function of the hourly demand of EVs are determined to evaluate the effectiveness of the proposed DES models in reducing the uncertainty factor of load forecasting caused by EV penetration.

Argade et al. [19] presented a probabilistic model for EV arrival time and the charge left in the battery when it arrives home. The end time of the last trip of the day was modeled as a normal distribution and the charge left was modeled as the lognormal distribution [19].

The data provided by Zhou and Vyas [27] were fitted to the appropriate probability distribution functions using MATLAB Simulink program tools. After fitting the data to the right destructions, the results were checked again using MATLAB Simulink tools for verifying validity.

3.1 Arrival Time of Electric Vehicles

Argade et al. [19] founded that the probability density function of the arrival time of an EV $f_a(t)$ is

$$f_a(t) = 5.00 + \mathcal{N}(13.2\,, 3.35) \tag{3.1}$$

Using the same approach by fitting the available data for the arrival times of more than 250,000 data point provided by Zhou and Vyas [27], $f_a(t)$ founded to be normally distributed density function with a five hour shift horizontally with a mean (μ_a) of 11.83 and standard deviation (σ_a) of 3.68:

$$f_a(t) = 5.00 + \mathcal{N}(11.83\,, 3.68) \tag{3.2}$$

3.2 Departure Time of Electric Vehicles

Similarly, to the arrival time computation using the same data provided by Zhou and Vyas [27], the departure time of EVs can be represented by the probability density function $f_d(t)$ as

$$f_d(t) = \log\mathcal{N}(6.3814\,, 0.3474) \tag{3.3}$$

$f_d(t)$ is lognormal probability density function with mean (μ_d) of 6.3814 and standard deviation (σ_d) of 0.3474.

3.3 Charge Left in Electric Vehicle at Time of Arrival

For the charge left in an EV at arrival ($g(\mathcal{C})$), Argade et al. [19] founded it to be lognormal probability density distribution function with mean ($\mu_\mathcal{C}$) of 3.78 and standard deviation ($\sigma_\mathcal{C}$) of 0.58209.

$$g(\mathcal{C}) = \log\mathcal{N}(3.78{,}0.58209) \tag{3.4}$$

$g(\mathcal{C})$ shown in equation (3.4) would be used in this research.

3.4 Uncertainty Modeling

Uncertainty in this work is defined as the effect of EVs charging randomness on load forecasting by utilities. The predictability of EVs load is difficult because it is random. Figure 3 and Figure 4 show the same base load curves (red continuous line) with two different added EVs load (blue dash line). Each EV has different load profile, which increase the complexity of load forecasting. It is very clear that EVs load is hard to predict which causes uncertainty in forecasting (predict) next day load profile for utilities.

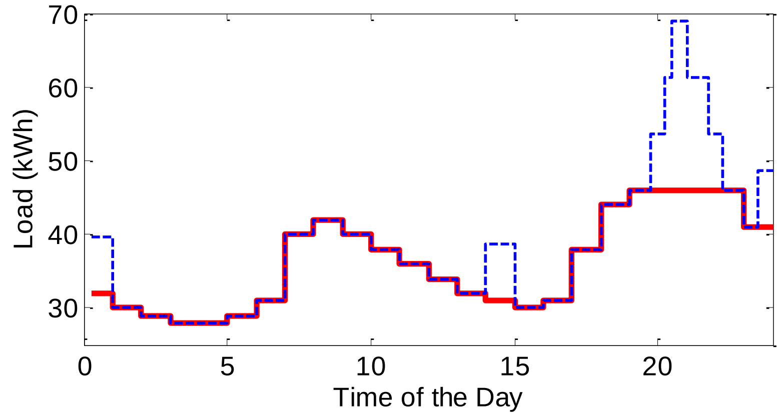

Figure 3. Base load curve with day 1 EVs penetration load

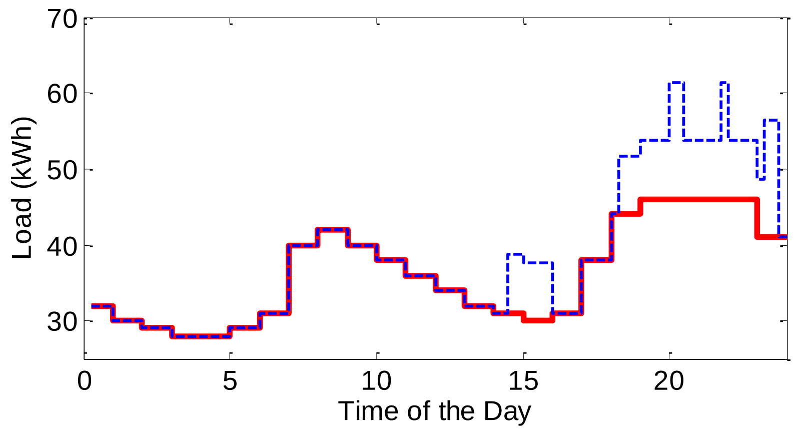

Figure 4. Base load curve with day 2 EVs penetration load

Uncertainty in forecasting the load due to the penetration of EVs is a concerning issue, especially, from utilities' point of view. Demand forecasting is affected by the behavior of the consumers and their usage of electricity. Furthermore, the focus of this work is to evaluate the uncertainty of demand forecasting due EVs penetration.

As mentioned previously, the uncertainty that is based on demand due to EVs charging is difficult to quantify because the charging of EVs is based on the consumers behavior and the time they arrive home to charge their EVs. For example, EV owner arrived home on day 1 with 30% charge left in battery at 17:30 and left at 6:30. In the second day, the same owner arrived with 50% charge left in battery at 14:00 and left at 5:30. These unpredicted behaviors would result in uncertainty in load forecasting because the human decision making nature is unpredictable.

The load of EVs (charging rate) needs to be discretized to states (predefined interval) with computing the probability of being in each state, for the computation of uncertainty factor. The reason behind discretizing the charging rates is that the uncertainty factor cannot be evaluated continuously. It needs to be evaluated during predefined intervals. Figure 5 shows a flowchart of the producer of evaluating the uncertainty factor of the system.

The contribution of each state to the uncertainty factor of the load caused by EVs is computed for a single hour by:

$$U^k = \sum_{\substack{i=1 \\ p_i \neq 0}}^{s} \left(\frac{P_i l_i - \sum_{i=1}^{s} P_i l_i}{\sum_{i=1}^{s} P_i l_i} \right)^{2n} \tag{3.5}$$

where U^k is the uncertainty factor of the k^{th} hour of the day, p_i is the probability of i^{th} predefined state of the k^{th} hour, s is the number of the predefined charging states, l_i load of the i^{th} state, and n is heuristic number.

The significant of $2n$ is to eliminate the negative numbers that could result from the computation of $\left(\frac{P_i l_i - \sum_{i=1}^{s} P_i l_i}{\sum_{i=1}^{s} P_i l_i} \right)$. n is heuristic number that decreases the effect of small variation of p_i and l_i on the final result of uncertainty factor. Bigger n leads to less impact of tiny variation on the uncertainty factor.

Using equation (3.5) the uncertainty factor of the whole day (U) is computed:

$$U = \sum_{k=1}^{24} U^k \tag{3.6}$$

The uncertainty factor is an indication of the fluctuation of forecasted demand of EVs charging at every hour of day. The lower the uncertainty factor is, the better the proposed model.

