CHAPTER 3

RESEARCH METHODOLOGY

3.1 V2G System Specifications

In this thesis, both offline and online charging and discharging scheduling models are developed. EVs in this study are considered to be connected to the electricity grid for charging and discharging in a public charging station, which is a smart parking lot. The objectives of both scheduling optimization problems are to maximize EV owners' satisfaction in the V2G system (Egbue & Hosseinpour, 2014, Hosseinpour & Egbue, 2015).

We consider customers are satisfied if they; 1) make the maximum profit from discharging their EVs 2) charge their EVs at the minimum electricity cost 3) get the minimum difference between the departure state of charge (SOC) and the desired state of charge (Egbue & Hosseinpour, 2014) and 4) switch their EV battery between different charging and discharging modes as little as possible.

In the V2G system considered in this study, EVs enter a public charging station which is a parking lot equipped with EV charging stalls. This parking lot is managed and controlled by an aggregator. The V2G system architecture is depicted in Figure 5. Main components of the V2G system are EVs, aggregator, and the power company.

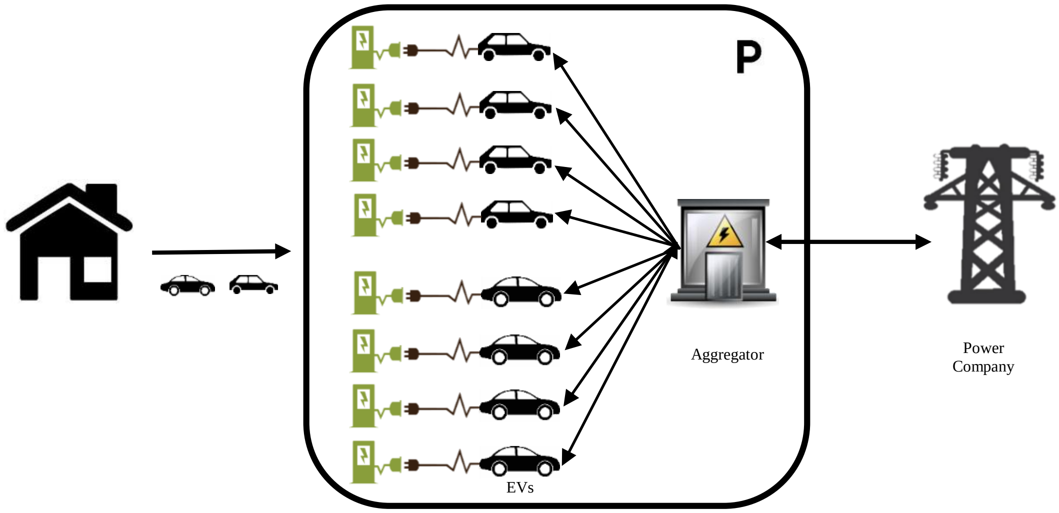

Figure 5. *V2G system architecture (Hosseinpour & Egbue, 2015)*

In both offline and online charging and discharging scheduling models, three different scenarios are developed. In the first scenario, only EV owners' profit from discharging and cost of charging are addressed in the objective function. So, the model is expected to schedule EVs so that they discharge more than being charged. In the second scenario, unfulfilled charging requests are considered as well as the profit from discharging. Thus, a penalty cost for uncharged electricity is added to the objective function of the second scenario. In the third scenario, a limit is taken into account for the maximum number of switches an EV battery can have, based on its battery age. This limit is incorporated in the constraints of the model. So, the objective function of the third scenario remains the same as the second scenario.

3.2 Offline Scheduling Model

3.2.1 Overview

In the offline problem, all of the information, such as the specification of the electricity grid as well as EVs are known in advance. Assuming that everything is known for the parking lot management ahead of time, a mathematical model is developed for the offline problem. The V2G management can plug all of the parameters of EVs and the grid into the mathematical model and find the optimal charging and discharging scheduling for electric cars.

3.2.2 Model Notations:

As previously explained, the offline scheduling problem is developed in three different scenarios in order to compare the effect of different factors in the optimization model. The indices, parameters and variables used in all the three scenarios are presented below.

Indices:

i EV index

t Time index

Parameters:

a_i Arrival time of EV i

d_i Departure time of EV i

$isoc_i$ Initial state of charge for EV i in terms of electricity units

u_i Desired state of charge for EV i in terms of electricity units

cp_t Electricity capacity in terms of electricity units, available for the smart parking lot to be used for charging EVs in period t

c_t Price of each electricity unit (in cents) for charging EVs in period t

p_t Price of each electricity unit (in cents) from discharging EVs in period t

mr_i Minimum desired number of electricity units to keep in the battery of EV i during discharging

mc_i Maximum battery capacity for EV i in terms of electricity units

ba_i Battery age of EV i

nsw_i Maximum number of switches allowed for EV i

Variables:

x_{it} Binary variable representing EVs' charging. $x_i = 1$ only if EV i is being charged in period t ,and $x_{it}=0$ elsewhere. Since only one electricity unit can be charged to each EV in each period, the value for x_{it} also represent the number of electricity units being charged to the EV i in period t.

y_{it} Binary variable representing EVs' discharging. $y_{it}=1$ only if EV i is being discharged in period t ,and y_{it}=0 elsewhere. Since only one electricity unit can be discharged from each EV in each period, the value for y_{it} also represent the number of electricity units being discharged to the EV i in period t.

md_{it} Mode of EV i in period t . This shows whether EV is being charged, discharged, or is idle. $md_{it}=1$, only if EV i is being charged at period t (x_{it}=1), $md_{it}=-1$, only if EV i is being discharged at period t ($y_{it}=1$), and $md_{it}=0$ when EV i is idle in period t.

z_i Integer variable representing number of unfulfilled electricity units for EV i.

soc_{it} State of charge of EV i in period t in terms of electricity units.

sw_{it} Binary variable representing if EV's battery switched or not. $sw_{it}=1$ only if EV i is switched in period t ,and $sw_{it}=0$ elsewhere.

When an EV enters the system, there is certain information that are required to be sent to the aggregator of the parking lot. Arrival time (a_i) will be captured as the time the ith EV entered the charging station. The EV owner provides the parking lot management with the time they will depart the system (d_i), the initial state of charge of the EV (*isoc*), the desired state of charge for the EV when exiting the system (u_i), the battery capacity (mc_i), and battery age (ba_i) of their EVs, along with their desired minimum number of electricity units which the battery should not be discharged below in each period (mr_i). Note that, mr_i is specified by the EV owner to make sure their EV has the minimum amount of charge if they want to depart the parking lot before the estimated d_i.

3.2.3 Mathematical Modeling:

The objective function for the first scenario is explained in equation (1).

Maximize (Customer Satisfaction)=Max (Price of discharging), Min (Cost of charging) (1)

From equation (1), in order to maximize customer satisfaction, EV owners should make the maximum amount of money from discharging electricity back to the grid and pay the minimum amount of money to the utility for charging their EVs. This objective function is described mathematically in equation (2).

$$Max\ (\sum_t \sum_i y_{it} *\ p_t - \sum_t \sum_i x_{it} * c_t\ ) \qquad (2)$$

To make customers more satisfied, unfulfilled electricity units (z_i) are added in the second scenario. By unfulfilled electricity units, the author means the difference between the identified desired state of charge of ith EV and the actual state of charge of that EV when departing. Specifying a desired state of charge shows that customers prefer to leave the V2G system having that amount of charge for their EVs. Unfulfilled electricity units are incorporated into the objective function. To normalize it with other cost factors in the objective function, a weight (pc_i) is used. This weight is the penalty cost for unfulfilled electricity units. Based on this new parameter, the objective function for the second scenario is shown in equation (3) and equation (4) below.

Maximize (Customer Satisfaction)= *(3)*

Max (Price of Discharging), Min (Cost of Charging), Min (Unfulfilled Charge)

$$Max\ (\sum_t \sum_i y_{it} *\ p_t - \sum_t \sum_i x_{it} * c_t - \sum_i pc * z_i\ ) \qquad (4)$$

Note that the objective function of scenario three is the same as scenario two. Therefore, objective function of the third scenario is the same as equation (4).

Model constraints for all three scenarios are explained respectively. The constraint in equation (5) controls the charging and discharging of EVs in the system. Based on this equation, the total electricity units from charging, summed with the unfulfilled electricity units minus the total discharged electricity units should be equal to the desired state of charge minus the initial state of charge of that EV.

$$\sum_{t=a_i:\, d_i} x_{it} - \sum_{t=a_i:\, d_i} y_{it} + z_i = u_i - isoc_i \qquad \forall\, i \tag{5}$$

Equation (6) puts a cap on the amount of electricity which can be used for charging EVs in the parking lot. The sum of the total charged electricity units for all EVs in all the periods must be less than or equal to the defined grid capacity. The electricity capacity available for the parking lot to be used in V2G, cp_t, is equal to electricity generation in each period, minus the non-EV electricity demand in that period

$$\sum_{i} x_{it} \leq cp_t \qquad \forall\, t \tag{6}$$

The state of charge of each EV in every period is calculated using Equation (7). According to this constraint, the SOC in each period for each EV is equal to its SOC in the previous period, plus the amount of charge the EV gained minus the amount of electricity the EV discharged at that period. Equation (8) defines the state of charge for the *i*th EV in period 0 as the initial state of charge of that EV.

$$soc_{it} = soc_{\,i(\,t-1)} + x_{it} - y_{it} \qquad \forall\, i\,, t \mid t \geq 1 \tag{7}$$

$$soc_{i0} = isoc_i \quad \forall i \tag{8}$$

The following two equations consider a lower limit and an upper limit for state of charge of each EV in each period. According to Equation (9), the state of charge for EVs in each period should not be less than the minimum desired number of electricity units for that particular EV. Respectively, Equation (10) implies the state of charge for each EV in each period should not be more than its battery capacity.

$$soc_{it} \geq mr_i \qquad \forall\, i\,, t \tag{9}$$

$$soc_{it} \leq mc_i \qquad \forall\, i\,, t \tag{10}$$

Equation (11) controls charging and discharging of each EV in each period to prevent concurrency.

$$x_{it} + y_{it} \leq 1 \qquad \forall\, i\,, t \tag{11}$$

According to equations (12) and (13), EVs must not be charged or discharged before arriving at the parking lot or after departing the system.

$$X_{it} = 0 \qquad \forall\, i, t \mid t > d_i \;\&\; t < a_i \tag{12}$$

$$y_{it} = 0 \qquad \forall\, i, t \mid t > d_i \;\&\; t < a_i \tag{13}$$

All the above explained constraints are common in all three scenarios. Scenarios one and two have the same constraints but different objective functions. Scenario three has the same objective function as the second scenario, but, besides all the constraints in scenarios one and two, scenario three has the switching number constraint as well. According to Grahn & Söder (2011), as the number of charging and discharging increased, the battery would exhaust faster. Therefore, as explained above, to make customers more satisfied, a limited number of switches is considered in the third scenario. The maximum number of switches (*nsw*) for each EV is identified by their battery age. Based on the assumption made, if the battery age is less than or equal to 3 years, the nsw_i is 8. It is less than or equal to 7 years but greater than 3 years, nsw_i would be 7. Finally, if the battery age is more than 7 years, the allowed number of switches is 5. The battery age information, ba_i, is given by the EV owner to the parking lot upon arrival to the system. Then, based on the battery age and the rules defined above, the nsw_i for each EV is considered. According to these explanations, the following equations are added as the extra constraints for the third scenario.

