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Penetration and Impact of Electric Vehicle Loads on System Operation

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Abstract

The penetration level of plug-in electrical vehicles (PEVs) is expected to steadily increase in the near future. However, a major obstacle facing massive introduction of PEVs is the significant impacts of PEV charging demand on power system. To overcome this barrier, modelling the PEVs charging demand is necessary to mitigate the negative impacts on the distribution system. After the PEVs charging demand is estimated, analysis of the impact of PEVs charging load on distribution system can be done by two approaches: uncontrolled operation and optimal operation of distribution system. This report presents the modelling techniques of PEVs charging demand. Moreover, the methodology of assessment the impact of PEVs charging demand, in addition to, impact metrics are investigated. In addition, the report presents M/M/c queuing model of charging demand for a single charging facility. The impact of PEV charging demand on distribution system is examined using optimal power flow. These models are duplication of some parts of study presented in [1].

1 Introduction

Plug-in electric vehicles (PEVs) represents a huge step forward a green transportation system, which have many economic and environmental benefits to the society. However, one of the main challenges that hindering the improvement of PEVs is its impact on power system, since, PEVs are considered a highly demanded application for electric power. Various techniques proposed to solve this problem starting from PEVs charging coordination till the introduction of charging stations that utilize renewable energy and energy storage elements. This report investigate the impacts of introducing PEVs on power system and PEV charging demand estimation.

The future deployment of PEVs leads to an increase in electricity demand, and large-scale penetration of PEVs is expected to significantly influence peak demand, feeder loss, and voltage fluctuations in distribution systems. To assess the impacts on the power system, an estimation of PEVs charging demand is required. Estimation of PEV load profiles helps utilities to mitigate its impacts and optimize this new load into their system. Utilities are then able to upgrade the distribution systems, or install of new charging infrastructure.

Estimation of charging profile of PEVs in a given area is a complex stochastic process, because it depends on different random variables such as the driving behavior, remaining battery state of charge, charging location and charging time, which are uncertain and varies from one customer to another. PEVs charging demand estimation can be loosely grouped in three levels, which are:

- ***System-wide PEVs charging demand estimation*** is used when the charging profile of all PEVs in the system need to be investigated. Utilities use this estimation method, when the impacts of PEVs integration on power system need to be assessed. Utilities are then able to upgrade the current distribution system (ex. Transformers, cables, protection devices, etc.). Moreover, this estimation could be used when utilities need to establish new charging infrastructure or generation sources. Additionally, this type of estimation is used when dispatching of current generation sources or demand side management (DSM) programs are applied.
- ***Single charging facility demand estimation*** is used to estimate the charging profile of a certain charging station or parking lot. Utilities use this type of estimation when impact of certain charging station or parking lot need to be assessed. Service providers also use this type of estimation in planning of a new charging facility, which involve determination of charging station capacity, number of chargers and waiting positions of the new charging station based on the required blocking probability of new customers.
- **Network of charging stations demand estimation** is used to analyze the interactions among multiple charging stations. Utilities and service providers are use this estimation method in order to allocate power between charging facilities based on the expected charging profile. Moreover, this estimation is used to allocate (routing) customers among charging stations either by direct control or by incentives such as charging price. The joint optimal allocation of power and customers for the stations in such a network maximize the operator's profit.

The scope and usage of different levels of charging demand estimation is summarized in Table 1. In this report, the three levels of PEVs charging demand estimation are discussed in the following sections. Then, the methodology of assessment the impact of PEVs charging demand, in addition to, impact metrics are investigated. Modelling of a single charging facility based on M/M/c queueing model is presented, along with the implementation of optimal power flow (OPF) to assists the impacts of PEVs charging demand on the distribution system. Case study of 38-bus system is presented. This model is a duplication of a part of study presented in [1].

Table 1, Summary of different levels of PEV charging demand estimation

Estimation Level	Scope of The Analysis	Usage
System-wide	Estimate the charging demand of all PEVs in the system	Utilities • To upgrade distribution system • Planning of charging infrastructure • Planning of new generation sources

		• Dispatch current generation sources • Apply DSM programs
Single Charging Facility	Estimate the charging demand of a single charging facility in the system	Utilities • Analyze the impact of the charging facility on power system Service providers • Planning of a new charging facility
Network of Charging Stations	Analyze the interaction between charging stations	Utilities • Allocate power between charging stations Service providers • Capacity planning of charging stations • Allocate customers between charging stations (price-based control)

2 System-wide PEVs Charging Demand Estimation

The estimation of system-wide PEV charging demand in a given area is a complex task, because the demand is a stochastic process, depending on various factors such as the driving behavior, remaining battery state of charge (SOC), charging location and charging time, which varies from one customer to another. The charging demand of all PEVs in the system need to be modeled in this estimation level. The estimation is required to evaluate the impact of PEV integration on power systems and to develop a plane for necessary upgrade of the current distribution system (e.g., transformers, cables, and protection devices). Moreover, the estimation will help utilities in establishing new charging infrastructure and new generation sources, dispatching existing generation sources, and implementing demand side management (DSM) programs.

In order to estimate the charging demand of system-wide PEVs, three mean consecutive models are used, where each model utilizes the outcomes of the previous model(s). These models are: travel pattern model, energy consumption model, and power consumption model. Travel pattern model determines the daily travel distance of PEVs, in addition to, where and when PEV will be charged. The information can be represented by a time varying distribution of the number of simultaneously charging PEVs at each distribution node. Energy consumption model estimates the PEV batteries state of charge (SOC*)* at the time of starting the charging process. This model capture the PEV's battery discharging characteristics. Power consumption model estimates the charging power of the aggregated PEVs load profiles in the charging locations. Different charging scenarios, charging rates and durations, and charging circuits are taken into account during power consumption modelling. These models are discussed in the following subsections.

2.1 Travel Pattern Model

Travel pattern modelling is necessary when the charging demand of PEVs need to be estimated. This model determines the daily travel distance of PEVs, in addition to, where and when PEV will be charged. In most cases, a typical daily drive for any person starts at home, but, the destinations of most driving patterns is highly stochastic. The average mileage driven during any given day has been determined to be roughly 26 miles per day. However, using average and expected values for the number of miles driven per day is not accurate, and a more realistic model can be done using stochastic models. This model leads to more accurate estimation of PEVs charging demand[2].

There are three method proposed to analyze PEVs travel pattern. The first method directly use deterministic methods in analyzing the travel pattern of PEV. Predefined charging time and location are assumed in this method. The second method use stochastic simulation methods, which relay in travel survey data, in order to capture the uncertainty of the main variables describing PEVs travel behavior. The third method use stochastic modeling techniques to capture the spatial-temporal dynamics of PEVs, which leads to estimate PEVs nodal charging demand.