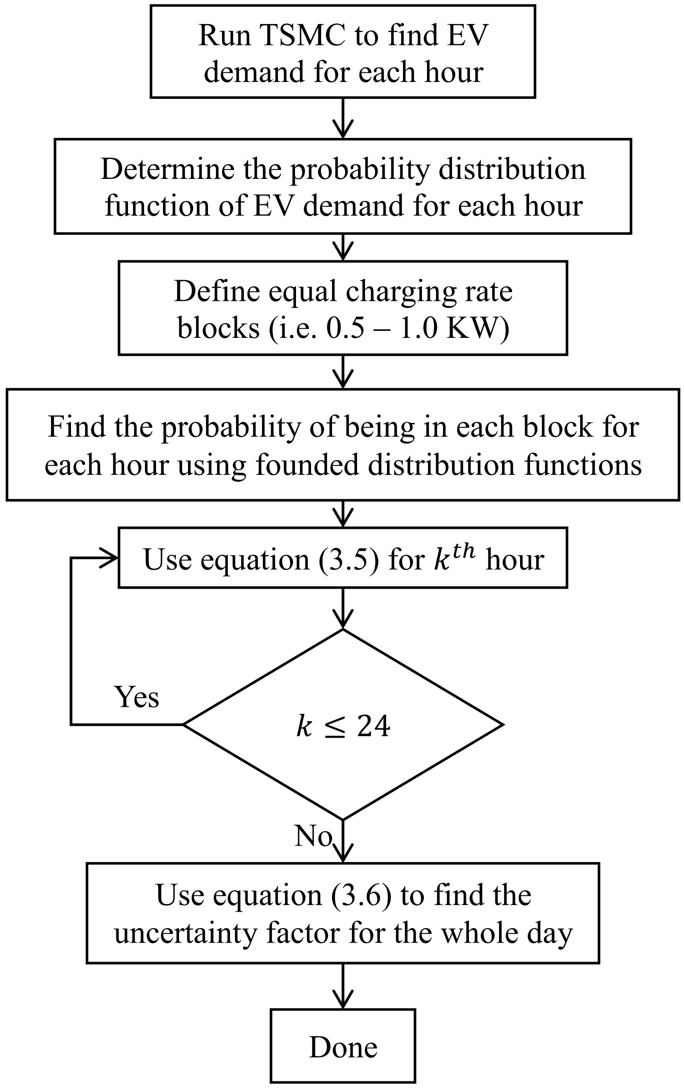

Figure 5. Flowchart of computing uncertainty factor

CHAPTER 4

PROPOSED DISCRETE EVENT SYSTEMS MODELS FOR EV

In this chapter, different DES models for the penetration of EVs at the residential level are developed and applied to manage the charging of EVs. Vehicle arrival time, departure time, and required charge for the next trip modeled in the previous section $f_a(t), f_d(t),$ and $g(\mathcal{C})$, respectively, where t is the random time of interest. The following models are developed to evaluate how a supervised control scheme could manage the impacts of EV charging.

4.1 No Control Charging Model

The No Control Charging Model was developed to find the state of the system as is without any interference of a controller. The idea is to have a discrete event model that represent the charging process and impacts with no controller and then compare it to the results with the implementation of different controllers.

A vehicle will be in the state traveling (T) until it arrives at the charging location. For No Control Model automaton shown in Figure 6, as soon as EV arrives home it starts immediately charging with the highest available charging rate, while being in the charging state (F), until it completes charging or it is disconnected from the charger due to departure and moves to complete state (C). This model is motivated by the behavior of the consumers. Consumer behavior requires the vehicles to be charged at the earliest possible time; which in turn reduces their anxiety.

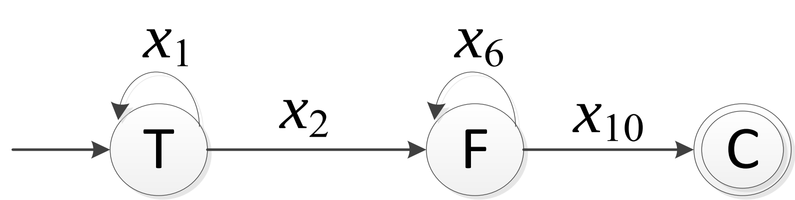

Figure 6. No Control Charging Model automaton

The following relationships are used to denote the events corresponing to the automaton given in Figure 6.

- $\boldsymbol{x_1}$: EV is on the road and is not capable to connect to charger
- $\boldsymbol{x_2}$: EV arrived home and is connected for charging
- $\boldsymbol{x_6}$: EV is not charged fully, thus it remains in the same state
- $\boldsymbol{x_{10}}$: EV Completes charging using the maximum charging rate

This work is based on the discrete time analysis. This assumption is fair as the signal from the distribution system operators to the residential will be sent periodically and therefore the conditions associated charging will change periodically. Therefore, work assumes that vehicles arriving at home can be combined into small time intervals and could be connected to the grid at the beginning of each interval. This assumption is necessary to compare the basic No Control charging model to the proposed control charging models. Using the arrival time distribution defined in section 3.1, at any random time *t* the number of vehicles that are still in the road is given by the following relationship:

$$Prob_{vehicle\ travelling} = 1 - \int_0^t f_a(\tau)d\tau \tag{4.1}$$

Therefore, if the time interval between charging is considered as Δt, then the event x_2 (probability that the vehicle will arrive during Δt and immediately connected to charge) can be represented by:

$$x_2 = \frac{\int_t^{t+\Delta t} f_a(\tau)d\tau}{1 - \int_0^t f_a(\tau)d\tau} \tag{4.2}$$

The event representing the vehicles that are still traveling can be mathematically modelled as:

$$x_1 = \frac{1 - \int_0^{t+\Delta t} f_a(\tau)d\tau}{1 - \int_0^t f_a(\tau)d\tau} \tag{4.3}$$

The probability that the vehicle will complete its charging at a random time t is given by:

$$x_{10} = P\big(g(\mathcal{C}) + c_{\ell}\big(n(kT)\big) > \mathcal{C}_{max}\big) \tag{4.4}$$

where, n is the number of hours the EV is connected to the grid (determined from the vehicle arrival probability) and $\mathcal{C}_{max}$ is the maximum charge required by the vehicle. Therefore, the probability that the vehicle will stay in the same state in the next period is given by:

$$x_6 = 1 - x_{10} \tag{4.5}$$

This model can be used to determine the state of a vehicle at a given time with no control mechanisms present.

4.2 Delayed Charge Control Model

This part extends the previous automaton by including a wait state. The EV will not be connected to the grid if the system operating conditions will not allow additional load and if the EV is parked at charger for longer sufficient time to its required charging time. The charge left on the EV is compared to the threshold ($\hbar_T$) which is computed based on the transformer loading availability. The available time for charging is compared with a threshold (T_T) and the relationship is:

$$T_{avi} = \big(f_d(t_1) - f_a(t_1)\big) < T_T \tag{4.6}$$

For the Delayed Charge Control Model (Single Mode Control automaton), when an EV arrives home it has two options. Either stay connected to charger without charging (H) or go immediately to full charging rate (F). Then, the EV either completes charging (C) as shown Figure 7.

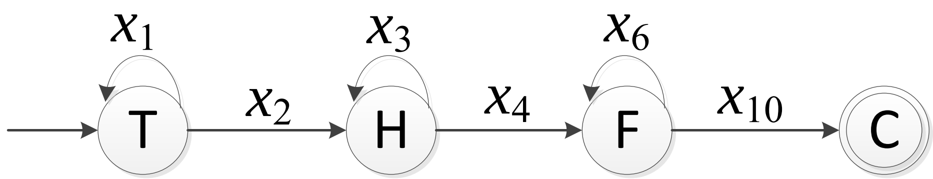

Figure 7. Delayed Charge Control Model automaton

The events x_1, x_2, x_6 and x_{10} are same as defined in the previous section. The two new events and their mathematical representation are:

- $\boldsymbol{x_4}$: EV is moving from standby state to charging state. The mathematical model for the event is:

$$x_4 = P(T_{avi} \leq T_T) \cap P(e_L(k) \leq \hbar_T) \tag{4.7}$$

where, $e_L(k)$ is EV battery state charge at k^{th} time interval.

- $\boldsymbol{x_3}$: EV is in the charging location but will not be charging, which is represented by:

$$x_3 = 1 - x_4 \tag{4.8}$$

This model can be used to determine the state of a vehicle at a given time with simple wait and charge control mechanism, which is defined as Single Mode Control automation.

4.3 Multi-State Delayed Control Model

Since the EVs have only two options either to charge or delay charging, the system will not be optimally utilized. A multi-state model is proposed to spread the EV charging load throughout the available time, instead of having only full charging rate. Each additional state corresponds to an EV charging at a partial rate. When an EV arrives home, it has *n* number of charging options. Then, EV could be either connected to the charger without charging (H) or chooses one of the available charging rates (F) or (P_i); until the EV completes charging (C).

The EV does not have the option to jump between charging rates, in other words each EV will be assigned a single charging rate based on the available charge and time. For example, if an

EV starts charging using 50% of full rate, it will continue charging at that rate until it completes charging even if there is another state becomes available at another time. Figure 8 shows Multi-State Delayed Control automaton with *n* number of partial charging rates.