Equation (14) determines the mode of each EV in each period. Based on this equation, if $X_{it}=1$, which means EV is being charged, the mode will be 1. Additionally, if the EV is being discharged, meaning $Y_{it}=1$, the mode will be -1. Furthermore, if none of charging or discharging happens (X_{it} and $Y_{it}=0$), it means EV is idle in the system, and the md_{it} will be 0.

$$md_{it} = x_{it} - y_{it} \qquad \forall\, i\,, t \tag{14}$$

Equations (15) and (16) altogether calculate the switching numbers and determine if switching happened or not. The method used with these two equations is to compare the mode of *i*th EV at period *t* with the mode of same EV at the previous period (*t-1*). As the result of these constraints, sw_{it} will be 1, if the mode of EV *i* is changed at period *t*, and it will be 0 if the mode of EV *i* is not changed. Based on the definition of mode and equations (15) and (16), switching happens when EV's mode changes in one of the following ways: from charging to discharging, from discharging to charging, from idle to charging, from idle to discharging, from charging to idle, and from discharging to idle.

$$md_{it} - md_{i(t-1)} \leq BigM * sw_{it} \qquad \forall\, i\,, t \geq 2 \tag{15}$$

$$md_{it} - md_{i(t-1)} \geq -BigM * sw_{it} \qquad \forall\, i\,, t \geq 2 \tag{16}$$

In the above calculations, *M* is defined as a large number. To elaborate more how the model determines if switching has happened ($sw_{it}=1$) or not ($sw_{it}=0$), further explanations are provided below.

Assuming the left hand side of the above inequalities (md_{it}-$md_{i(t-1)}$) is a variable named F_{it}, and based on the previous explanation about values for md_{it}, possible values for F are -2, -1, 0, 1, and 2. Switching happens if F is -2, -1, 1, and 2. Respectively, there will be no switching if F is 0. We should prove that for all possible values of F, the correct switching will be calculated using inequalities (15) and (16).

Starting from $F=-1$, which means EV mode changes from charging '1' to idle '0', ($F=0-1$) or from idle '0' to discharge '-1', ($F=-1-0$).

$$\begin{cases} F \leq M * sw \\ F \geq -M * sw \end{cases} \xrightarrow{\text{If } F=\,-1} \begin{cases} -1 \leq M * sw \\ -1 \geq -M * sw \end{cases} \xrightarrow{\text{Then}} \begin{cases} sw = 0 \text{ or } 1 \\ sw = 1 \end{cases}$$

As it has just been proved, the first row of the inequality does not find the *sw* value. According to this inequality, both *sw* of 0 and 1 are possible. However, the second inequality finds *sw* to be 1. In other words, the second inequality is correct only if *sw* is 1. So, if $F=-1$, the constraints (15) and (16) will be used to calculate the value of 1 for *sw*, as expected.

Now, for $F=-2$, which means EV mode changes from charging '1' to discharging '-1', ($F= -1-1$), *sw* calculations will run as bellow.

$$\begin{cases} F \leq M * sw \\ F \geq -M * sw \end{cases} \xrightarrow{\text{If } F=-2} \begin{cases} -2 \leq M * sw \\ -2 \geq -M * sw \end{cases} \xrightarrow{\text{Then}} \begin{cases} sw = 0 \text{ or } 1 \\ sw = 1 \end{cases}$$

Similarly to $F=-1$, the first inequality does not find the *sw* value; both *sw* of 0 and 1 are possible according to this inequity. Still, the second inequality calculates *sw* of 1. In other words, the second inequality is correct only if *sw* is 1. Thus, if $F=-2$, switching will be 1.

Moving to *F=1*, which means EV's mode changes from idle '0' to charging '1', (*F=1-0*), or from discharging '-1' to idle '0', (*F=0-(-1)*), the *sw* calculations will be as below:

$$\begin{cases} F \leq M * sw \\ F \geq -M * sw \end{cases} \xrightarrow{If\ F=1} \begin{cases} 1 \leq M * sw \\ 1 \geq -M * sw \end{cases} \xrightarrow{Then} \begin{cases} sw = 1 \\ sw = 0\ or\ 1 \end{cases}$$

This time, the second inequality does not define the value for sw. It is the first inequality which calculates the *sw* of 1, as it is expected to be.

The next possible value for *F* is 2; it happens when EV's mode changes from discharging '-1' to charging '1', (*F=1-(-1)*). This is illustrated by the following calculations.

$$\begin{cases} F \leq M * sw \\ F \geq -M * sw \end{cases} \xrightarrow{If\ F=2} \begin{cases} 2 \leq M * sw \\ 2 \geq -M * sw \end{cases} \xrightarrow{Then} \begin{cases} sw = 1 \\ sw = 0\ or\ 1 \end{cases}$$

Again, it is the first inequality which calculates the *sw* of 1 as it expected to be.

Finally, when *F=0*, which means no changing in modes happens for EVs, and EVs are in the same mode as their previous period; If they were being charged, discharged or idle in the period (*t-1*), they are being charged, discharged and idle in the period *t* as well. This is the same for other modes of discharging, and idle.

$$\begin{cases} F \leq M * sw \\ F \geq -M * sw \end{cases} \xrightarrow{If\ F=0} \begin{cases} 0 \leq M * sw \\ 0 \geq -M * sw \end{cases} \xrightarrow{Then} \begin{cases} sw = 0\ or\ 1 \\ sw = 0\ or\ 1 \end{cases}$$

As can be seen in the above, in the case of *F*=0, both *sw* of 1 and 0 meets both above inequalities and are possible for the model to be calculated as *sw*. So, these two constraints are not enough for the model to calculate the *sw* value. The best way of forcing the model to calculate a 0 value for switching when *F=0* is to use the objective function.

Since we have a maximization objective function, we manipulate the model by adding the switching in the objective function with a negative coefficient. This coefficient is a very small value such as "ε". Having this in the objective function, in the case of $F=0$, the model will choose sw of 0. The modified objective function for the third scenario is demonstrated in equation (17).

$$Max\ (\sum_{t}\sum_{i} y_{it} *\ p_t - \sum_{t}\sum_{i} x_{it} * c_t - \sum_{i} pc * z_i - \sum_{t}\sum_{i} sw_{it} * \varepsilon) \qquad (17)$$

After switching numbers is calculated for each EV using the above explanations, the limit for these switching is defined by equation (18) in the constraints of the model.

$$\sum_{t} sw_{it} \leq nsw_i \qquad \forall\ i \qquad (18)$$

Now that the model is complete, all the objective functions and constraints in all three scenarios are described in detail. The proposed offline mathematical model is solved using CPLEX Mixed-Integer Programming solver in the General Algebraic Modeling System (GAMS).

3.3 Online Scheduling Model

3.3.1 Overview

Unlike the offline model, none of the EVs' information is identified ahead of time in the online scheduling model. However, the V2G management is aware of all the grid specifications beforehand. But, the parking lot management does not know how many EVs are going to enter the system at each period, when they want to leave the system, how much charge they currently have, and how much electricity they need; it is a dynamic model which is more realistic compared to the offline model. For modeling this online scheduling problem, the Rolling Horizon Optimization (RHO) approach is used and linked with the mathematical modeling developed before. The RHO technique helps the V2G system to receive EVs' information, period by period, and send this data to the mathematical model in order to get the optimum scheduling for EVs in the system (Hosseinpour & Egbue, 2015). In the next subsection, the developed online scheduling algorithm is described.

3.3.2 Online Scheduling Algorithm

In the online scheduling algorithm, period by period, as EVs enter the parking lot, the aggregator acquires EVs' data. This data includes: EVs' arrival time, departure time, initial and desired state of charge, and EVs' battery capacity. The developed online scheduling algorithm which is based on the RHO approach is described in Figure 6.

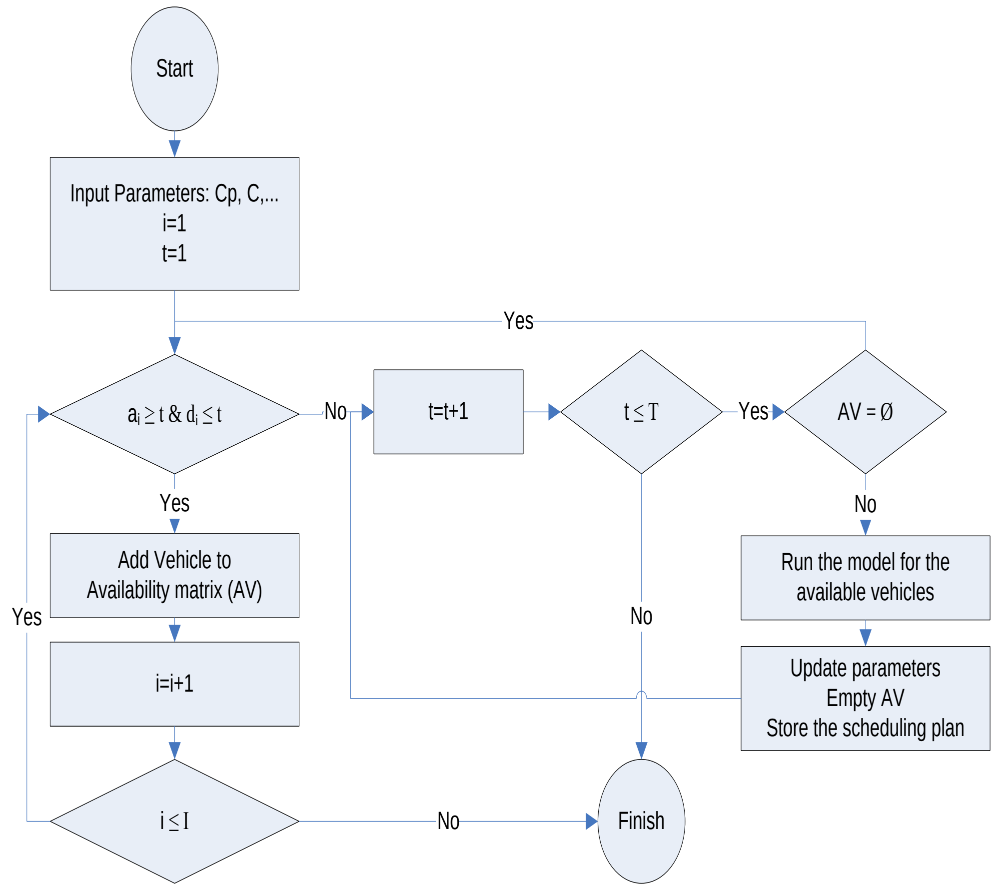

Figure 6. *Online scheduling algorithm (Hosseinpour & Egbue, 2015)*

The parameters used in the above algorithm are the same as the ones used for mathematical modeling in section 3.2.3. For example, a_i is the arrival time, and d_i is the departure time of EV i. One parameter is added here, AV, which is the availability matrix including indexes associated with available EVs.