2.1.1 Travel pattern modeling based on deterministic methods

Travel pattern of PEVs can be analyzed by deterministic methods based on PEVs travel survey data [3] or database obtained by GPS recording devices installed in PEVs[3]. However, due to lack of traveling statistics of PEVs, the traveling behavior of PEV users is assumed to be similar to the behavior of conventional vehicles users. So, the traveling demand of drivers will not affected by whether there vehicles are PEVs or not. This assumption may not be accurate because PEV's traveling capability may affect the travel pattern or users of PEVs have certain income level with certain traveling pattern [4].

Travel pattern can be analyzed based on statistical data such as National Household Travel Survey (NHTS) 2009 for U.S light duty vehicle fleet [4-6], UK National Travel Survey [7], and Danish National Travel Survey [8]. Surveys data contains information about trip origin and purpose, and trip distance. Moreover, these surveys contain information about the vehicles parking start/end time, the vehicles parking location (e.g., home, work, shopping, etc.). Vehicle travel patterns vary by household area (urban or rural) and day of the week (weekday or weekend).

From the databases of 2009 NHTS, two Microsoft Excel files are used in analyzing PEV users' travel behavior and extract valuable vehicle characteristics. These files are DAYV2PUB, which indicates trip characteristics and VEHV2PUB, which determines vehicles' characteristics[9]. Data about daily miles driven, starting time of charging, number of vehicles per house, and vehicle type of houses are extracted directly from the database. These data are utilized in the energy and power consumption models to estimate the PEVs load profile [9].

Deterministic methods can be also done based on database obtained by GPS recording devices installed in PEVs[3]. These devices record daily traveled distances, home arrival times, and home departure times, which is used to accurately estimate the travel behavior of PEVs. However, this method require installation of GPS devices in large number of PEVs, which is hard to achieve practically, and users' privacy may be violated.

2.1.2 Travel pattern modeling based on stochastic simulation methods

When data surveys is directly used, the inherent uncertainty of the driving patterns cannot be modeled. Therefore, stochastic simulation methods, which are also relay on travel survey data, can capture the uncertainty of the main variables describing PEV behavior. Stochastic simulation methods are proposed to account travel habits of PEV users. A probabilistic modeling can generate pdfs of PEV travel parameters based on survey data [3, 4, 6, 7], and these models will be more accurate if the correlation between travel parameters are considered [5, 8]. When queueing theory is used in modeling PEV charging demand, travel pattern model can be mapped into PEVs arrival process [10].

Based on data surveys, pdfs are obtained for home arrival time and daily traveled distances [3, 4, 6], and utilized in estimation of energy consumption of PEVs. Vehicles users' habits and diversity of usage are considered in [7], in which, Monte-Carlo Simulation (MCS) is used to generate virtual trip distances for each purpose. This model is consist of six stages, in each stage, different pdf is defined. These stages are pdf of the annual trip for each purpose, pdf of monthly trips per purpose, pdf of daily trips per purpose, pdf of hourly trips per purpose, pdf of trips per PEV, and pdf of distance per trip. The outcomes of the model by are the finished trips per hour per purpose for each PEV and the distance covered by each PEV.

A more accurate method is proposed, in [5, 8], in order to capture the uncertainty of PEVs travelling behavior. In these studies, synthetic datasets are generated based on travel survey data to comply with the uncertainty of the inputs. These synthetic datasets capture the whole uncertainty of the behavior of PEVs and are scalable to different PEV populations. The pdfs of three random variables are generated based on survey data, which are: the time of arrival at charging area, time of departure from charging area, and distance traveled in between. These variables are found to be correlated and to have nonstandard distribution functions. Then, a multivariate joint distribution function is created using a copula function, which represents the dependence structure between the variables.

Modeling travel behavior can be considered, when queueing theory is used to estimate PEV charging demand. As, the arrival process can be modeled as non-homogeneous Poisson process with a random arrival rate. Then, the inhomogeneous rate function can be forecasted based on travel survey data [10].

Unlike deterministic methods, stochastic methods use travel survey data in order to generate pdfs of three random variables, which are home departure time, daily traveled distance, and home arrival time. Stochastic methods not require accessing the complete vehicle usage data and are presented for regions where vehicle usage data are not available. Moreover, the accuracy of the stochastic methods increased when the correlation between random variables are accounted [3]. However, this method assumes that the spatial allocation of PEVs was predetermined instead of a probabilistic, as charging process is assumed to be at homes after arriving from trips. Therefore, this methods are incapable to predict the spatial-temporal characteristics of PEV travel pattern.

2.1.3 Travel pattern modeling based on spatial-temporal dynamics

Modeling the spatial-temporal dynamics of PEVs is necessary in anticipating PEVs nodal charging demand, which dynamically vary over space and time [11, 12]. In previous methods, predefined charging time and location is assumed. However, this method can be used to model the nodal PEVs charging demand. This method establish a probabilistic model in both time and space domains to present the moving PEVs charging demand with full randomness. In order to effectively model the spatial-temporal dynamics of PEVs, transportation system must be coupled with power system.

A probabilistic modeling of trip chain is used to model the spatial randomness of PEVs movements. A trip chain is a time-ordered trip sequence which consists of locations and routes of daily trips. The stochastic traveling and parking behavior is modeled in order to predict the traveling distance and route. For each PEV, the input parameters of this models are type of parking or charging location, occupations of driver, and combinations of daily trip chain. The shortest routes and daily trip distances are calculated based on graph theory, which utilized to bridge the traffic and power system. The spatial randomness of PEVs dynamics are probabilistically modeled as a daily trip chain of destinations and distances. Modelling the temporal dynamics of PEVs is used to capture the randomness in driving time, parking duration, and charging duration. In this model, the parking duration depends on parking location, and occupation of the driver. Moreover, charging duration is limited by parking duration. The daily spatial-temporal random movement of each PEV is simulated by MCS in each time segment of a day. Then a large number of PEVs is simulated in order to produce the dynamic profile of PEV charging demand on each bus [11].

Co-modeling of the transportation system and power system is investigated in [12]. In this study, activity-based travel demand modeling is done to address traveler’s choices behavior in transportation system.