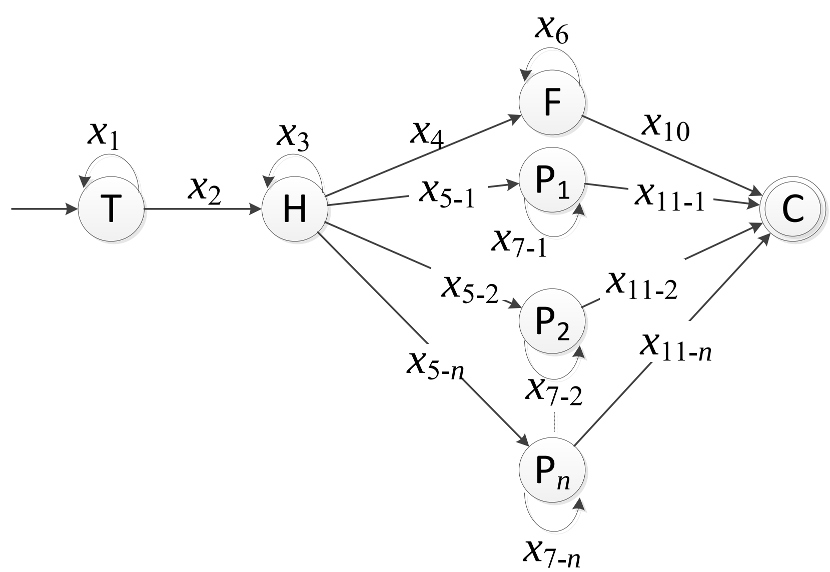

Figure 8. Multi-State Delayed Control Model automaton with n partial rates

The events $x_1, x_2, x_{,3} x_4, x_6$ and x_{10} are same as defined in the previous sections. The events associated with the partial charging are similar to the ones defined in the previous section and for the *i*th partial charging state the associated events are:

- $\boldsymbol{x_{5-i}}$: EV is moving from standby state to partial charging state. The mathematical model for the event is:

$$x_{5-i} = P(T_T^{i-1} \leq T_{avi} \leq T_T^i) \cap P\left(\hbar_T^{i-1} \leq e_L(k) \leq \hbar_T^i\right) \tag{4.9}$$

Where, superscript i denotes the thresh holds assigned to the particular state. However, if *i* = 1, then $T_T^0 = T_T$ and $\hbar_T^0 = \hbar_T$ as defined in the previous section.

- $\boldsymbol{x_{11-i}}$: EV has completed its charging. The mathematical model for the event is:

$$P\left(g(\mathcal{C}) + c_\ell^i\left(n(kT)\right) > \mathcal{C}_{max}\right) \tag{4.10}$$

Where, c_ℓ^i is the charging rate at the given state.

- x_{7-i}: EV has completed the charging and will move to the complete state. The mathematical model for the event is:

$$x_{7-i} = 1 - x_{11-i} \tag{4.11}$$

Figure 9 shows a special case with only one partial charging rate. Typically, partial charging rate can be 50% of the full charging rate. This could be easily achieved in a charger using power electronics control.

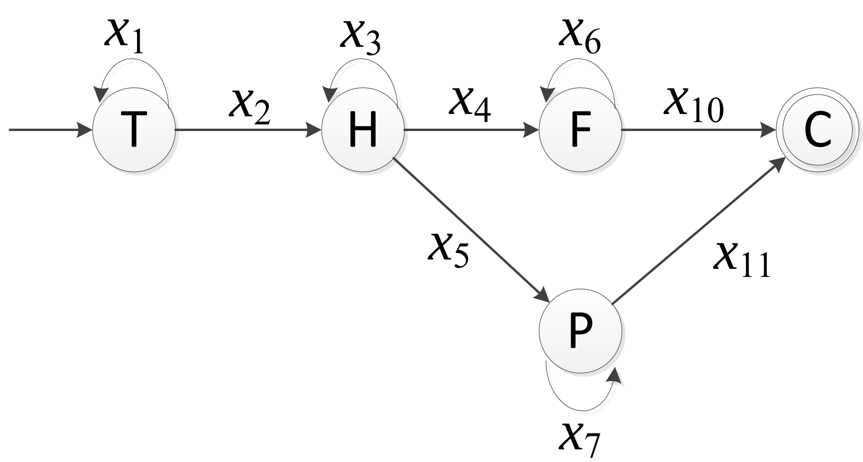

Figure 9. Multi-State Delayed Control Model automaton with one partial rate

4.4 Multi-State Full Control Model

Even with the Multi-State Delayed Control Model, the EVs will not be able to utilize the entire distribution grid capability and it has no ability to change its charging mode due to an unplanned event in the distribution system. Finally, a Multi-State Full Control Model is developed to incorporate the dynamic nature of the power grid.

A Full Control Model using only one partial state is shown in Figure 10. This work limits its analysis to one partial state model by combining Figure 9 and Figure 10 and extending the approach shown in these two models.

When an EV arrives home, it has three options. It could stay connected to charger without charging (H). The second option is to charge on full charging rate (F). Final option is to charge using the 50% partial charging rate (P). The EV also could hop from full charging rate to partial charging and vice versa based on time available for charging and remaining charge left in EV.

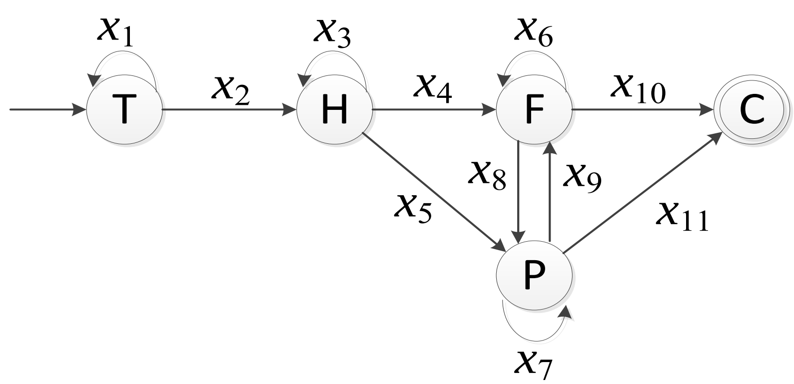

Figure 10. Multi-state full control model with one partial charging rate

The events $x_1, x_2, x_{,3} x_4, x_5, x_{10}$ and x_{11} are same as defined in the previous sections. The events associated with hopping between partial and full charging nodes are defined as:

- $\boldsymbol{x_8}$: EV is moving from full charging state to partial charging state. The mathematical model for the event is:

$$x_8 = P(T_{avi} > T_T) \cup P(e_L(k) > \hbar_T) \tag{4.12}$$

- $\boldsymbol{x_9}$: moving from partial charging state to full charging state. The mathematical model for the event is:

$$x_9 = P(T_{avi} \leq T_T) \cup P(e_L(k) \leq \hbar_T) \tag{4.13}$$

- $\boldsymbol{x_6}$ and $\boldsymbol{x_7}$**:** are the same as described in the previous sections, however their probability evaluation change with the addition of x_8 and x_9.

$$x_6 = 1 - x_8 - x_{10} \tag{4.14}$$

$$x_7 = 1 - x_9 - x_{11} \tag{4.15}$$

Due to the dynamic nature of the system T_T and $\hbar_T$ will change with time to accommodate optimal load. Full control automaton has an advantage of charging more vehicles at peak time by moving EVs from full charging rate to partial charging rate.

CHAPTER 5

NUMERICAL RESULTS AND ANALYSIS

This chapter discusses the simulation approach for the proposed DES models and the analysis of the load data matrices that result from the simulation of each proposed DES model. Then, the proposed DES models will be compared with each other to verify their validity. Finally, uncertainty analysis is preformed to validate the effectiveness of the proposed DES models.

5.1 Simulation Approach

The Time-Sequential Monte Carlo simulation technique was used in this research because of the stochastic proprieties of the inputs (arrival time, departure time, and the state of charge left at the time of arrival). Using the TSMC technique is expected to generate a random output where estimating the distribution density function representing the output is needed. For this research one type of EVs is used because the goal of the research is to model and control the charging of EVs, not to find what is the impact of different types of EVs.

In addition, Level 2 residential charger is used since it has the biggest impact on the secondary distribution equipment such as secondary distribution transformers as mentioned section 1.2. The charging rates are equally spaced so, the impact of multiple charging rates is observable.

MATLAB Simulink program was used in this research to model all proposed DES models discussed in Chapter 4. This research used the electricity retail price and transformer capacity as tools to manage the load of charging EVs.

For the electricity retail price, two different approaches were tested. First, fixed electricity price where the time of day does not play a role in the decision of charging an EV. In this case, the consumer cost of charging an EV is not affected by the time of the day. The goals in this approach were charging the EVs without overloading the system and distribute the load caused by EVs charging with minimizing the peak load.