The algorithm starts at period 1 ($t=1$). Then, it checks if there is any vehicle available in the system or not. Vehicle availability is defined by $a_i \geq t$ & $d_i \leq t$. This means the vehicle's arriving time should be more than or equal to the current system time and its departure time should be less than or equal to the current time. If there is no available EV at that specific period, the algorithm moves to the next period. Otherwise, if there are some available vehicles in the system, the model adds them in the *AV* matrix. The algorithm gets the input parameters of the available EVs and moves to the next available EV at the same period. This will continue through the last EV in the system at that period (Hosseinpour & Egbue, 2015).

In the next step, the algorithm sends the information to the mathematical optimization model to identify the optimal charging and discharging plans for those EVs. The optimization model is the same as the offline scheduling mathematical model described before in the section 3.2.3. As explained before, the mathematical model is considered to be a Mixed Integer Programming with the objective function of maximizing EV owners' satisfaction. Just like the offline mode, three scenarios are considered in the online model as well. After storing the charging and discharging plans for the available vehicles, the algorithm updates the system parameters and makes the *AV* matrix empty again. Moving to the next period, different vehicles enter the system and get their charging and discharging schedules for their duration in the system.

The proposed online scheduling model is solved using CPLEX Mixed-Integer Programming solver in the General Algebraic Modeling System (GAMS), and MATLAB software.

CHAPTER 4

RESULTS

4.1. Numerical Example

To test the efficacy of the proposed offline and online scheduling models, the system of a smart parking lot has been considered and a numerical example is generated respectively. In this parking lot, 500 electric vehicles are assumed to participate in the vehicle to grid system. The model simulation is conducted for one day, 24 hours. System time is divided into 30 minute periods, which results in 48 planning periods {1,…,48}. Arrival times of EVs in the parking lot are assumed to be uniformly distributed between 6 a.m. and 6 p.m. or period 13 and period 37. Moreover, EVs' departure times are also uniformly distributed between their arrival times and the last period in the system (48). Based on the generated arrival and departure times, parking lot utilization during the 48 planning horizon periods is demonstrated in Figure 7.

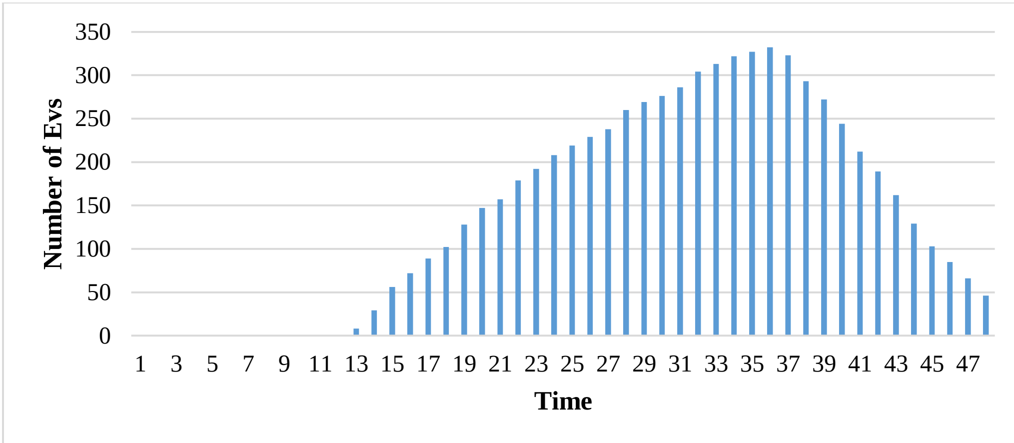

Figure 7. *Parking lot utilization*

There are three charging levels available for plug-in EVs. The level one charger uses a standard 120 voltage circuit that is typically available in buildings in the United States. If EVs need to be charged at homes overnight, level one charging is the most suitable charging level to utilize (Dong et al., 2014). The advantage of level one charging is that it is already available and no infrastructure investments are required, but it takes longer for a full charge (Grahn & Söder, 2011). The level two charger uses a 240 voltage circuit. It requires a system upgrade for installing level two charging stalls, and it can be employed in public charging stations. The level three charger is the fastest, charging EVs at a very high rate. With a level three charger a Nissan Leaf can be charged to the 80% level of its battery capacity in 30 minutes. Installing level three chargers is very costly, and it requires a lot of infrastructure changes (Dong et al., 2014).

Given the information above, the parking lot in this study is equipped with level two charging stalls (240 VAC, 3.3 kW/hour) for EVs to connect to the electricity network for charging and discharging.

It is important to note that in this study, the electricity for charging and discharging is measured in terms of "electricity units". Based on 30 minute planning interval considered in this study, and for a level two charging, each "electricity unit" is equal to 1.65 kW per period.

Furthermore, there are two types of electric vehicles participating in the V2G parking lot in this study; BEVs and PHEVs. We assumed that all the PHEVs are Chevy Volts and all the BEVs are Nissan Leafs. Random numbers are generated to specify the types of EVs. Based on the randomly generated numbers, we have 264 PHEVs, and 236 BEVs in our numerical example. According to the U.S. department of energy, Nissan Leaf and Chevy Volt have a maximum battery capacity of 24kWh and 16.5kWh respectively (U.S. Department of Energy, 2011a, U.S. Department of Energy, 2013). Therefore, the maximum battery capacity, mc_i, for BEVs is 15 in terms of electricity units. Accordingly, PHEVs' mc_i is 10 electricity units.

Next, the minimum desired electricity units retained when discharging, mr_i, is calculated. mr_i values are generated based on the assumption of being uniformly distributed between 1 and 20% of EV's mc_i. Based on this assumption, the values for mr_i, are 1, 2, or 3 electricity units. And, EVs' battery cannot be discharged beyond these values. The mr_i frequencies are shown in Figure 8.

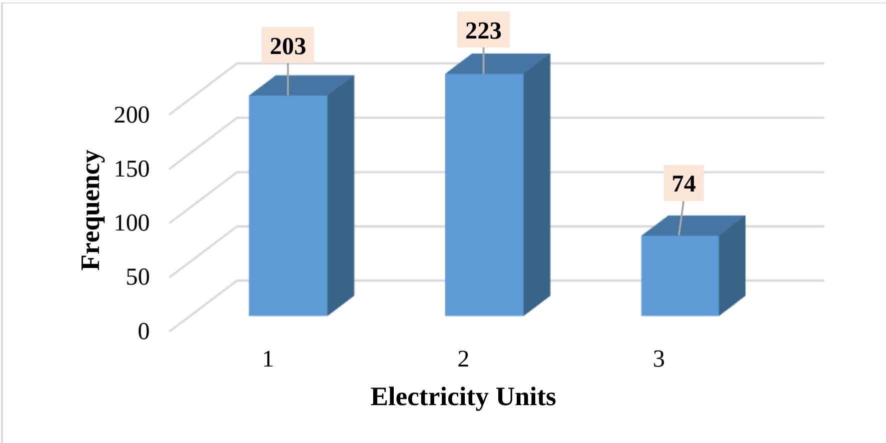

Figure 8. *EV mri value frequencies*

When EVs enter the parking lot, their battery has a certain level of charge. This level of battery charge, called "initial state of charge" in this study (*isoc*), is assumed to be uniformly distributed between mr_i and $mc_{i.}$ The values for *isoc* are generated as the minimum of 1 and maximum of 14 electricity units. The distribution of *isoc* values are shown in Figure 9. The EV owners also desire to leave the parking lot with a specific charge level. This parameter, defined as the "desired state of charge" (*u*), is randomly generated as well. *U* values are uniformly distributed between *isoc* and $mc_{i.}$ The minimum and maximum generated values for *u* are 1 and 15 electricity units respectively. Figure 10 shows the frequency of *u* values.