Surveys data are used to extract information about charging stations specification, PEVs, and populations. These data are used along with traffic network topology to feed the transportation system simulator. The simulator then generates the individual traffic behavior such as routs, parking time and PEV charging needs. Transportation system and distribution system are mapped to local the charging facilities on transportation network, which is performed based on geographic information system (GIS). Simulation of the co-model indicates the number of PEVs using transportation system over time, in addition to, the arrival time of each PEV and distance traveled. This lead to extract the spatial and temporal characteristic of PEVs.

2.1.4 Comparison between travel pattern modelling techniques

The advantages and disadvantages of the travel pattern modelling techniques are summarized in table 2.

Table 2, Comparison between travel pattern modeling techniques

Travel Pattern Modelling Technique	**Advantages**	**Disadvantages**
Deterministic Methods	• Simple if the travel data, whether it from survey or GPS, is available	• Not accurate as it assume predefined charging location and time • Uncertainty of PEVs mobility is not analyzed
Stochastic Simulation	• Not required a large database of PEVs usage • Uncertainty of PEV mobility is considered • More accurate result obtained if the travel random variables are correlated	• Predefined charging location is assumed
Spatial-temporal Dynamics	• Probabilistic model of charging time and location	• Transportation system and power system must be co-modelled, which complicate the system

2.2 Energy Consumption Model

The discharging characteristics of PEVs' batteries, which is known as the energy consumption model of PEVs, can be represented by PEVs' batteries state of charge (SOC). SOC is a measure of the amount of energy stored in a battery. In this model, SOC refers to the percentage of energy remained in the battery when PEV start the charging process, after daily trips [9].

The SOC of PEV battery is a random variable and depend on other random variables such as the energy consumed by PEV per unit travel distance, the daily travel distance that PEV traveled in all electric range (AER) [4], and the energy required to maintain the cabin temperature comfortable for the vehicle driver and passengers [7]. These variables are defined as following:

- The energy consumed by PEV per unit travel distance depends on several parameters such as vehicle characteristic (e.g. vehicle weight, aerodynamics drug coefficient, etc.), diving habits, geographical location, road conditions and others. This random variable is assumed to have normal distribution with mean depend on vehicle class in [4]. However, only the average value is considered in [7].
- The daily travel distance of PEV depends vehicle travel pattern, which discussed in the last subsection. Therefore, the PEVs energy consumption model utilize the outcomes of travel pattern model of PEVs [4]. A linear relationship between SOC at the beginning of charging and distance traveled since last charging is applied [8, 9].
- The effect of ambient temperature is taken into consideration in [7], when calculating the energy consumption of PEVs. This energy is required for heater or air conditioner during severe weather conditions.

2.3 Electrical Power Consumption Model

Estimation of total electrical charging power by PEVs in the system is a challenging process. The difficulty in this estimation because of the inherent dependence on many variables, which are number of simultaneously charging PEVs in the system, charging scenarios, charging circuit, charging duration, and Priority based approach charging. These variables can be defined as follows:

- The probability of a certain number of simultaneously charging PEVs in a certain charging node and a certain time is in estimated in [11], when the spatial-temporal dynamics of PEVs is modeled. The probability of simultaneously charging PEVs can also be estimated by queueing theory [5]. Moreover, deterministic method based on survey data is introduced in [9].
- Electrical power consumption is also depends on charging scenarios whether it is controlled or uncontrolled charging. Charging scenarios determine the charging start time and charging rate. Uncontrolled charging of PEVs means that PEVs start charging immediately after plugged-in the power grid, and the charging rate is fixed. In this scenario, the PEVs home arrival time, which extracted from travel pattern model, is considered the time to start the charging process [7]. Controlled charging, which can be price based control or smart charging, means that there are some sort of coordination over the PEVs charging process. In price based control, utilities use time of use (TOU) electricity price to shift the charging load of PEVs to off-peak times. In smart charging,

utilities, with existence of communication link, directory adjust the charging start time and charging rate. Controlled charging optimize the scheduling of PEVs charging process, in order to maximize the benefits of utilities and users [4, 13, 14].

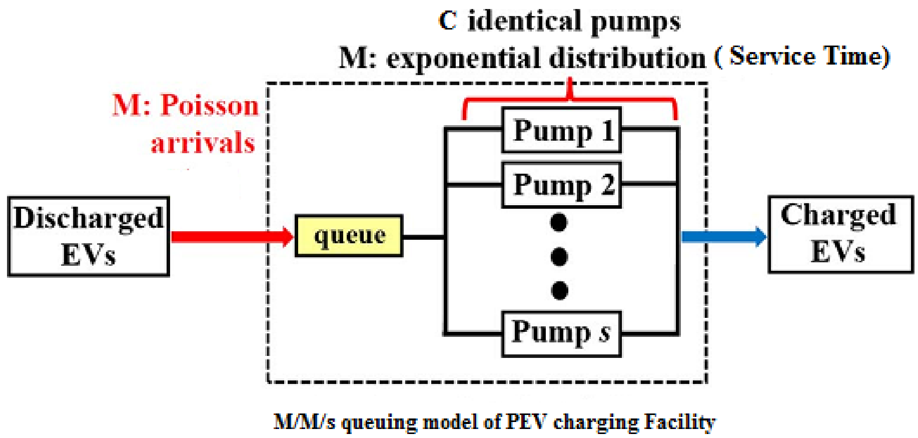
- Priority based approach charging, which is known as Charging Quality of Service (CQoS), is considered some types of charging coordination that affect total power consumption of PEVs [15]. In this approach, customer charging are classified into different charging schemes, each scheme characterized by its price and charging duration.
- Charging level (circuit) also affect the power consumption of PEVs. The standard charging levels for PEVs is summarized in table 3. As shown in this table, AC level 1 charger, which is called normal charger, needs a smaller power over a larger charging time. AC level 1 charger is commonly used as homes charger. AC level 2 and DC fast charger need a huge amount of power to charge PEV's batteries in small charging time. These types of chargers are suitable for public and commercial areas, in which, charging stations are deployed [16].
- There are different types of PEV's batteries, and each battery have its own characteristic. Charging duration depend on charging level, charging rate, PEVs' batteries capacity and the available SOC when PEVs start charging, which is estimated from the energy consumption model [2, 14].

Table 3, Standard charging Levels for PEVs

Charging Level	**Voltage**	**Current**	**Rated Power**	**Charging Time**
AC level 1	120 VAC, single phase	12-16 A	1.4-1.9 kW	7-17 h
AC level 2	240 VAC, single or three phase	Up to 80 A	19.2 kW	3-7 h
DC fast charging	200-500 VDC	Up to 80 A	Up to 40 kW	20 min – 1.2 h

3 Single PEVs Charging Facility Demand Estimation

As discussed before, charging facility can be either a fast charging station or a parking lot (i.e. slow charging facility). Modeling the charging demand of a single charging facility can be used in impact assessment of charging facility on power system [17] or in the planning phase of a new charging facility [18]. In contrast to the system-wide PEVs charging demand estimation, only single charging facility is studied in this models, in which, the demand profile of this station is estimated.