The other approach was with dynamic retail price where the utility provides a day ahead electricity price forecast where the time of charging the EV does contribute to the overall cost of electricity consumers pay for charging their EVs. The goals in this approach were charging the EVs without overloading the system and distribute the load caused by EVs charging with minimizing the peak load and cost of charging for the consumer.

Nissan Leaf was used in this research due to the availability of information about the vehicles. In addition, Nissan Leaf is an EV that has only one source of power from batteries and does require charging for power grid.

The desired output from the simulation is to have the estimated load for each hour for all the trials and average load of EVs penetration to the system for each hour of the day for all different DES proposed models. Table 2 shows the parameter used in the simulation.

TABLE 2

SIMULATION PARAMETERS

Number of EVs	5 and 250 Vehicles
Number of trials	10,000, 20,000 and 45,000 trials
Maximum Charging Rate	7.6 KW/h
Two Charging Rates Model	(100 and 50) %
Five Charging Rates Model	(100, 80, 60, 40, and 20) %
Battery Size	24 KWh
Arrival Time	Equation (3.2)
Departure Time	Equation (3.3)
Charge Left in EV at Arrival	Equation (3.4)
Dynamic Electricity Prices	Com-Ed Chicago [28]

The simulation of the of all DES proposed models resulted in the average load caused by the penetration of five EVs. Arrival time, departure time and the charge left in EVs at the time of arrival where randomly generated for the number of EVs at each trail

5.2 No Control Automaton

For the proposed No Control model shown in Figure 6, the resulted average power consumption follow the arrival time distribution density function $f_a(t)$ as expected, since EVs start charging as soon as the owner arrives home. According to the $f_a(t)$ the average arrival time of an EV is $11.83 + 5 = 16.83 = 16{:}49$.

This shows that the average power consumption of the output of proposed No Control Model is as expected. Therefore, this confirms the validity of the proposed model. Figure 11 shows the average power consumption of the penetration of five EVs resulted from the proposed No Control Model.

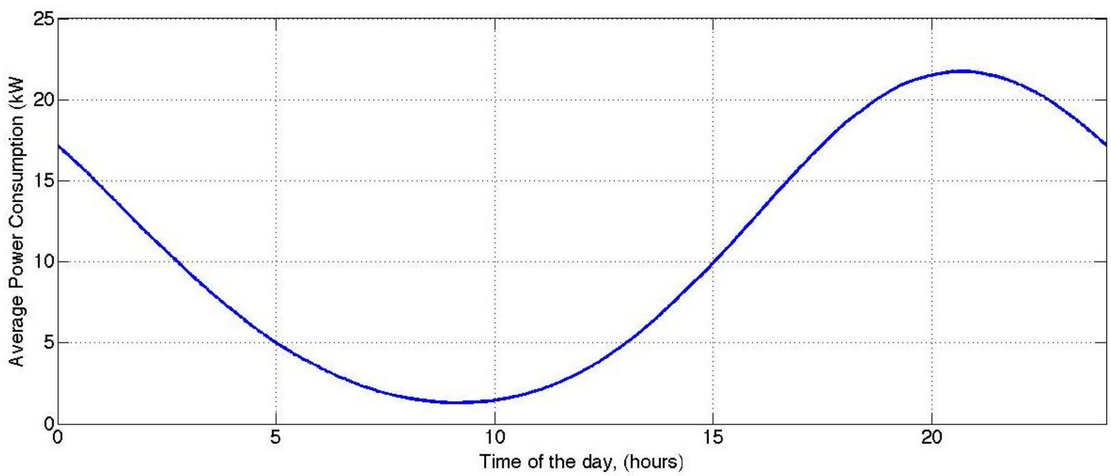

Figure 11. Average power consumption of No Control Model for five EVs

On the other hand, mean and standard deviation of the power consumption data for a single EV is shown in Table 3. Figure 11 and Table 3 show as expected that the load caused by the arrival of EVs to the charger at home will increase the power demand of the houses that has EVs. In addition, that increased demand caused by EVs is in the same interval of the peak power consumption time of the day which commonly starts around 5:00 PM and end around 10:00 PM. This results in increasing the peak power consumption during the peak time and possibly overloading the secondary side distribution transformers and equipment.

TABLE 3

HOURLY MEAN AND STANDARD DEVIATION FOR SINGLE EV

Hour	Mean	Std. Dev.
1	3.1801	0.2280
2	2.6479	0.2211
3	2.1132	0.2087
4	1.6141	0.1909
5	1.1804	0.1688
6	0.8273	0.1455
7	0.5620	0.1212
8	0.3822	0.1003
9	0.2863	0.0869
10	0.2739	0.0845
11	0.3508	0.0949
12	0.5262	0.1160
13	0.8109	0.1410
14	1.2074	0.1669
15	1.7044	0.1895
16	2.2755	0.2083
17	2.8749	0.2224
18	3.4394	0.2291
19	3.9068	0.2324
20	4.2234	0.2310
21	4.3525	0.2304
22	4.2890	0.2300
23	4.0483	0.2306
24	3.6640	0.2301

5.3 Delayed Charge Control Model Automaton

Delayed Charge Control Model shown in Figure 7 has a control only over the time of charging by delaying the charging of an EV if needed based on the defined thresholds. As shown in Figure 12, the Delayed Control automaton did not reduce the average peak of power consumption and it is very close to the No Control Model. However, the proposed Delayed Control Model shifted the peak power consumption to off peak time where commonly the demand on power is very low in comparison to peak hours.

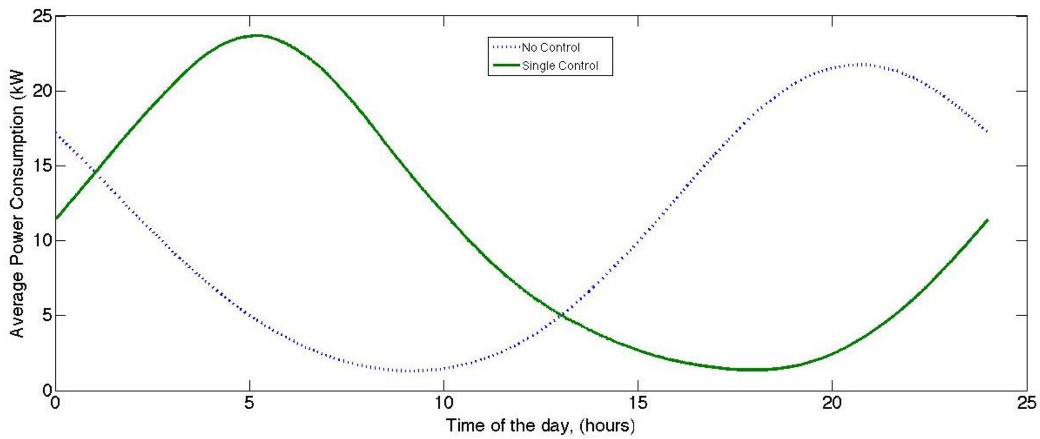

Figure 12. Average power consumption of No Control Charging and Delayed Charge Control Models for five EVs

Even though the Delayed Charge Control Model automaton helps in reducing the probability of overloading secondary side distribution equipment, it did not reduce the average power consumption of each hour of the day with charging EVs. The reason is that the Delayed Control automaton always charges EVs at the maximum charging rate.

5.4 Multi-State Delayed Control Automaton

As mentioned in the previous section, the Delayed Charge Control Model helped shifting the peak power consumption to off peak time but it did not reduce the peak of average power consumption because EVs are always charging at full charging rate. Multi-State Delayed Control automaton is expected to reduce the peak of power consumption to be valid since it uses multiple charging rates instead of only one.

Figure 13 shows the average power consumption by charging five EVs for the proposed No Control, Delayed Control with full charging rate, Delayed Control with two charging rates (100 & 50) %, and Delayed Control with five charging rates (100, 80, 60, 40, 20) % Models.