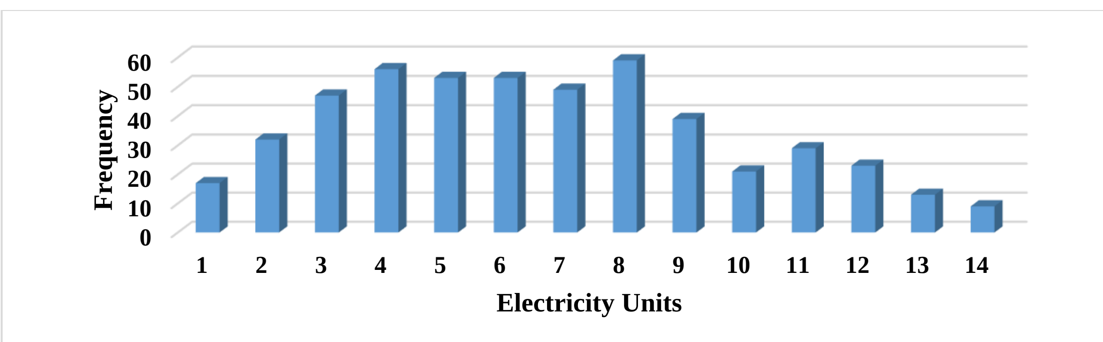

Figure 9. *Distribution of isoc values*

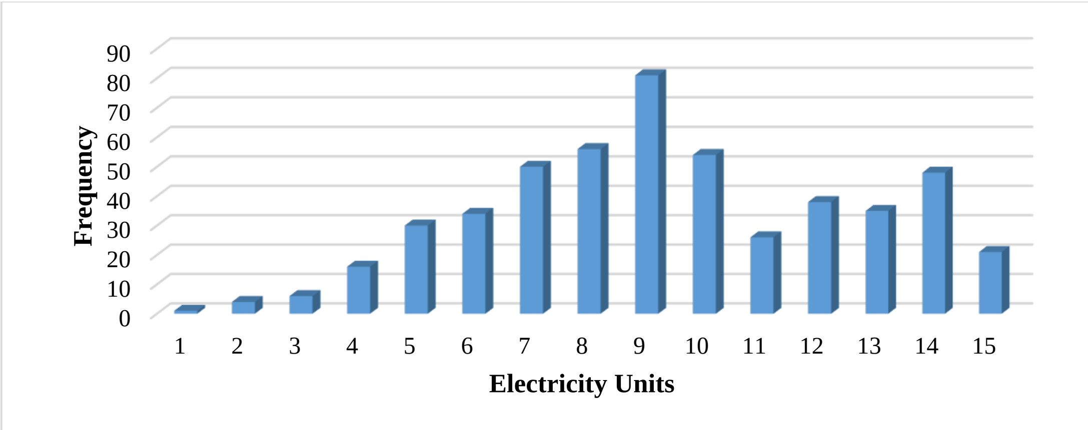

Figure 10. *Distribution of u values*

Figure 11 demonstrates both *isoc* and *u* values at the same time for 50 randomly selected EVs.

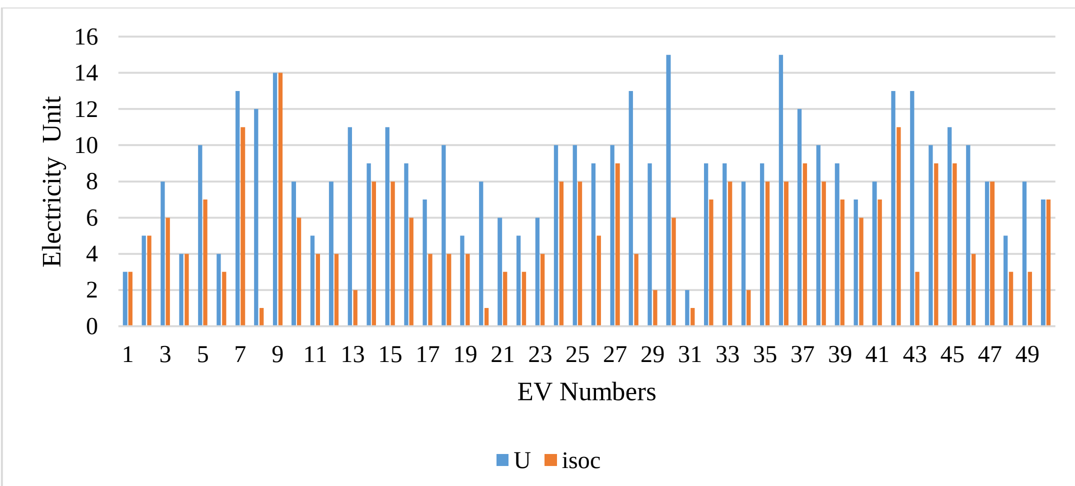

Figure 11. *isoc and u values for 50 randomly selected EVs*

It should be mentioned that EV owners determine their desired state of charge rationally and based on their duration in the parking lot.

Every EV's battery has a specific age. The battery age for EVs, ba_i, are generated using random numbers between 1 and 10. This parameter is shown in Figure 12.

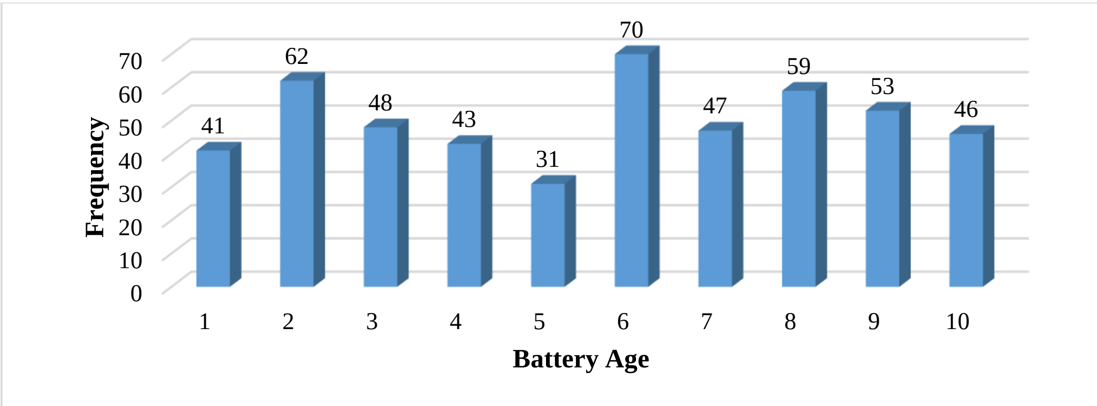

Figure 12. *EVs' battery age*

There is a maximum number of switches being considered in the third scenario of both offline and online models. This maximum number of switches for each EV, nsw_i, is defined based on EV battery age. Table 1 shows the *nsw* values based on battery ages.

Table 1. *Maximum number of switches*

Battery Age	NSW (Maximum Number of switches)
ba<=3	8
3<ba<=7	7
ba>7	5

As shown in the table above, EVs with less than or equal to 3 battery ages have an *nsw* of 8. For the cars that have a battery age greater than 3, but less than or equal to 7, the EV can be switched 7 times. Finally, for battery ages older than 7 years, the maximum number of switches is 5 times.

C_t, the price of every electricity unit during charging in period t, is extracted from the graph provided in one of the previous studies (Xu, Xie, & Singh, 2010), using Plot Digitizer software. We converted the prices to determine the electricity price in cents and each electricity unit of 1.65kW per 30 minutes. Furthermore, the price of each electricity unit during discharging in period t, P_t, is assumed to be the same as C_t.

The next grid parameter defined is the electricity capacity available at the smart parking lot to be used for charging EVs. This parameter, which is noted as cp_t, is calculated using equation (19).

$$cp_t = [\textit{Electricity generation at period } t] - [\textit{Non-EV electricity demand at period } t] \quad (19)$$

Non-EV electricity demand is extracted from the study by Xu et al. (2010) using Plot Digitizer software. According to their study, the maximum load is calculated to be 10 MWh. Considering the maximum electricity load, we assumed that the maximum electricity generation should be higher than the maximum load (10 MWh), and is equal to 10.5 MWh. Also, in this study, we asserted that only 10% of this electricity is available for the parking lot. All cp_t values are calculated in terms of electricity units.

To compare the rationality of the generated values for load, capacity, and price, capacity and load are plotted against time. Figure 13 shows the available electricity units versus the price of electricity units at each period. Figure 14 shows the non-EV electricity demand at each period versus the price of electricity respectively.

Figure 13*. Available electricity capacity vs price of electricity units*

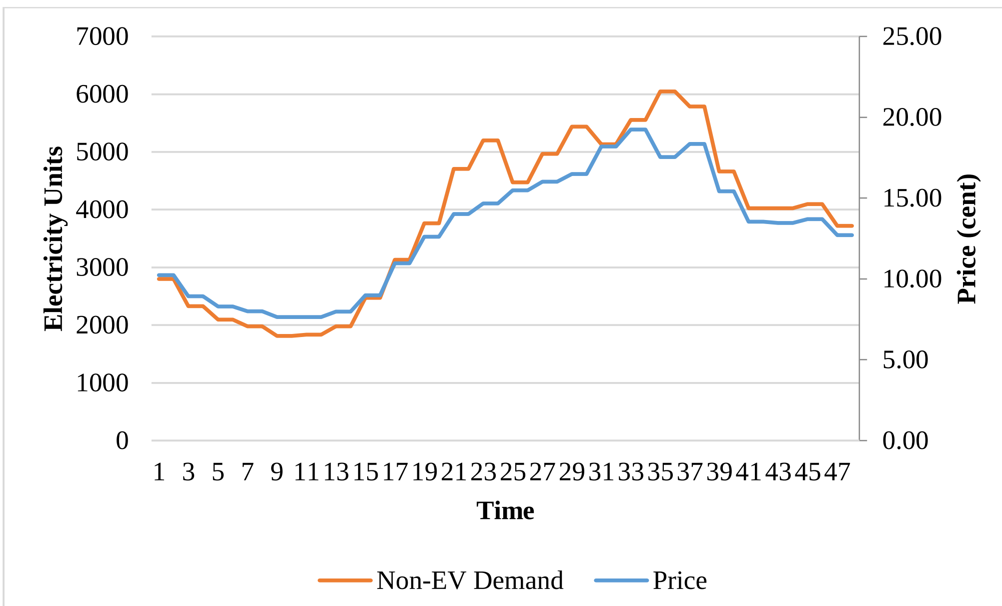

Figure 14. *Non-EV electricity demand vs price of electricity units*

As it can be seen in the above graphs, whenever the load is higher, the price of electricity goes up as well. Moreover, the price of electricity is lower at the periods when there is more electricity capacity available.

4.2. Offline Model Results

In the first scenario, the objective function is to maximize the money EV owners earn from discharging. No unfulfilled electricity units are considered in this scenario. After running the model, in total, 1,368 electricity units were used for charging EVs, and 3,599 electricity units were discharged back to the grid. As it can be seen, the system schedules more discharging than charging for EV batteries.

There are more discharged electricity units because of V2G management's emphasis on maximizing financial benefits to the customers regardless of the effect of unfulfilled electricity units on their satisfaction. As a result, a large number of customers depart the parking lot without getting their desired state of charge. Moreover, since there is no switching limit in the first scenario, the numbers of switching are high, as expected.

In the second scenario, penalty cost for unfulfilled electricity units is added to the objective function. This parameter, *pc*, is determined as the maximum price of electricity unit in the planning periods, which is 19 cents. Now that the system includes the desired state of charge of customers, it is expected to have more scheduled charging, compared to the first scenario. The result of running this model shows that altogether, 3,042 electricity units are charged and 1,745 electricity units are discharged in the system. In this scenario, the maximum number of switches is not incorporated in the model. Therefore, there are uncontrolled numbers of switching in this scenario.