Queuing model of a single charging station [19]

Most of studies that model the single charging facilities use queuing theory, in which, fast charging stations are modeled as M/M/C queue model, as shown in Figure 1, [1, 17, 19] or M/M/C/S queue model [18] and parking lots are modeled as M/M/C/k/N_{max} ($C \leq k \leq N_{max}$) queue model [17]. As, the users of chargers in the parking lots are privately owned or shared only by limited number of users. This is not the case in the fast charging stations, in which, unlimited number of users use the charging facility[17]. The queuing modeling of a single charging facility is done based on the following assumption:

- The arrival process of PEVs to the charging facility is assumed to follow the Poisson distribution[17, 18]. The arrival rate of a discharged PEV at a charging station located in a highway exit is identified based on fluid traffic theory in [19]. A nonhomogeneous Poisson processes is assumed in [1], in which, arrival rate is either estimated based on mobility statistics or changing as a function of electricity prices.
- The charging competition rate is assumed independent and exponential distribution, with a mean approximated to a function of the average charging power per PEV and the average recharged SOC per PEV at charging station[19]. PEV battery charging behavior is taken into account when modeling the service time in [1]. As, there are a nonlinear relation between the charging time and PEV battery SOC. This nonlinear relation is approximated by a piece-wise linear relationship.

Based on queueing theory, the expected number of PEVs that simultaneously charged at any time can be extracted. Then, the charging current of PEV during the charging period is determined based on the daily recharge energy of a PEV, charging duration and charging voltage. After that, the total expected charging demand of all PEVs in the charging station over the time can be estimated based on the charging current and charging voltage for the expected number of PEV at any time[1, 17]. Once PEV charging profile is estimated, the impact of the charging station on power system can be analyzed [1].

In planning of PEVs fast charging facility, the decision variable is the PEV charging demand. Based on PEV charging demand, the number of chargers and the size of waiting space in the charging facility is optimized to meet the specified blocking probability for incoming customers. The optimal number of chargers and waiting positions maximize the profit of services providers [18]. For parking lots the decision variables are the charging rate and/or charging start time, which are optimized to follow a target charging profile (i.e., valley-filling approach)[18]. Energy Storage Systems (ESS) can be deployed in charging station in order to charge PEVs during peak time by the energy stored from the off-peak time or from the output of renewable sources installed at the charging station. The size of ESS in charging stations can be determined based on charging station demand profile [19].

4 Network of PEVs Charging Station Demand Estimation

The estimation of charging demands among a network of charging stations and the utilization of each station is a complex process. As, it depends on the dynamic and random mobility of PEVs, and hence traffic density in stations' surrounding area. However, this estimation is essential for utilities and system operators to allocate power and customers among charging stations in this network. Allocation of power and customers among the network ensures the lowest blocking probability of new customers, which leads to highest quality of service and hence highest profit for system operator.

Utilities have a limited power sources that must be optimally allocated among charging stations to meet their spatial and temporal demand. To maximize the system operators' profits, some charging stations are equipped with ESS to meet the stochastic charging demand. Utilities and system operators specified a certain blocking probability of new customers for every charging station in the network. From utilities prospective, power is allocated to the charging stations based on the spatial-temporal charging demand of each charging station in the network and the available power resources [20]. From charging stations operators prospective, the minimum amount of grid resources for charging stations, which guarantee certain blocking probability for each customer class, is determined in [21]. This optimization problem is done given the customer arrival rates.

Distribution of the incoming customers to charging stations in such network can be controlled by either a direct control or incentives such as charging cost. In [22], charging demand estimation of a networked charging stations is investigated as a function of charging prices and number of charger in each station. A BCMP queuing network model is developed to capture the interaction between charging stations. In this model, the arrival of PEV users to the charging stations changes in response to charging prices. Since, the charging demands of nearby charging stations are closely correlated to each other and depend on vehicle drivers' response to charging prices. A BCMP queueing network model is presented to characterize relations among the charging demands of multiple charging stations, taking into account the factors such as single PEV charging demand, charging decision making processes of PEV drivers, PEV traffic flow, and road system.

To implement the BCMP model of a network of charging stations, the daily energy consumption of a single PEV in an urban (or rural) area on a weekday (or weekend) is modeled, and each PEV is assumed to be charged once a day. The charging time is assumed to be exponentially distributed that is based on energy consumption of each PEV and charging power of each charger at charging station. The charging decision of each PEV user is based on charging prices. Energy consumption of PEVs to travel among different charging stations is assumed negligible. The arrival to each charging station is assumed to follow Poisson process with a rate can be obtained based on traffic monitoring technique. The routing between charging stations is modeled as infinite server as road system is assumed without congestions. PEV users' preference charging time is not modelled, and only the worst case scenario of PEV charging demand at each charging station is estimated. A relation between charging demand of each charging station, number of chargers, and charging price is estimated based on queuing network analysis.

5 Assessment of the Impacts of PEVs on Power System

In last sections, the spatial-temporal PEVs charging demand is estimated, whether for system-wide PEVs, single charging station, or a network of charging stations. Utilities also have an estimation of the conventional load demand of different customers' classes on the system, i.e., residential, commercial, and industrial. The total load of the system will be the conventional load demand profile in addition to the PEVs charging profile. Load growth is another factor that must be taken into consideration, when PEVs impact are investigated. Load growth is the new customer additions and new uses of electricity, during the time period of study[9, 23]. Charging demand of PEVs has a negative impact on the distribution network, these impact are summarized as following:

- **Impact on load profile:** charging of PEVs adds an additional load to the power grid, which affects the load profile of the power grid. Specially, when large number of PEVs charging at the same time in a given area, which cause peak load at that area. Many solution are proposed to solve this problem such as TOU tariff and charging management strategies.
- **Impact on system components:** As PEVs considered a highly demanded application, a huge amount of power transmitted from generators to loads. This can cause overloading on system components specially distribution transformers and cables. Proper network planning and load management is necessary to adopt the future loading of PEVs.