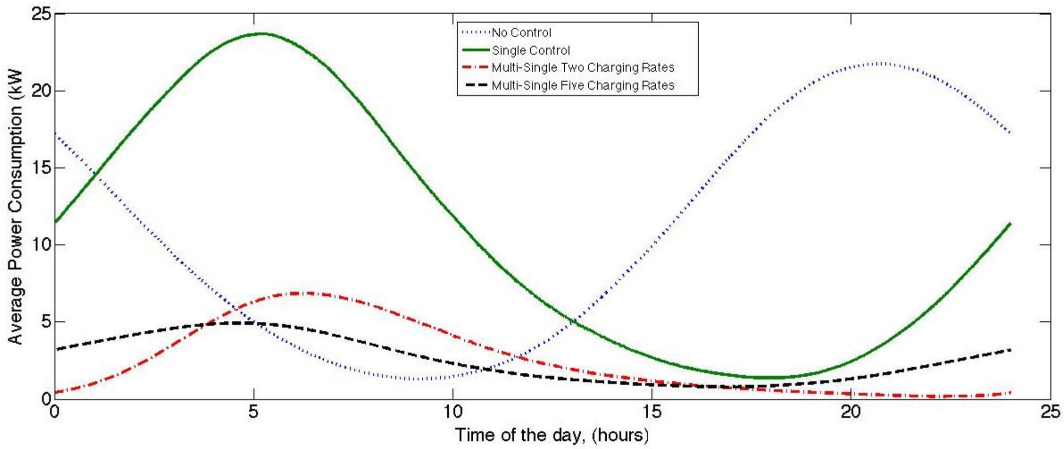

Figure 13. Average power consumption of No, Delayed, Delayed with two charging rates and Delayed with five charging rates Control Models for five EVs

The Multi-State Delayed Control Model has reduced the average power consumption caused by charging of an EV significantly which validate that the proposed Multi-State Control Models.

Delayed Multi-State with five charging rates automaton reduced the average power consumption more than Delayed Multi-State with two charging rates automaton. However, the difference is not significant between both. In addition, the average power consumption changes based on the time of the day as shown in Figure 14, during certain intervals Delayed with two charging rates Control automaton exceed the other model and in other intervals, the opposite happened.

The goals, which were achieved of the proposed Multi-State Delayed Control automaton, are:

- To reduce the average power consumption caused by charging an EV
- To shift the charging of EVs to off peak time
- Charge all connected EVs that have sufficient time availability for charging

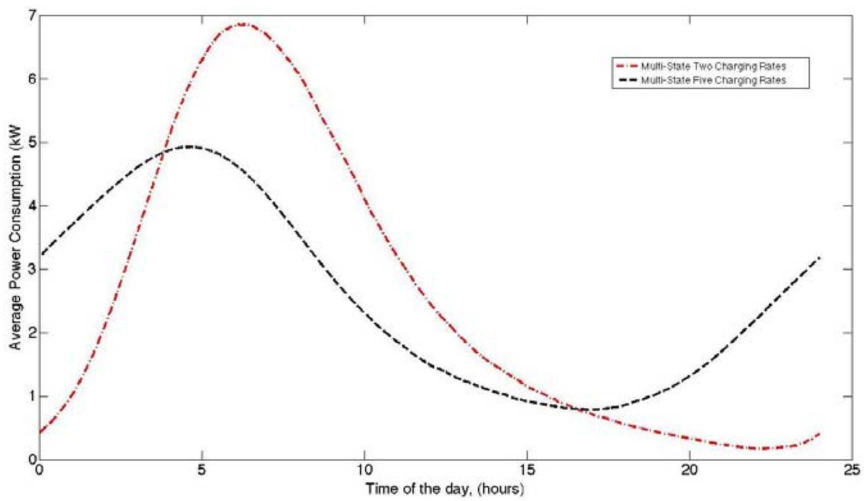

Figure 14. Average power consumption of Delayed with two charging rates and Delayed with five charging rates Control Models automatons for five EVs

All the previous results shown in Figure 11 - Figure 14 were for fixed electricity prices. Therefore, the cost of charging an EV is not affected by the time of the day since the retail price of electricity does not change throughout the whole day.

To study the effects of dynamic electricity prices on the controller behavior Multi-State Delayed Control with two charging rates Model were compared as shown in Figure 15 with both fixed and dynamic electricity prices. The random day real time price signal published by Com-Ed Chicago was used as tool to control the charging of EVs [28].

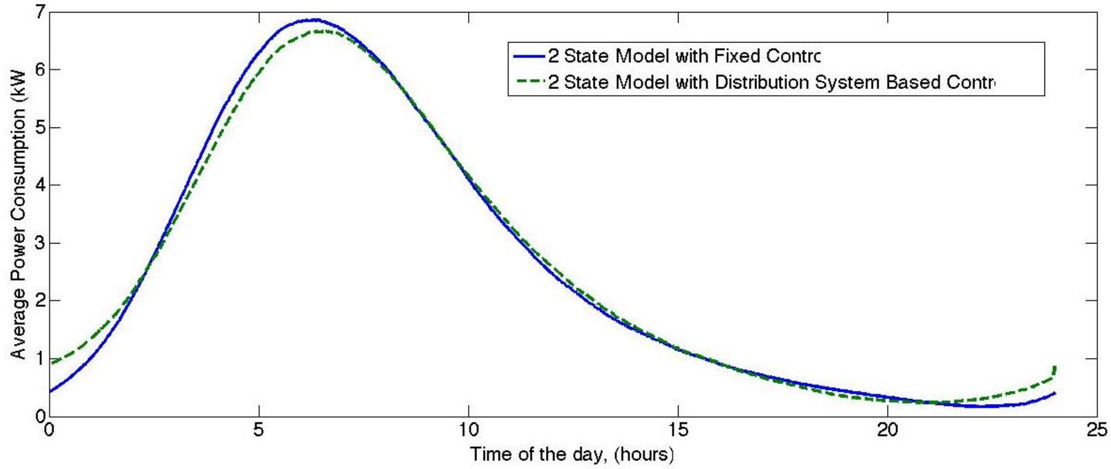

Figure 15. Average power consumption of Delayed with two charging rates Control Models of fixed and dynamic electricity prices for five EVs

The difference between both fixed and dynamic electricity prices proposed models are not significant. However, dynamic electricity prices model has a slightly lower peak of average power consumption.

5.5 Multi-State Full Control Automaton

Multi-State Delayed Control Model performed very well in reducing the average power consumption due to EVs charging and shifted the peak of the average power consumption to off peak time. Furthermore, the addition of hooping event between charging rate are evaluated in Multi-State Delayed Control Model. Since Multi-State Delayed Control Model charging with two charging rates with dynamic electricity prices automaton preformed the best between all the proposed models that were previously discussed. The proposed Multi-State Delayed Control Model charging with two charging rates automaton used to compare with Multi-State Full Control Model with two charging rates automaton. Both models were simulated using dynamic retail electricity prices as tool of managing the charging of EVs as shown in Figure 16.

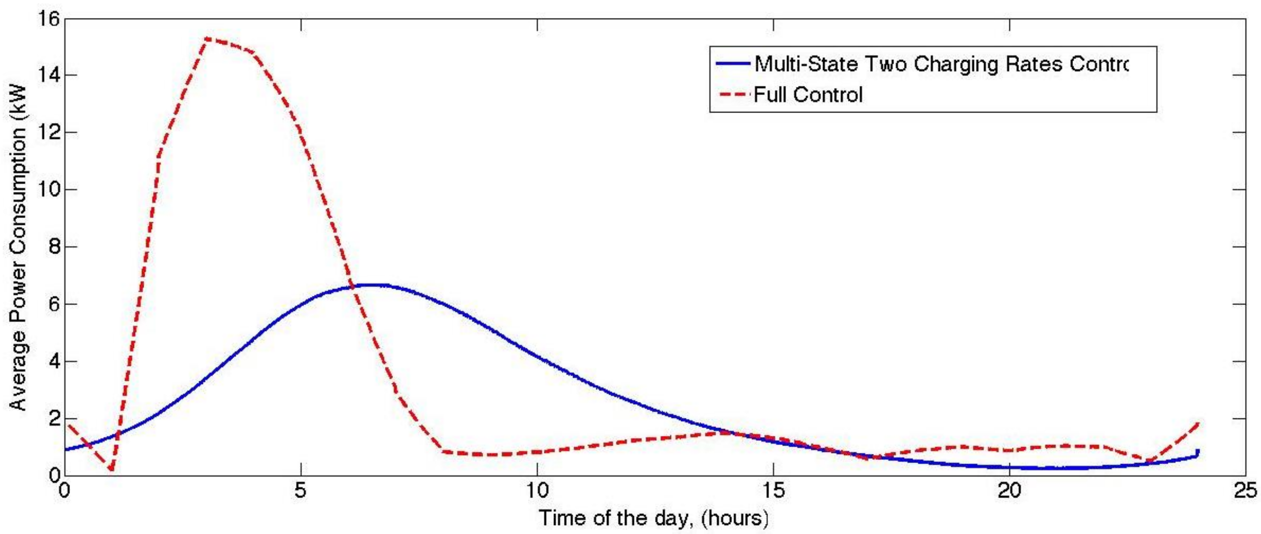

Figure 16. Average power consumption of Delayed and Full, both with two charging rates Control Models automatons for five EVs

As it shown in Figure 16, the proposed Multi-State Full Control automaton has a narrower interval of charging in comparison to the Multi-State Delayed Control automaton. However, the Full Control automaton has higher average of power consumption during that narrow interval. Therefore, according to the observation of the proposed Multi-State Full and Delayed Control Models, both are sufficient to minimize the peak of the average power consumption, to charge all the EVs with sufficient time availability, and shifted the peak of the power consumption to off peak hours.