In the third scenario, the upper limit of switching is added to the model. These switching constraints limit the maximum number of switches for an EV with respect to its battery age. As previously illustrated in Table 1, the maximum number of switches for the youngest cars is 8. Thus, we expect the model to function as planned, since this limit is added in the constraints of the model. Figure 15 demonstrates the frequency of different numbers of switches in the different scenarios.

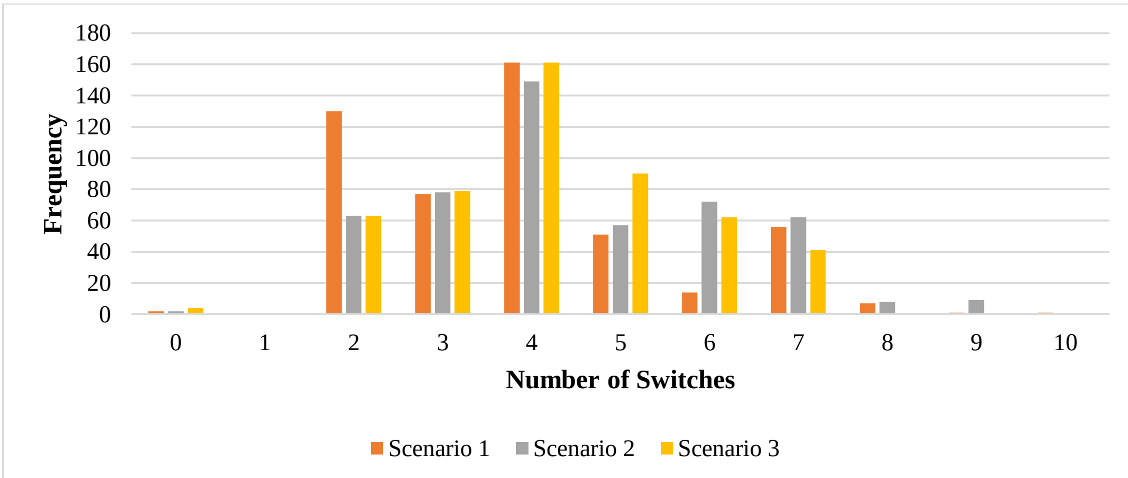

Figure 15. *Frequency of number of switches in the offline all three scenarios*

Furthermore, there are 3,012 electricity units from charging and 1,723 electricity units from discharging in this scenario, which are very close to the ones in the scenario two. Figures 16 and 17 show EVs charging and discharging comparison for all three scenarios. From these figures, it can be observed that in the first scenario, discharging occurs more often compared to scenario two and three. Also, charging is higher in the second and third scenario compared to the first one.

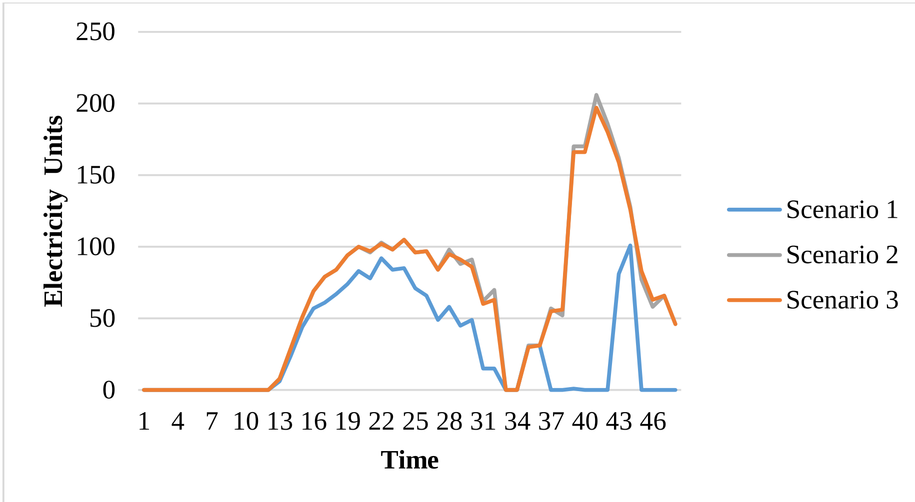

Figure 16. *Charged electricity units comparison for all scenarios of offline model*

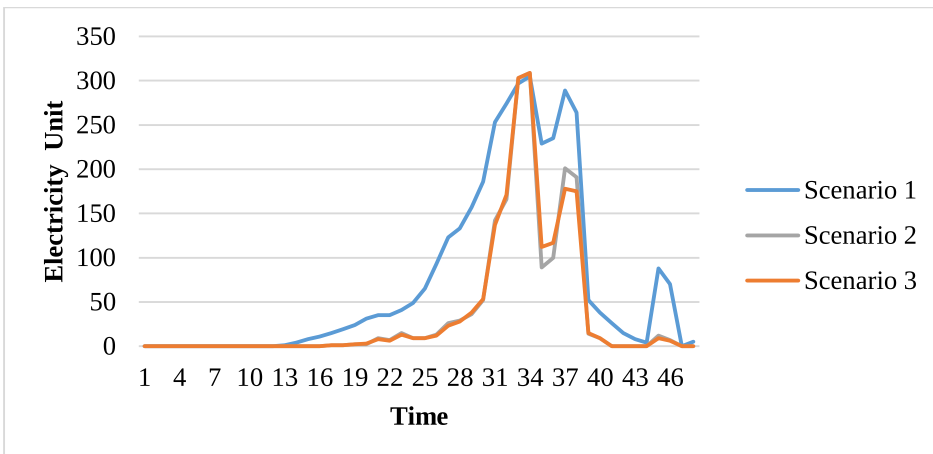

Figure 17. *Discharged electricity units comparison for all scenarios of offline model*

Figure 18 compares electricity prices with scheduled charging and discharging in scenario three. As intended, it can be observed that charging is mainly scheduled during lower prices of electricity, and discharging happens mostly when electricity prices are higher.

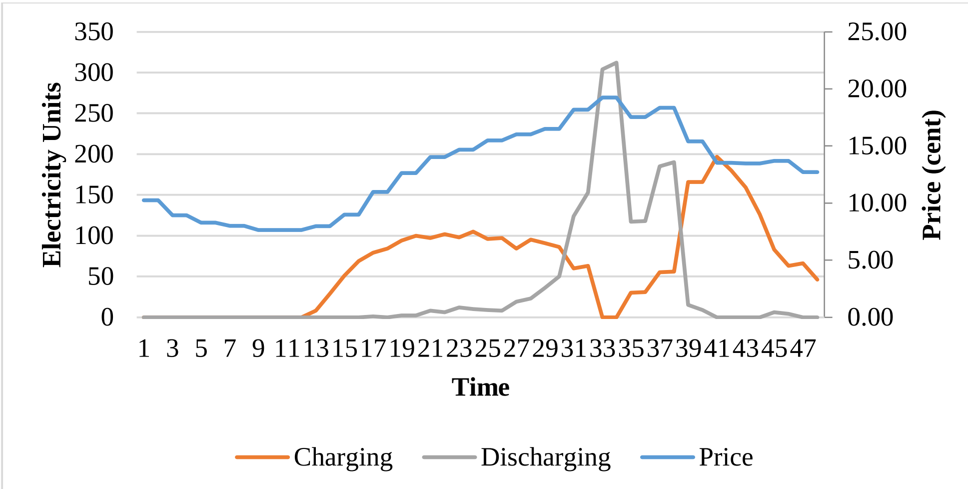

Figure 18. *Offline scenario 3 charging and discharging comparison vs electricity prices*

Figures 19 shows z values in the first, second, and third scenarios respectively. It can be observed that z values are much higher in the first scenario. In the second scenario, z values for 451 EVs are equal to 0, which means that these EVs leave the system with exactly the desired state of charge. The same follows in the third scenario, which z values are still low, and there are 438 cars with 0 unfulfilled electricity units, which is a little lower compared to the second scenario because of limited number of switches added in the third scenario.

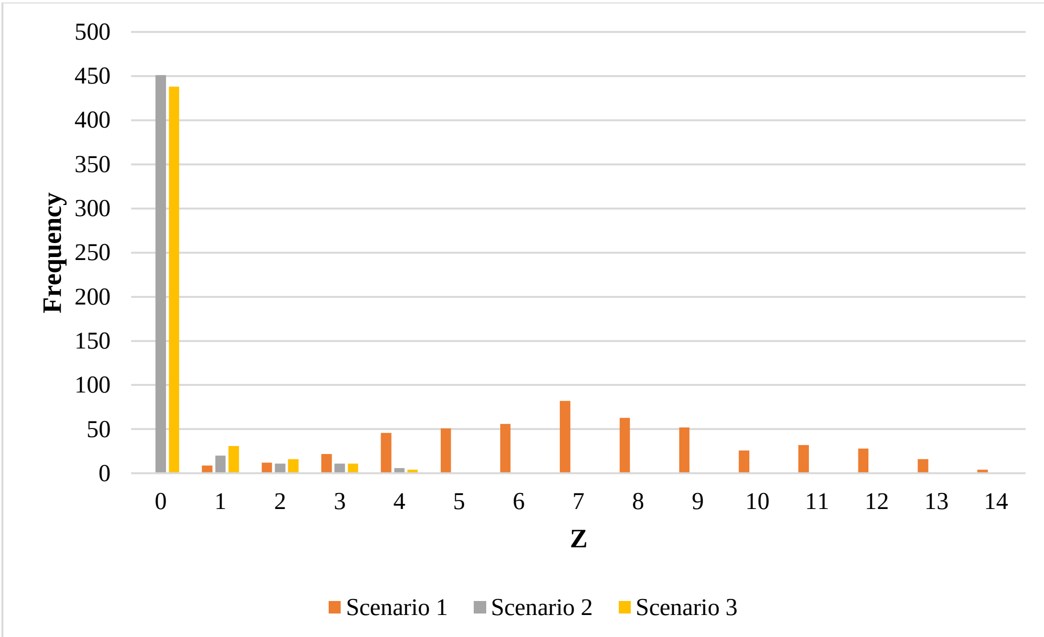

Figure 19. *Frequency of unfulfilled electricity units in the offline all three scenarios*

To observe and compare unfulfilled electricity units at the same time, Figure 20 shows *z* values for 50 randomly selected EVs in all three scenarios. As previously explained and shown in this figure, *z* values for the first scenario are a lot higher than scenario two and three, which have mostly the same *z* values. In the second and third scenarios, the customers would be more satisfied, since their demand in terms of state of charge are almost met to the desired level.