- **Impact on system losses:** PEVs charging cause more power flow through the network, which cause more system loss. Coordinate EVs charging and usage of DGs near charging station can reduce system loss.
- **Impact on voltage profile and phase unbalance:** voltage drop and voltage deviation can be happen at the interconnection point during PEVs charging. Therefore, network voltage requirements can be violated if large number of EVs charging at the same time. Additionally, phase unbalance may happened by using single phase AC charger. Voltage regulators and voltage support strategies can maintain the voltage profile at the acceptable limit, and load management strategies can prevent phase unbalance problem.
- **Harmonic impact:** As PEVs chargers contain power electronic circuits, it cause some harmonics to the power grid, which can be eliminated by using filters.
- **Stability impact:** PEVs integration makes the power grid more sensitive to disturbance, and needs more time to reach the steady state. This means that power system become less stable with integration of PEVs.

Analysis of the impact of PEVs charging load on distribution system can be done by two approaches: uncontrolled operation and optimal operation of distribution system [1].

- In uncontrolled operation of distribution system, power flow (PF) analysis is used to calculate the impacts of total load on every node on the distribution system. PF is a tool that provides a steady state analysis 'a snapshot' of the state of the system. The output of PF consists of node voltages, line currents, transformer loadings, and peak losses in both lines and transformers, which have been calculated based on the new load profiles [23, 24]. To capture the randomness and uncertainty of the load demand, probabilistic power flow (PPF) [17] or MCS [25, 26] is used to determine average losses, ranges of voltages and branch currents variations at feeder nodes and sections. Security violations and system performance indices are then calculated. In this approach, Line Drop Compensator (LDC), which is a device that facilitate the adjustment of bus voltages, will not take any operational and control action to manage the system voltages[1].
- In optimal operation of distribution system, Optimal Power Flow (OPF) is used to determine the instantaneous optimal steady state, which is achieved by controlling LDC to minimize an objective function such as minimize feeders loss. LDC's optimal operation actions controls system voltages to ensure system security [1]. To capture the uncertainty of PEV charging demand, stochastic OPF is used to examine the impact of total system loads on distribution system operation to minimize an objective function such as the expected feeder losses [1].

Three mean time-varying impact indicators are used when the spatial-temporal impacts of PEVs charging demand is analyzed [24, 25]:

- The first is level of congestion LoC of line I – j at time k, which indicates the shortage in transmission line capacity to meet the waiting load.

$$LoC_{i,j,k} = \frac{Actual\ power\ flow\ on\ line\ i-j}{Rated\ power\ flow} * 100\%$$

- The second index is nodal voltage deviation NVD at node I at time k, which determine the voltage drop in system nodes.

$$NVD_{i,t} = \frac{|Actual\ voltage\ of\ bus\ i-j| - |low\ limit\ of\ bus\ i\ voltage|}{|low\ limit\ of\ bus\ i\ voltage|}$$

- The third index is system energy loss rate ELR, which represents the percentage system daily energy loss in the total daily energy consumption

$$ELR = \sum_{k}\sum_{i,j} \frac{P_{loss}}{P_{loss} + P_{base} + P_{PEV}} * 100\%$$

6 System Model

In this section, a queuing analysis of a single PEV charging facilities is introduced. The expected PEV charging demand is estimated based on $M_1/M_2/c$ queuing model [1]. In this model, M_1 is represent the arrival rate (λ) to the charging facility, which considered as non-homogeneous Poisson process. The PEVs arrival rate depends on consumers' convenience which is determined by the number of PEVs on road. When the number of vehicles on the road is high the arrival rate is high, irrespective of the price or local distribution company (LDC) operational constraints. M2 represents the mean service or charging time of PEVs, which is assumed to follow the exponential distribution. The service time is modeled as exponential distributions with upper and lower limits randomly assigned to each PEV. Service time is depended on charging level, battery capacity, battery SOC, and battery charging behavior (BCB). As charging station is considered a fast charging technique, the charging power typically starts at a high rate, and drops off as the battery SOC approaches its full capacity, which explains the BCB of PEVs. C represent the number of chargers at the charging facility.

Arrival rate to the charging facility is assumed to be proportion to the number of vehicles on roads in the given study area, which is Waterloo, Ontario, Canada in our case. This information is based on the assumption that the driving and usage behavior of PEVs is exactly similar to the conventional vehicles, which may not be accurate because PEV's traveling capability may affect the travel pattern or users of

PEVs have certain income level with certain traveling pattern. Using the available survey data from the Waterloo Region Transportation Tomorrow Survey (TTS), the mobility statistics of vehicles can be known over the time of day, as shown in Figure 1. Table 4 is describe the relation between the number of vehicles on roads and the number of PEVs arrived at the charging facility.

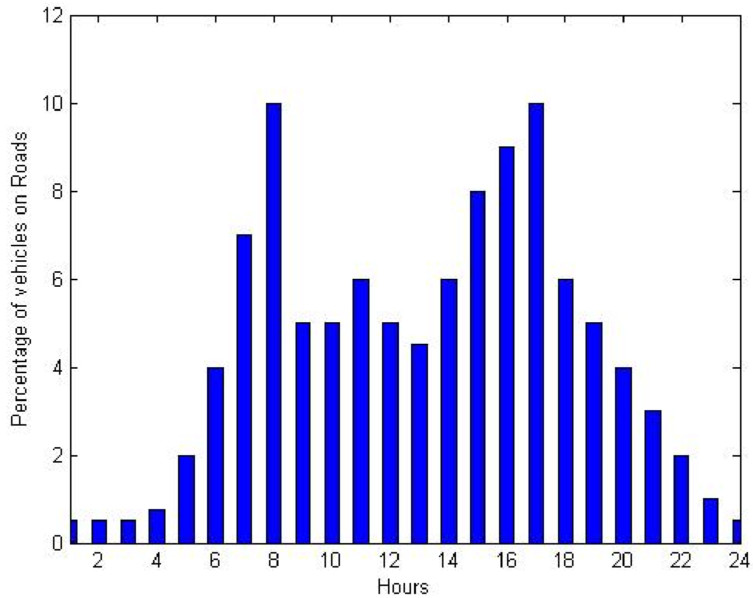


Figure 1, Percentage of vehicles on roads based on TTS data [1]

Table 4, relationship between vehicles on road and arrival rate to the charging facility

Percentage of vehicles on roads	Number of arriving PEVs to the facility
<= 4 %	Uniform distribution between 1 to 4 PEVs
>4% and <= 7%	Uniform distribution between 5 to 11 PEVs
> 7 %	Uniform distribution between 12 to 17 PEVs

The mean charging time of PEVs depended on several factors such as the battery capacity, the type of charger, current SOC of the battery, and battery charging characteristics. In this model, Battery Charging Behavior (BCB) model is employed [1]. In order to estimate the required charging time for PEVs, the SOC of the arriving PEVs must be firstly approximated. This required an information about the distance (DD) traveled by the PEVs. TTS survey data can be used again to provide this information. As shown in Figure 2, the distance traveled by PEVs is proved to follow the long normal distribution with mean 40 miles and variance 20 miles [1].