When it comes which one to use between the two shown in Figure 16, it should be decided based on the utility's objective either reduces the peak power consumption or ensure EV charges as soon as possible. For example, one utility company wants to have very low average power consumption during the entire 24 hours period. Therefore, this utility should use Multi-State Delayed Charging Control Model. On the other hand, if the utility objective is to limit the charging period of EVs to a narrow period without worrying about the average peak of the power consumption. Then, this utility should use the Multi-State Full Control Model.

5.6 Uncertainty Analysis

The uncertainly analysis was performed on three different DES proposed models which are No Control, Multi-State with two charging states Control, and Multi-State Full Control models. Each model was simulated for the assumption of five EVs penetration and 250 EVs penetration.

Five EVs penetration will represent secondary side distribution transformer that would commonly be connected to five to ten houses. On the other hand, 250 EVs will represent substation where commonly hundreds of houses are connected to the substation.

In addition, the models ran for different number of trials mentioned in Table 2 to validate the convergence of the data where the variation between the resulted load data due EVs penetration is not significant. The load is discretized to 16 states with range of 0.5 KW for each state starting from 0.0 KW to 8.0 KW. Using equations (3.5) and (3.6), the uncertainty of each case was computed.

5.6.1 Verification of Simulation Convergence

The verification of simulation convergence is required to validate the results obtained by the simulation. To test for convergence, the simulation was run for No Control, Multi-State Delayed Control and Multi-State Delayed Full Control Models with 20,000 and 45,000 trials for five EVs penetration to asset the validity of the result obtained.

The resulted demand of five EVs for each of three models used to compute the uncertainty factor the uncertainty factors obtained in Section 5.6.2 for the same number of EVs. As shown in Table 4, the variation between the uncertainty factor calculation of 20,000 trials and 45,000 trials is small (8.00% or less for all three proposed models shown in Table 4) which means that the resulted demand data for the simulation of 20,000 trials is valid.

TABLE 4

COMPARISON OF UNCERTAINTY FACTOR FOR SIMULATION CONVERGENCE VERIFICATION

No Control		Difference (%)
20,000 Trials	45,000 Trials	
217.09	227.95	5.00
Delayed Two Charging Rates Control		**Difference (%)**
20,000 Trials	**45,000 Trials**	
84.08	85.91	2.18
Delayed Full Two Charging Rates Control		**Difference (%)**
20,000 Trials	**45,000 Trials**	
75.16	81.28	8.13

5.6.2 Secondary Side Distribution Transformer

In this section, the uncertainty factor analysis was done on secondary side distribution transformer with five EVs penetration and 20,000 trials for three different models. The results of the analysis and uncertainty factor computation are shown in Table 5.

TABLE 5

HOURLY AND TOTAL UNCERTAINTY FACTORS FOR SECONDARY SIDE DISTRIBUTION TRANSFORMER

Time (hours)	No Control	Delayed Control	Delayed Full Control
1	10.90	6.21	10.25
2	10.94	5.12	9.98
3	10.95	4.12	9.96
4	7.13	3.15	8.73
5	6.34	4.20	3.51
6	7.61	4.39	1.85
7	7.03	3.79	1.60
8	6.41	3.41	0.95
9	6.72	4.04	0.88
10	5.74	3.54	1.63
11	6.45	3.86	1.32
12	5.95	3.16	2.10

TABLE 5 (continued)

Time (hours)	No Control	Delayed Control	Delayed Full Control
13	7.41	3.39	1.99
14	9.97	2.60	1.96
15	10.73	2.74	1.99
16	10.58	2.83	1.18
17	10.55	2.91	0.85
18	10.62	2.93	0.98
19	10.66	2.97	1.61
20	10.74	2.98	1.28
21	10.81	1.93	1.27
22	10.94	2.40	2.08
23	10.94	3.35	1.57
24	10.98	4.05	5.61
Total (Day)	**217.09**	**84.08**	**75.16**

Notes: uncertainty computations for 20,000 trials, penetration of five EVs, $n = 5$, and two charging rates for the Multi-State Delayed and Full Control Models.

As shown in Table 5, The total uncertainty factor of forecasted demand of EVs penetration with five EVs penetration on secondary side distribution transformer is reduced for from 217.09 in No Control Model to 84.08 (about 61% reduction) in Delayed Control Model. It was reduced further in Full Control Model to 75.16 (about 65% reduction). The contribution of the proposed control models (Delayed and Full) in reducing the uncertainty factor is significant.

Figure 17 is visual presentation of the probability of each state of charging rate for proposed No Control Model. The figure confirms the data presented in Table 5 where the uncertainty factor of load demand due EVs penetration is significant. Therefore, utilities (electricity provider) would have difficulty in predicting the day ahead load caused by EVs charging since the uncertainty factor is large.

In Figure 17, the uncertainty factor during the peak time of power consumption is high according to Table 5. The peak time of power consumption during the day is critical time and the possibility of overloading the power grid during that time is high. Therefore, the uncertainty of load forecasting due EVs penetration is going to add to the complexity of overall demand forecasting especially during peak time. In addition, it would increase the possibility of not being able to forecast the day ahead demand accurately.

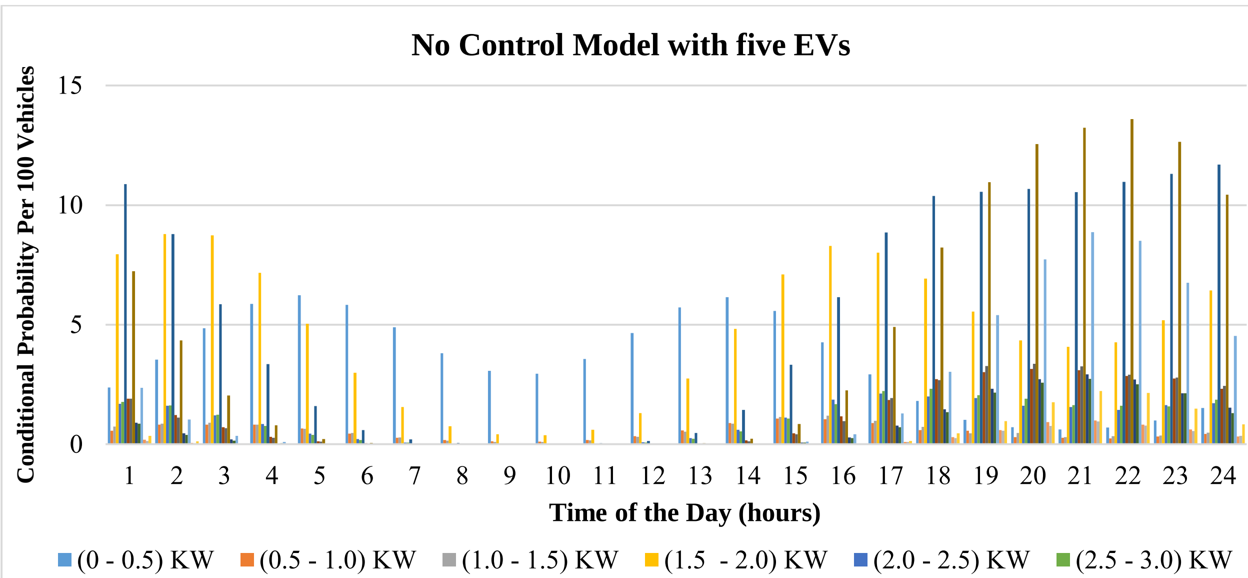

Figure 17. No Control Charging Model discrete hourly probability of each charging state for five EVs

On the other hand, proposed Multi-State Delayed Control Model as shown in Figure 18 and Table 5 reduced the uncertainty factor significantly. Proposed Multi-State Delayed Control reduced the uncertainty factor especially during the peak time of power consumption (usually between 5:00 PM to 10:00 PM).