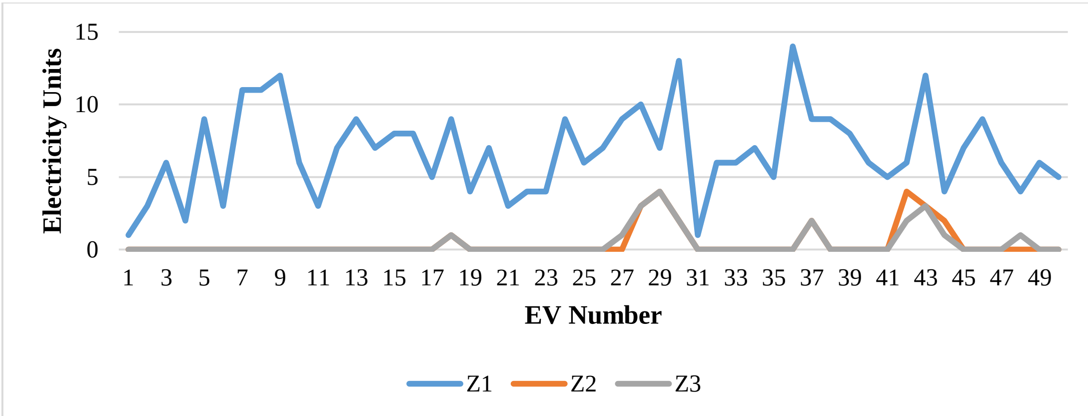

Figure 20. *Z values comparison for 50 random EVs in three scenarios of offline model*

To observe how the proposed model performed with respect to the capacity, Figure 21 demonstrates charged electricity units in scenario three compared to the available capacity. This figure shows charging never exceeds the capacity, as expected. Also, during some periods with limited electricity available for the parking lot (peak hours), almost all the capacity is used for charging EVs.

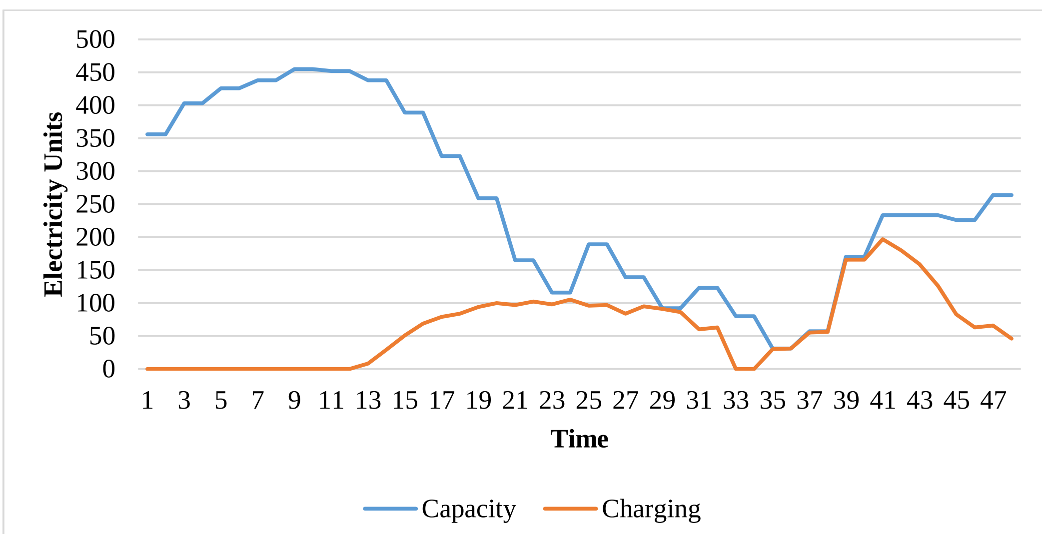

Figure 21*. Capacity versus charged electricity units in offline scenario three*

4.3. Online Model Results

To solve the online model, MATLAB and GAMS software are linked together. The developed rolling horizon algorithm explained in Figure 6 in chapter 3 are coded in MATLAB. According to this algorithm, MATLAB receives the information regarding EVs in each period, does some analysis on the input data to find out available and ready to schedule EVs, and then sends this information to the GAMS in order to find the optimal charging and discharging schedules for EVs. GAMS is then run, and sends the output back to MATLAB. Afterward, based on the information received from GAMS, MATLAB will update parameters, and move to the next period, repeating the process until all EVs are scheduled in the parking lot.

All three scenarios presented in section 4.3 apply to the online model. Based on the objective function, it is expected that discharging will be scheduled more than charging in scenario one. The output of MATLAB and GAMS show that 1,313 electricity units were consumed for charging EVs, and 3,482 electricity units were consumed for discharging EVs. Not having a penalty cost for unfulfilled electricity units makes a significant number of customers leave the system with a state of charge below what they desired.

In the second scenario, a penalty cost for unfulfilled electricity units is considered. The objective function is the same as scenario two in the offline model. The same as the offline model, *pc* is 19, equal to the maximum price of electricity unit in the planning periods. With this being stated, it is expected to have more scheduled charging and less discharging compared to scenario one. The result of this model demonstrates 2,973 electricity units of charging and 1,754 electricity units of discharging.

In the third scenario, the objective function does not change and is the same as the second scenario. The difference between second and third scenario is in the switching constraints added to scenario three. Therefore, it is expected to have almost the same total number of charging and discharging electricity units in scenario three and two. The result of this scenario shows there are 2,953 electricity units charged to EVs and 1,747 electricity units discharged from EVs to the grid. If we compare these numbers with the numbers in scenario two, it can be seen they are very close to each other. Both Figures 22 and 23 show EVs charging and discharging comparison in all three scenarios. As explained before, it can be seen that discharging is scheduled more in scenario one compared to scenario two and three, and charging occurs more in the second and third scenario with respect to the first scenario.

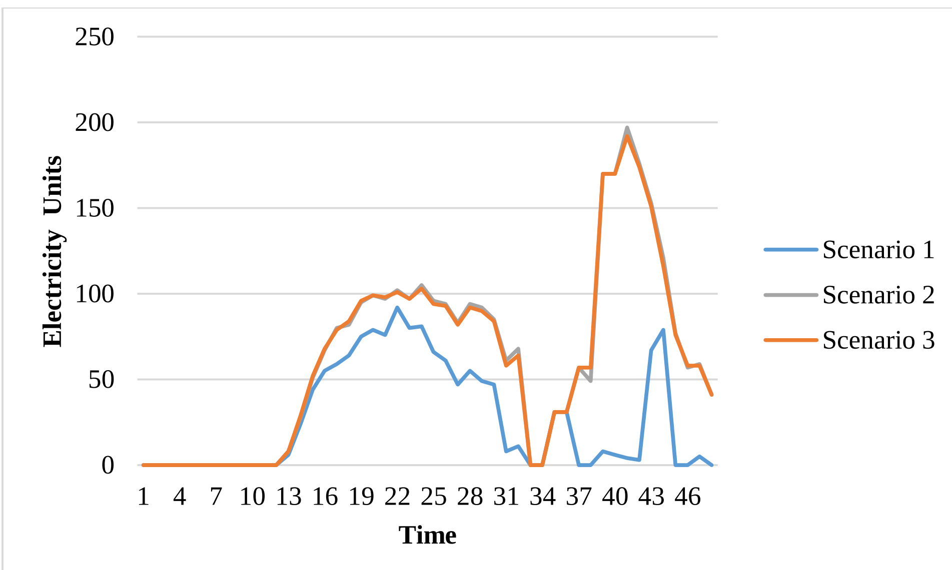

Figure 22. *Charged electricity units comparison of all scenarios of online model*

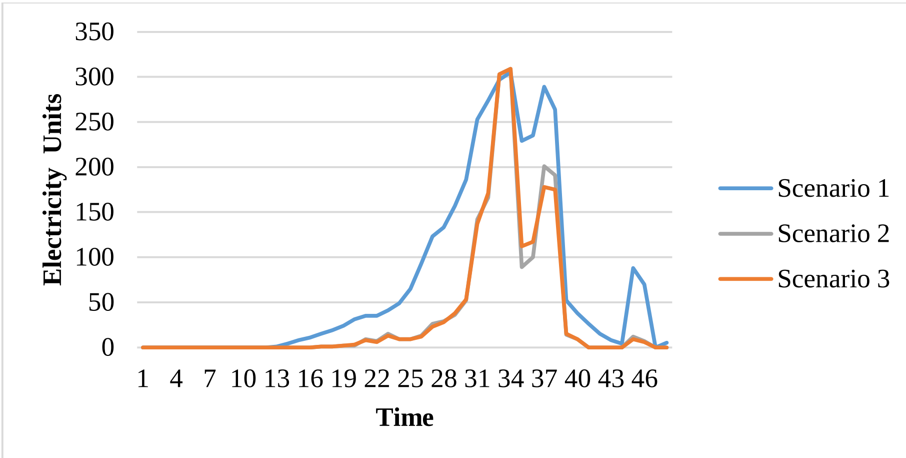

Figure 23. *Discharged electricity units comparison of all scenarios of online model*

Figures 24 demonstrates *z* values in the first, second, and third scenarios.

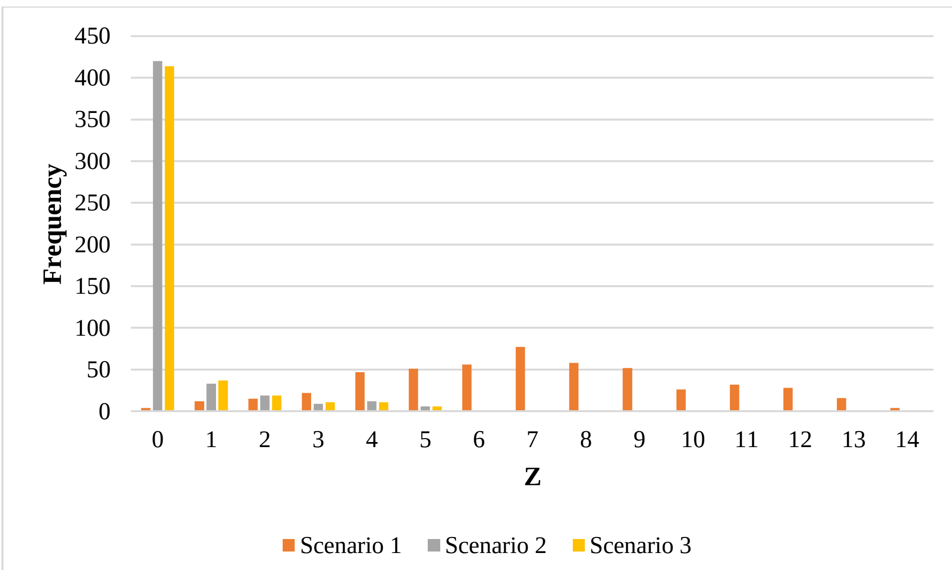

Figure 24. *Frequency of unfulfilled electricity units in the online scenarios one, two and three*

As shown in the above figures, *z* values are higher in scenario one. In the second and third scenarios, 420 and 414 EVs leave the system with exactly 0 unfulfilled electricity units respectively.