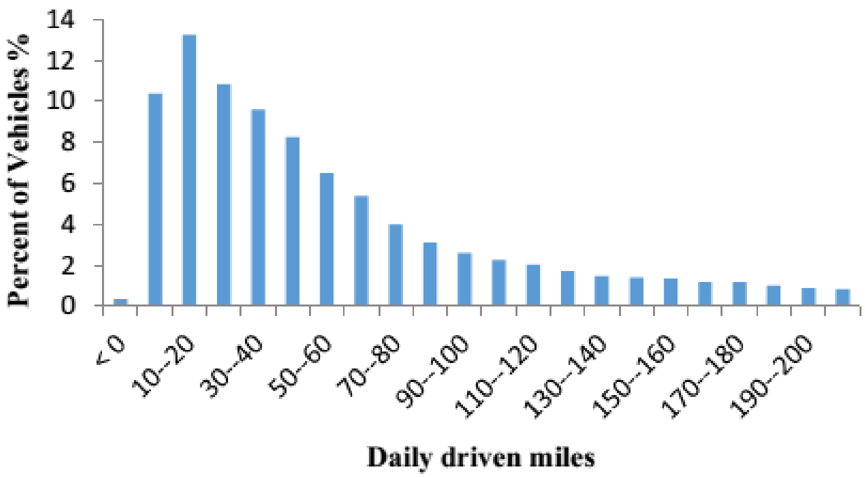


Figure 2, Long normal distribution of distance traveled by PEV based on TTS data [1]

Information about battery capacity (C_{bat}) and energy consumption per mile (E_M) are needed in this model. These information are depend on the type of vehicle, and four class (y) of vehicles are considered in this work. Table 5 summaries the parameters related to each class of vehicles.

Table 5, Parameters of PEVs class

PEV class	Compact	Economy	Mid-size	Light-truck / SUV
C_{bat} , kWh	8 – 12	10 – 14	14 – 18	19 – 23
Em , kWh/mile	0.2 – 0.3	0.25 – 0.35	0.35 – 0.45	0.48 – 0.58

The daily energy consumed (E_{Cy}) by each class of PEVs can be the calculated as following:

$$E_{C_y} = \begin{cases} C_{bat\ y} & ,if\ DD_y \geq DD_{max} \\ E_m * DD_y & ,if\ DD_y < DD_{max} \end{cases} ,\forall\ y$$

The maximum driving distance of different class of PEVs is given by:

$$DD_{max} = \frac{C_{bat\ y}}{E_{M\ y}} ,\forall\ y$$

The SOC of the arrived PEVs to the charging facility can know be calculated as following:

$$SOC_y = 1 - \frac{E_{C\ y}}{C_{bat\ y}} ,\forall\ y$$

To consider the constraint of battery charging characteristics, SOC of the arriving PEVs are assumed between 0.2 and 0.85. Therefore, limits should be applied to the values of SOC as following:

$$SOC_y = \begin{cases} 0.2\,, & if\ SOC_y \leq 0.2 \\ SOC_y, & if\ 0.2 < SOC_y \leq 0.85 \\ 0.85\,, & if\ SOC_y \geq 0.85 \end{cases} ,\forall\, y$$

The required mean charging time can be calculated based on the information about SOC of different classes of PEVs, and using the Piece-wise approximation of battery charging characteristics, as shown in Figure 3. Therefore, the mean charging time can be calculated based on the following:

$$T = \frac{SOC_{l\,y} - b_l}{a_l} ,\forall\, l\ \in (1,2,3,4), \forall\, y$$

Where a_l and b_l are the slop and intercept of each linear piece of the battery charging characteristics.

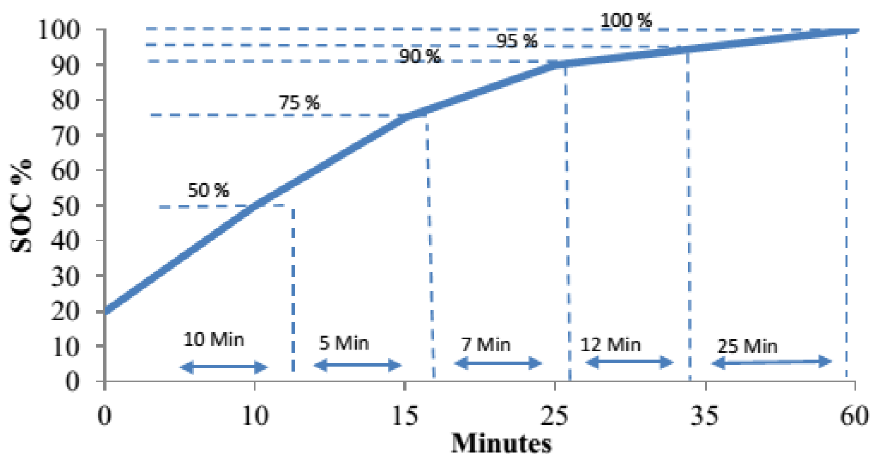


Figure 3, Battery charging characteristic of compact PEV [1]

The M/M/c queuing analysis is used in order to calculate the probability of a number of simultaneously charging PEVs at the charging facility $P_k(n)$.

$$P_k(n) = \frac{\rho^n}{n!} P_k(0),\ n = 1,2, \dots \dots, C\ ,\forall\, k$$

$$P_k(0) = \left[\sum_{n=0}^{c-1} \frac{\rho^n}{n!} + \frac{\rho^c}{c!\,(1-a)} \right]^{-1} ,\forall\, k$$

$$\rho = \frac{\lambda}{\mu}\ \ ,\ \ a = \frac{\rho}{c}$$

In case of the arrived PEVs to the charging facility is larger the number of chargers, the PEVs will wait for the service. To find the probability of waiting PEVs $P(n \geq c)$ and the expected waiting time W, the following equations are used:

$$P(n \geq c) = \frac{\frac{\rho^c}{c!}}{(1-a)\sum_{n=0}^{c-1}\frac{\rho^n}{n!} + \frac{\rho^c}{c!}}$$