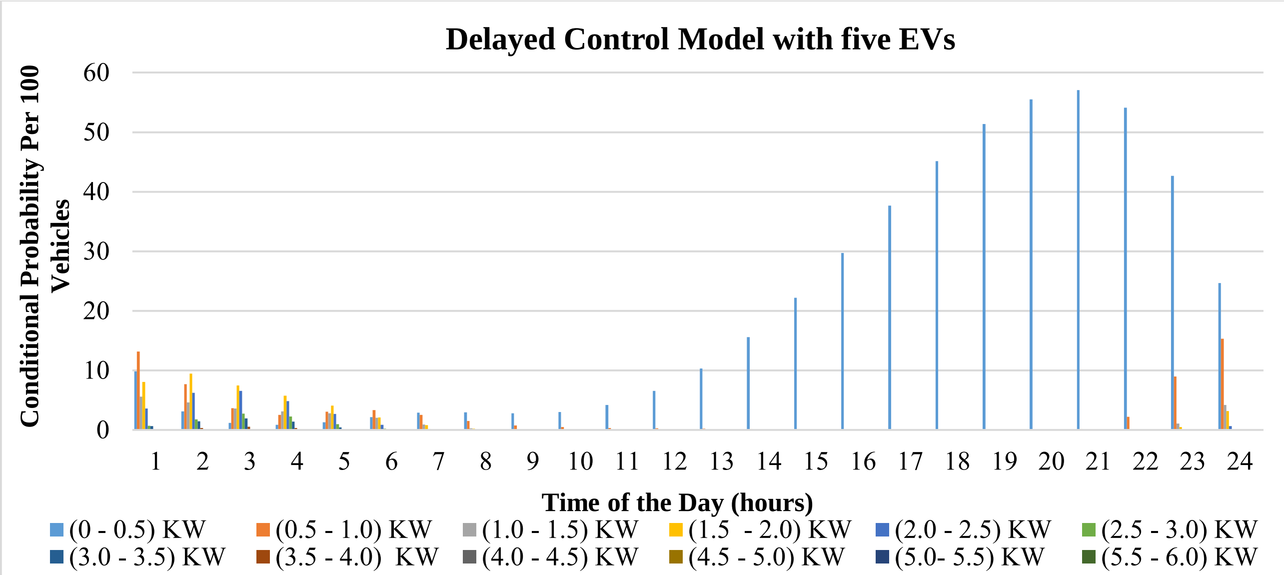

Figure 18. Multi-State Delayed Control Model discrete hourly probability of each charging state for five EVs

For the Multi-State Delayed Full Control Model, the uncertainty factor as shown in Figure 19 and Table 5 is smaller during the peak time of power consumption.

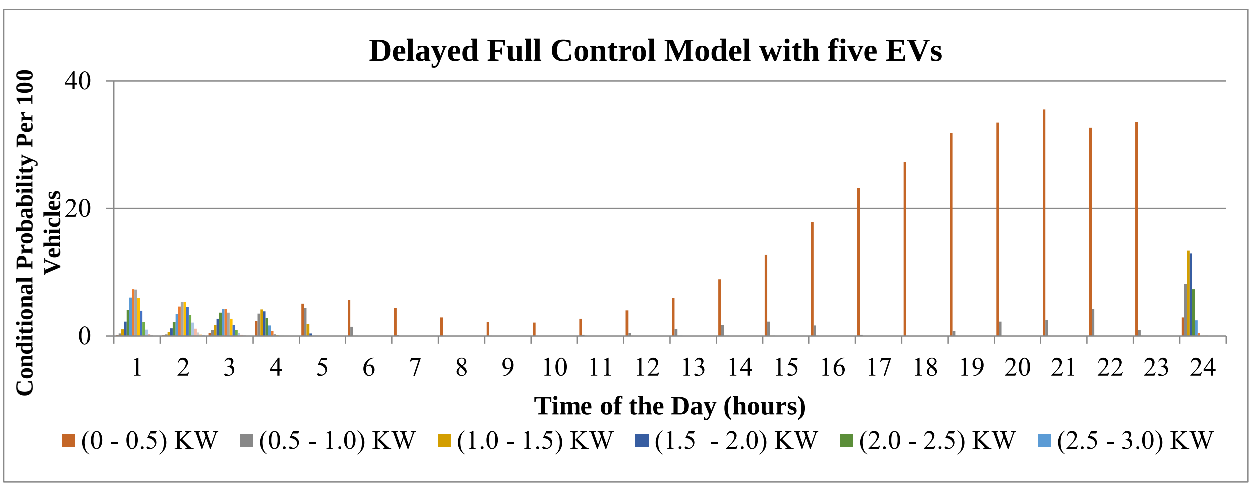

Figure 19. Multi-State Delayed Full Control Model discrete hourly probability of each charging state for five EVs

However, it is very high during the time between 12:00 AM and 4:00 AM that is the time where Multi-State Delayed Full Control Model automaton usually charges EVs.

5.6.3 Uncertainty Analysis for Substation

Similar to the analysis done in Section 5.6.2 the uncertainty factor analysis was done for substation with 250 EVs penetration and 10,000 trials for three different models. The results of the analysis and uncertainty factor computation is shown in Table 6.

As shown in Table 6 The total uncertainty factor of forecasted demand of EVs penetration with 250 EVs penetration on substation is reduced for from 60.44 in No Control Model to 29.27 (about 51% reduction) in Delayed Control Model and It was reduced in Full Control Model to 29.87 (about 50% reduction). The contribution of the proposed control models (Delayed and Full) in reducing the uncertainty factor is significant.

TABLE 6

TOTAL UNCERTAINTY FACTORS FOR SUBSTATION

DES Models	Total Uncertainty Factor (Day)
No Control	60.44
Multi-State Delayed Control	29.27
Multi-State Delayed Full Control	29.87

Notes: uncertainty computations for 20,000 trials, 250 EVs penetration, $n = 5$, and two charging rates for the Multi-State Delayed and Full Control Models.

Comparing Multi-State Delayed and Delayed Full Control Models' uncertainty factors, both are almost the same. So, either one of these two models are good controllers in terms of reduction uncertainty factor for substation load forecasting.

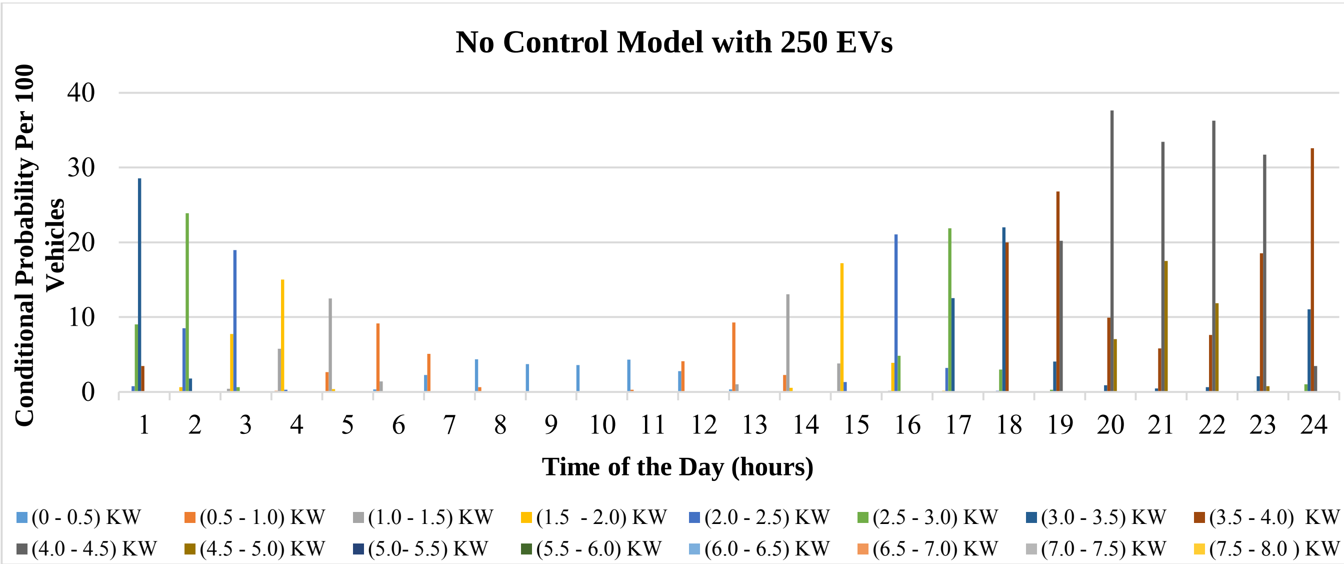

Figure 20. No Control Model discrete hourly probability of each charging state for 250 EVs

Comparing 5 EVs penetration shown in Figure 17 and 250 EVs penetration shown in Figure 20 on secondary side distribution transformer and substation, respectively. It very clear that the uncertainty factor is lower in Figure 20 and the probability of better load forecasting for substation due EVs penetration is higher.