Figure 25 is plotted to show z values for 50 randomly selected EVs in all three scenarios. As previously explained, z values for scenarios two and three are lower than scenario one, which means a lower level of customer satisfaction in the first scenario.

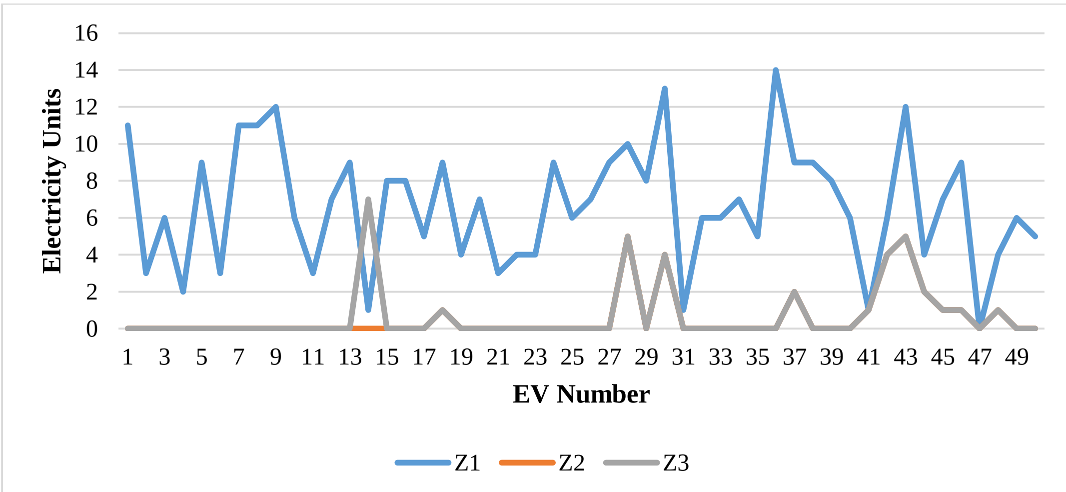

Figure 25. *Z values comparison for 50 random EVs in three scenarios of online model*

In the next step, we examine the effect of having an upper limit for number of switches in the online model. In the first and second scenario, there is no switching limit in the model, therefore the numbers of switching, *sw*, are expected to be high. Figures 26 demonstrates the frequency of different numbers of switching in the first, second and third scenarios. As can be observed from this graphs, in scenarios one and two, some EV batteries switch for 13 or 14 times between different modes, which is very high.

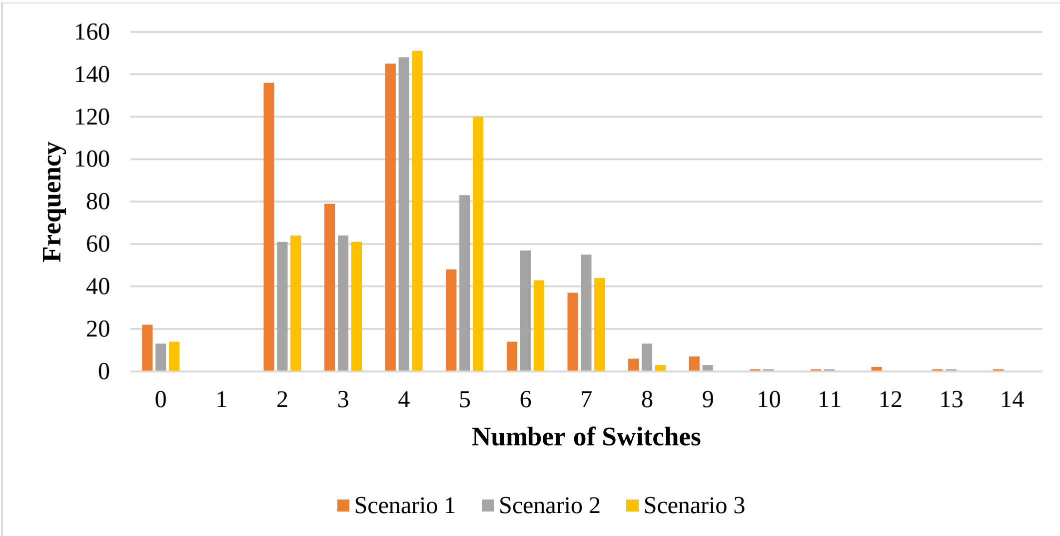

Figure 26. *Numbers of switches in online scenarios one, two and three*

Furthermore, to test the efficacy of the model, a comparison of electricity prices with scheduled charging and discharging in scenario three is plotted in Figure 27. This figure shows that charging is mainly scheduled during lower prices of electricity, and discharging happens mostly when electricity prices are high.

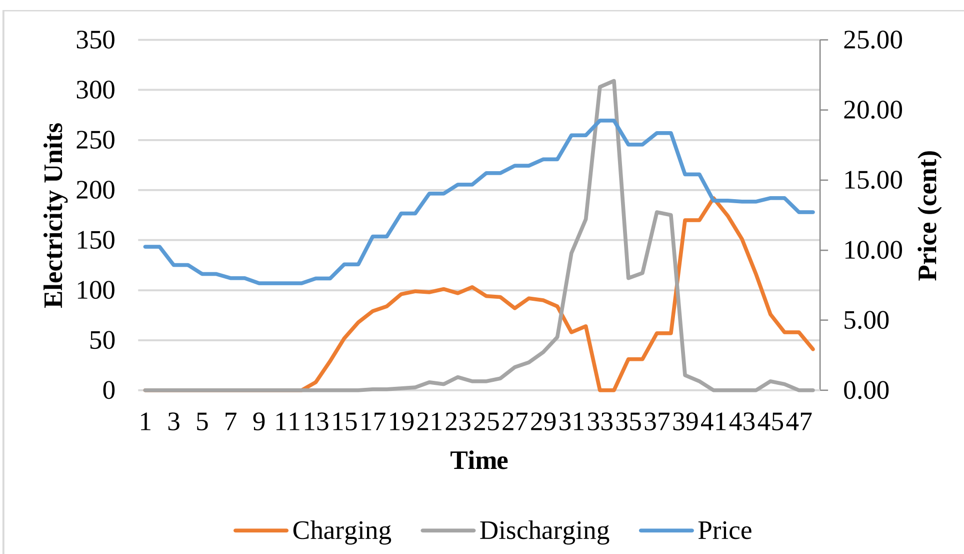

Figure 27. *Online scenario 3 charging and discharging vs electricity prices*

Moreover, to test the performance of the model with respect to the parking lot's electricity capacity, Figure 28 plots charged electricity units in scenario three versus the available capacity. As expected, this figure demonstrates charging never goes beyond the capacity.

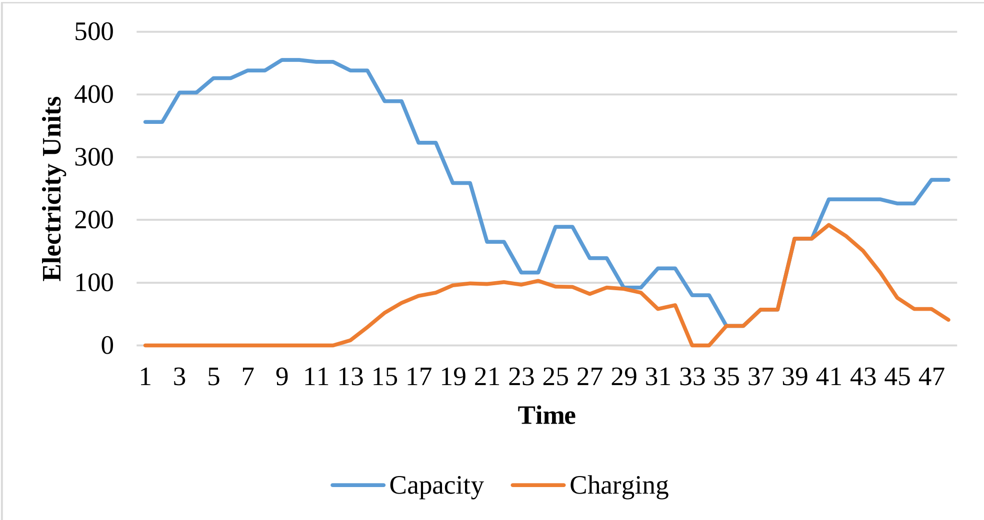

Figure 28. *Capacity versus charged electricity units in online scenario three*

4.4. Offline and Online Model Comparison

In the offline model, it is assumed that all EV information is known ahead of time; the model solves the scheduling optimization problem considering all EVs information. The output of this model is the optimized solution. On the other hand, in the online model, flow of EVs into the system and their specifications are not identified in advance. In such dynamic problems, heuristic or meta heuristic algorithms are the most common mythologies used. There is no guarantee that the result of these algorithms would be globally optimal, and most of the time, worse than the results of the offline model which is the optimal solution.

In this thesis, rolling horizon optimization approach is applied to the online model instead of heuristic or meta heuristic algorithms. Using RHO allowed the author to link the online algorithm with the optimization tool, which resulted in a global optimal solution. The main reason for applying RHO in this study is to get an optimal solution even if the problem is dynamic. Therefore, it is not expected the results of offline and online models will be very different. To examine the performance of the proposed models, plots of comparing online and offline are developed in this section.

Tables 2 and 3 demonstrate the total number of charged and discharged electricity units in each of the three scenarios for both offline and online models. As table 2 shows, total charging in scenario one for both offline and online models are very close to each other, 1,368 and 1,313 units. The same conclusion applies for scenarios two and three, and for discharging as well.