$$\bar{W} = \frac{P(n \geq c)}{\mu\, c\,(1-a)}$$

In this model, level-3 DC fast chargers is assumed to be used, with maximum charging current 63 A, and charging voltage 400 V. The total expected charging power of PEVs can be calculated by firstly calculate the charging current of each PEV. Then, calculate the charging power of a single PEV. Finally, the total expected charging power can be determined based on the probability of the number of simultaneously charging PEVs, as following:

$$I_{k,y} = \min\left(\frac{E_{c,y}}{VT_k}, I_{max}\right)$$

$$P_{ch_k} = I_{k,y}V$$

$$E\left[P_{ch_k}\right] = \sum_{n=0}^{c} P(n)P_{ch_k}\ , \forall k$$

Now, the total expected charging demand of PEVs around the day is calculated. To assets the impacts on distribution system, Optimal Power Flow (OPF) with objective to minimize the feeders' losses is employed as following:

$$P_{loss} = \frac{1}{2}\sum_{k=1}^{24}\left[\sum_{i=1}^{N}\sum_{j=1}^{N} G_{i,j}\left(V_{i,k}^2 + V_{j,k}^2 - 2V_{i,k}V_{j,k}\cos\left(\delta_{j,k} - \delta_{i,k}\right)\right)\right]$$

If the charging facility is connected to the bus I in the distribution system, active power P_{ch} will consumed in addition to the power demand at that point. Therefore, the power flow equations are given by:

$$PG_{i,k} - PD_{i,k} - Pch_{i,k} = \sum_{j=1}^{N} V_{i,k}V_{j,k}Y_{i,j}\cos\left(\theta_{i,j} + \delta_{j,k} - \delta_{i,k}\right), \forall i, k$$

$$QG_{i,k} - QD_{i,k} = -\sum_{j=1}^{N} V_{i,k}V_{j,k}Y_{i,j}\,\mathrm{Sin}\left(\theta_{i,j} + \delta_{j,k} - \delta_{i,k}\right), \forall i, k$$

The voltage magnitude constraint are given by:

$$V_i^{min} \leq V_{i,k} \leq V_i^{max}, \forall\, i \in load\ buses, \forall k$$

Limits on real and reactive power generation are given as follows:

$$P_i^{min} \leq P_{i,k} \leq P_i^{max}, \forall\, i \in Genration\ buses, \forall k$$

$$Q_i^{min} \leq Q_{i,k} \leq Q_i^{max}, \forall\, i \in Genration\ buses, \forall k$$

The slack bus voltage magnitude and voltage angle are fixed and given by:

$$V_{sb,k} = 1\, pu \quad , \quad \delta_{sb,k} = 0$$

7 Case Study

The analysis of PEV charging demand is done based on 11-kV 38-node system representing a typical U.K. distribution system which is shown in Figure 4 [27]. The system is connected to grid at bus 1. The PEVs' charging facility is assumed to be implemented on Bus-5. The charging facility is assumed to be DC level 3 charger with maximum current 63A and voltage of 400V. The simulation model in this report is consist of two parts: PEVs total charging demand estimation, and OPF analysis of the 38-bus system including the PEVs charging demand.

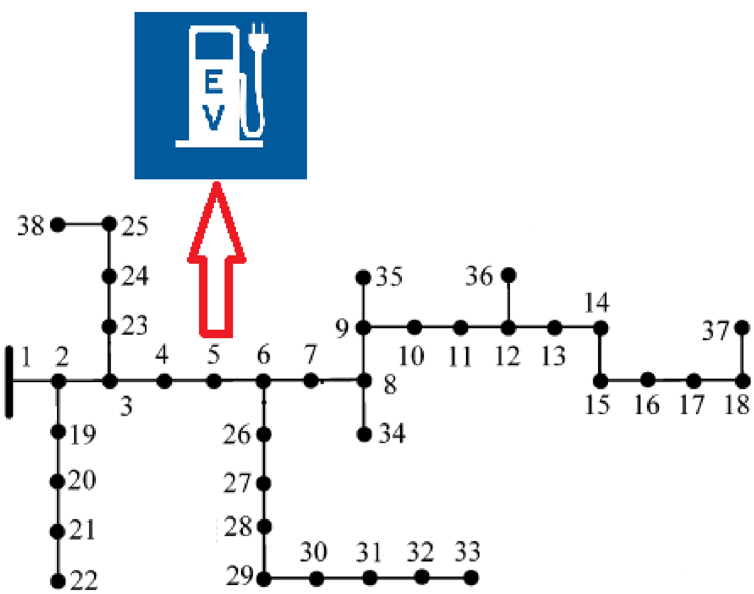


Figure 4, 38-Bus system [27]

The first part, which estimates the PEVs charging demand, is implemented on MALTAB. The model consist of M\M\c queuing model along with the battery charging model and the nonhomogeneous Poisson arrival process. The output of the model is the total expected PEVs charging demand, which is an input to the second part of the simulation model. A sample of the arrival rate to the charging facility is shown in figure 5. However, the queuing model is simulated for the 24 hour with 2000 iteration in each hour to ensure the accuracy of the results. The total expected PEVs charging demand is shown in figure 6.