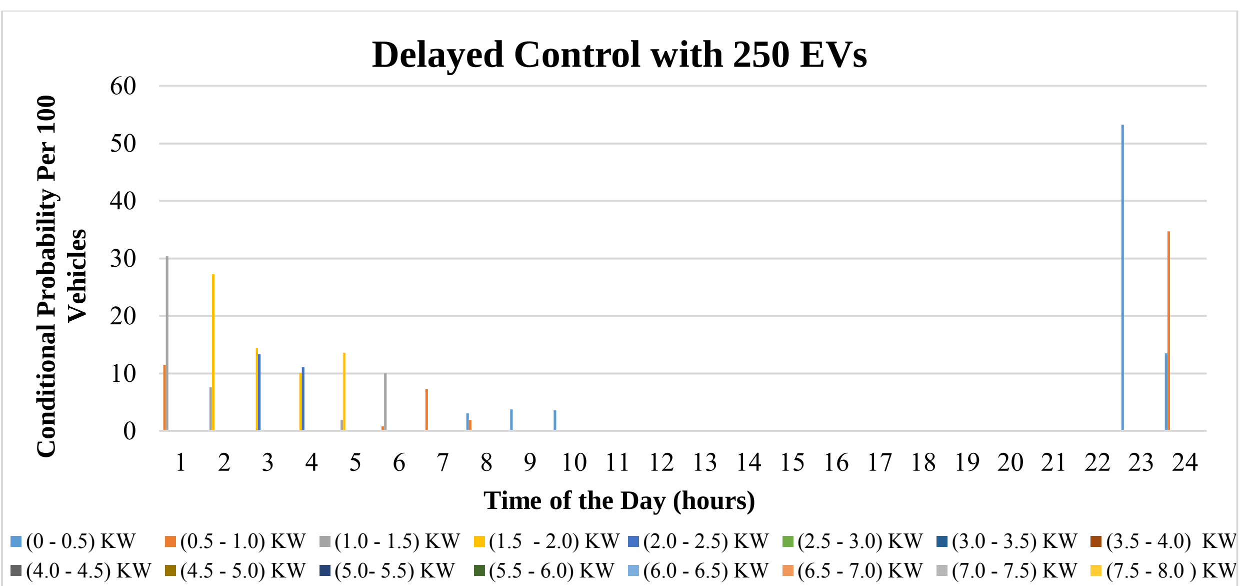

Figure 21. Delayed Control Model discrete hourly probability of each charging state for 250 EVs

The same observation can be seen in the cases of Multi-State Delayed as shown in Figure 21 and Delayed Full Control Models as shown in Figure 22. On the other hand, as shown in Table 7, the uncertainty factor reduced significantly for the same models when compared for the secondary distribution transformer and substation.

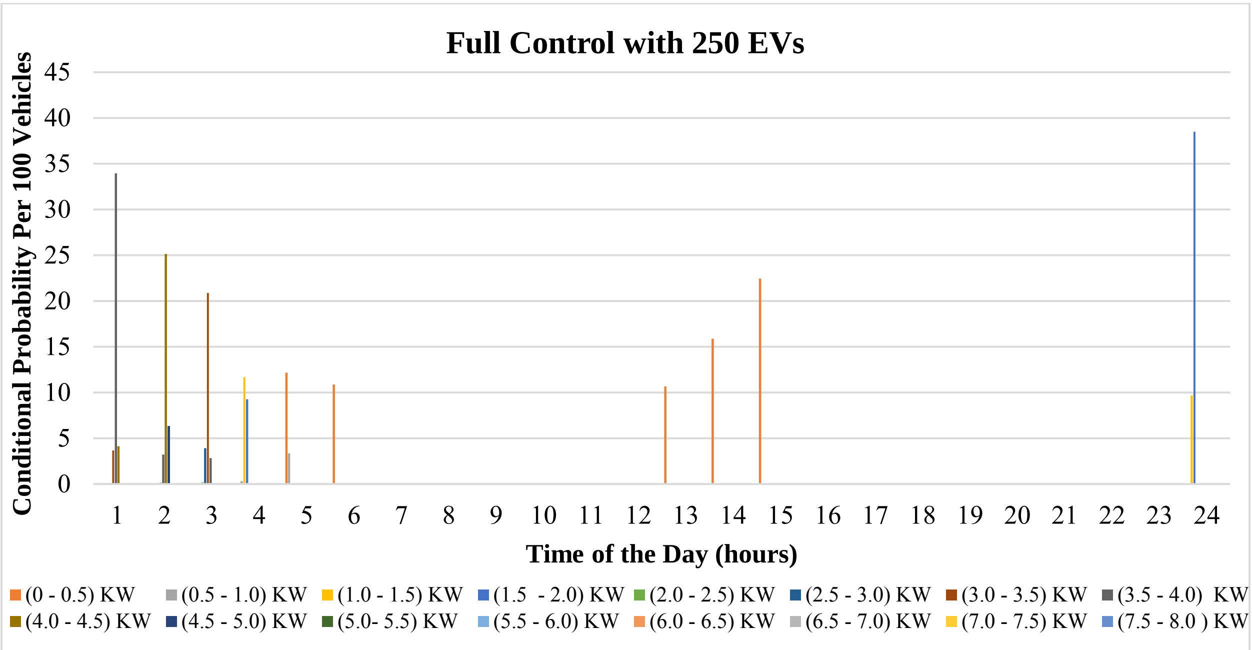

Figure 22. Delayed Full Control Model discrete hourly probability of each charging state for 250 EVs

The reason behind the significant decrease is that substation sees the overall load due the penetration of EVs as bulk load, which does not vary much due to the large number of EVs in comparison to distribution transformer. Substation in this thesis is 50 times larger than secondary side distribution transformer, which sees the average load of 250 EVs. The large number of EVs will reduce the uncertainty factor because of averaging EVs demand. For example, if the system sees 500 EVs penetration, the uncertainty factor is going to be lower than 250 EVs.

TABLE 7

COMPARISON OF UNCERTAINTY FACTOR FOR SECONDARY SIDE DISTRIBUTION TRANSFORMER AND SUBSTATION

No Control		**Reduction (%)**
Distribution Transformer	**Substation**	
217.09	60.44	72.16
Delayed Two Charging Rates Control		**Reduction (%)**
Distribution Transformer	**Substation**	
84.08	29.27	65.19
Delayed Full Two Charging Rates Control		**Reduction (%)**
Distribution Transformer	**Substation**	
75.16	29.87	60.25

CHAPTER 6

CONCLUSION

6.1 Conclusion

The research conducted in this thesis has resulted in new methods of modeling the load caused by the EVs charging using residential Level 2 charger. In addition, the research resulted in multiple DES proposed control models that were modeled, simulated, analyzed and discussed in this thesis.

The uncertainty factor was developed and the analysis was performed in this work to evaluate the ability of utility to forecast the load caused be EVs penetration for each model.

The DES proposed controller models (Multi-State Delayed and Delayed Full) reduced the impact of EVs penetration on the grid by minimizing the average power consummation by EVs, minimizing the cost of charging EVs in dynamic electricity prices system, charging all EVs that have sufficient availability time for charging, and reducing the uncertainty factor for demand forecasting of EVs.

The uncertainty factor of load forecasting for EVs impact on secondary side distribution transformer is higher than the impact of substations in all the proposed models. Finally, the validation and verification of all proposed DES models and simulation result was performed, which verified the validity of the proposed DES models and Simulation.

6.2 Future Work

In the future, additional power grid components could be modeled and integrated with the proposed models of EVs such as renewable energy sources and distributed generators. In addition, demand response studies with controlling EVs as energy storage device could be evaluated.

Furthermore, evaluating the distribution transformer loss of life and aging with and without the control of EVs charging of EVs is one of the possible direction to extend this work.

Finally, optimizing the proposed Multi-State Delayed Full Control Model by optimizing the mechanism used to choose the thresholds used as tools to control the charging of EVs could be undertaken in future work.

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