Table 2. *Total number of charging comparison*

Model	Total Charging		
	Scenario 1	Scenario 2	Scenario 3
Offline	1,368	3,042	3,012
Online	1,313	2,973	2,953

Table 3. *Total number of discharging comparison*

Model	Total Discharging		
	Scenario 1	Scenario 2	Scenario 3
Offline	3,599	1,745	1,723
Online	3,482	1,754	1,747

Figures 29, 30, and 31 show offline and online charging and discharging comparison in each of scenarios one, two, and three respectively. As can be observed from these figures, the charging for offline and online are mostly the same in all three scenarios.

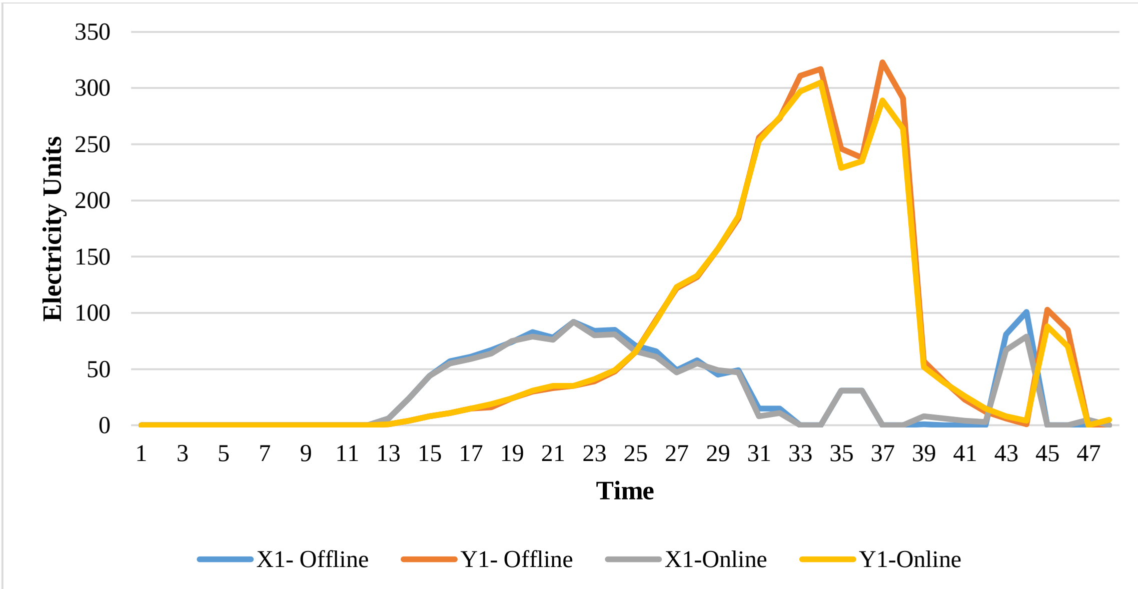

Figure 29. *Offline & online charging and discharging comparison in scenario one*

As with charging, it can be observed from these figures that discharging for offline and online are also mostly the same in all three scenarios.

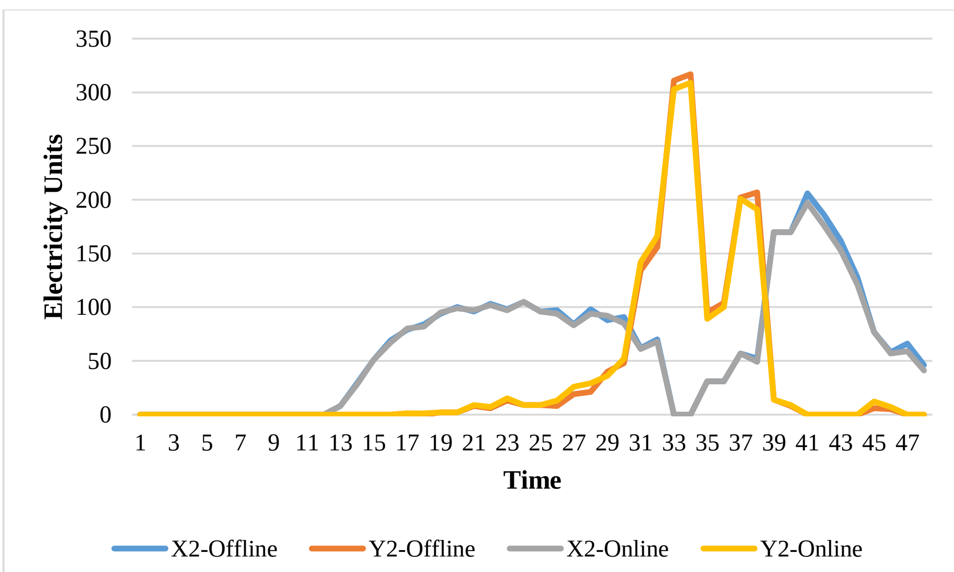

Figure 30. *Offline & online charging and discharging comparison in scenario two*

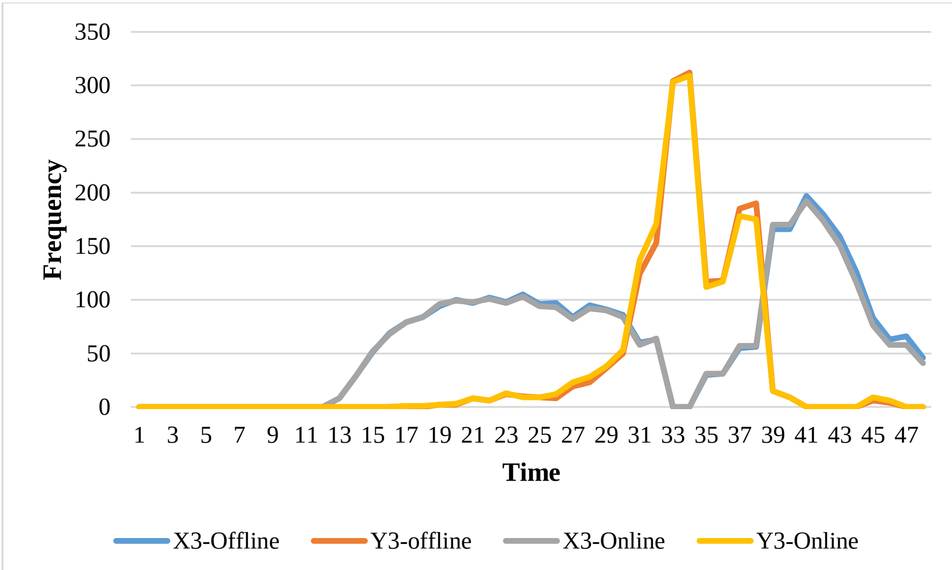

Figure 31. *Offline & online charging and discharging comparison in scenario three*

Figures 32, 33, and 34 show offline versus online *z* values for scenarios one, two, and three.

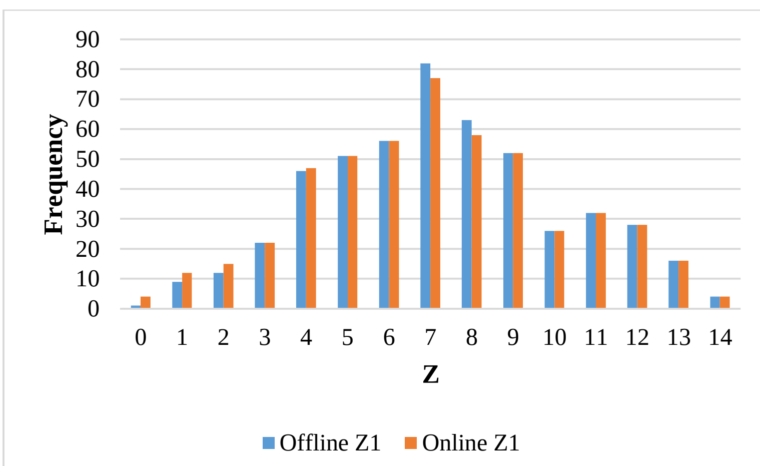

Figure 32. *Offline & online Z values comparison in scenario one*

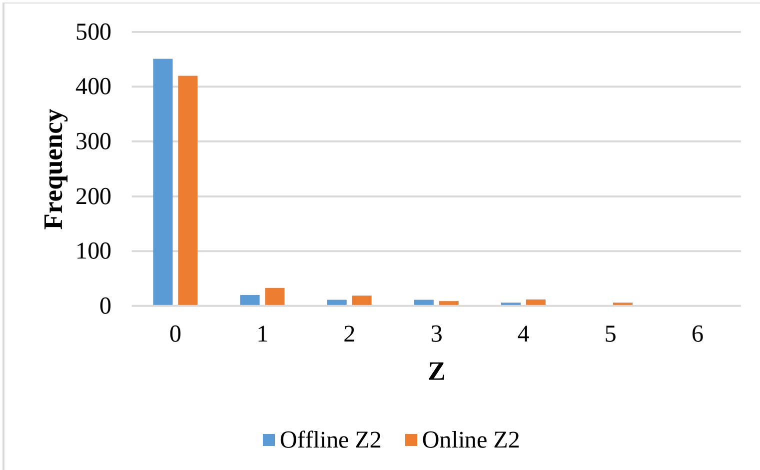

Figure 33. *Offline & online Z values comparison in scenario two*

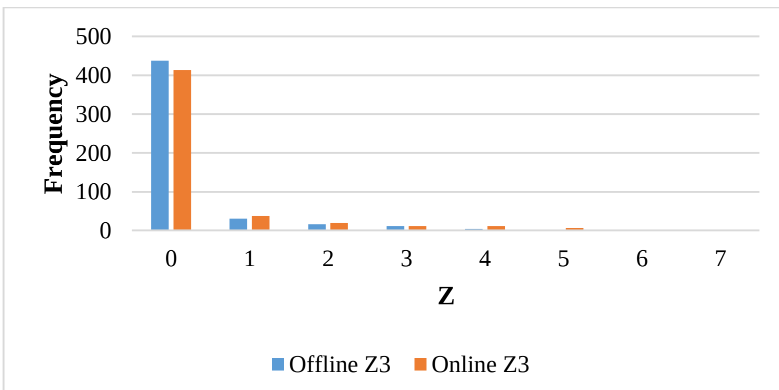

Figure 47. *Offline & online Z values comparison in scenario three*

As can be observed, *z* values are almost the same in offline and online models, with the online *z* values in scenarios two and three slightly higher than the offline model. This can be interpreted as the difference between the online model where the V2G system schedules EVs in one period without knowing what is going to happen next; in the offline model, all the EV information is taken into account.