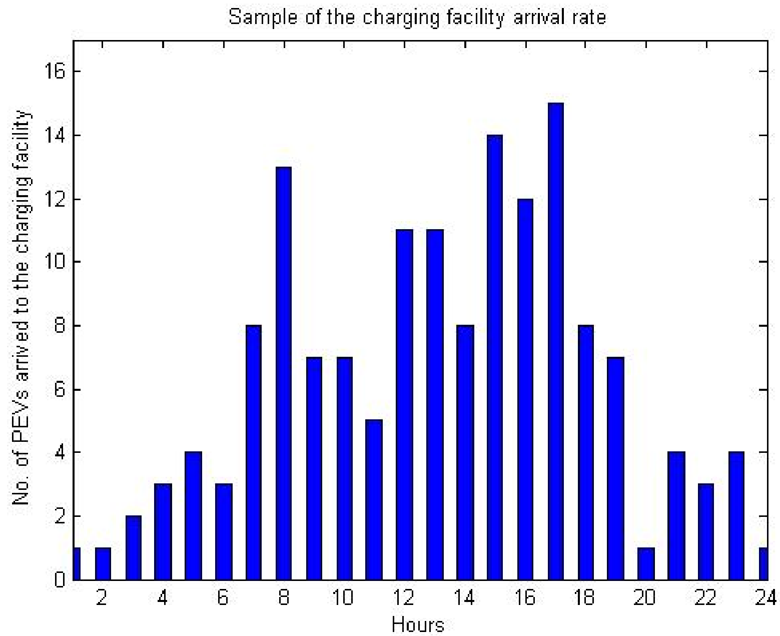


Figure 5, Sample of the charging facility arrival rate

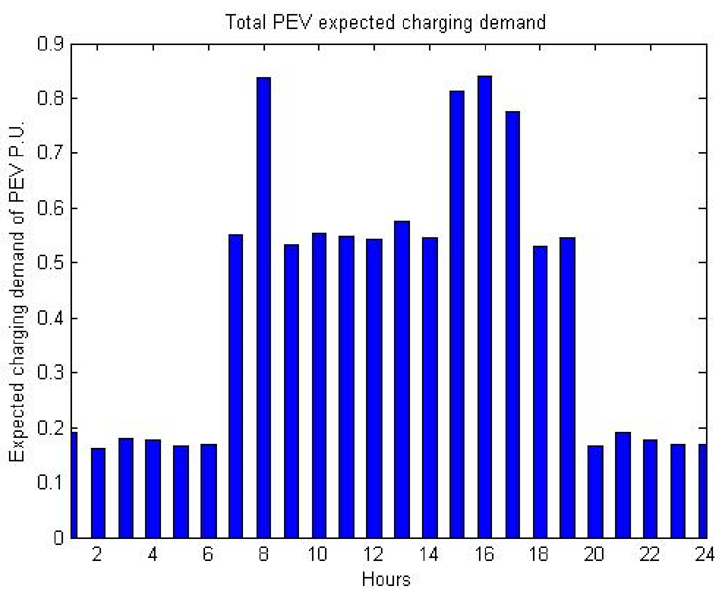


Figure 6, Total expected PEV charging demand

The second part of the simulation model is to implement the OPF. The optimization problem is modeled using GEMS environment. The voltage profile of bus 5 in the system is shown in Figure 7. The voltage profile shows that the bus experienced low voltage when the PEVs charging demand is high. The expected power loss of the system due to PEVs charging demand is shown in Figure 8. System loss increased as function with the increase in the PEVs charging demand increase. In this simulation model, OPF is performed with the objective of minimizing the power loss. However, there are other operation and control actions that can be done to control LDC that adjust the voltage level at the feeders, in addition to, father minimizing of the losses

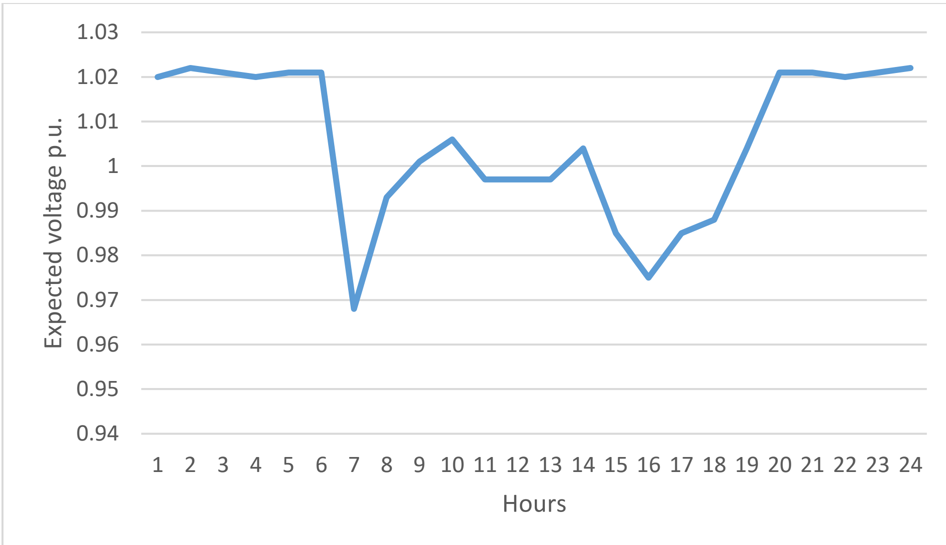


Figure 7, hourly expected voltage profile on bus 12 with PEVs load

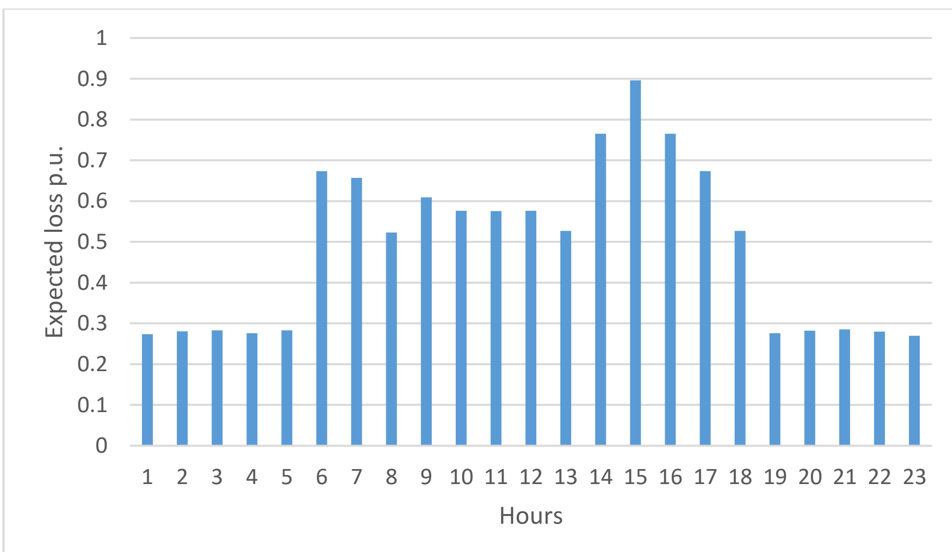


Figure 8, Hourly expected system loss with PEVs load

Conclusion

In this report, estimation of the PEVs charging demand based on three levels are introduced: system-wide PEVs demand estimation, single charging facility demand estimation, and network of charging facilities demand estimation. The usage of each estimation level is also presented. In order to estimate the system-wide PEV charging demand, three subsystem models are used in tandem, where each model utilizes the outcomes of the previous model(s). These models are: travel pattern; energy consumption; and power consumption. These models are discussed in the report. After the total load profile is estimated, analysis of the impact of PEVs charging load on distribution system can be done by two approaches: uncontrolled operation and optimal operation of distribution system. Both approaches are introduced, along with the three performance indexes: level of congestion, nodal voltage deviation, and total energy loss. Queueing model of a single PEV charging facility is introduced to estimate the total expected PEV charging demand. The impact on distribution system is presented by perform OPF with objective function of minimizing total system loss.

Source Code of the simulation models is available through this link <Source Code>

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