A Method to Evaluate the Maximum Hosting Capacity of Power Systems to Electric Vehicles

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***Abstract*—This paper proposes a smart charging/discharging-based method to evaluate the expected maximum hosting capacity (EMHC) of power systems to electric vehicles (EVs). The rapid growth in the use of EVs increases the challenges to satisfy their charging demand using existing power system resources. Therefore, a method to quantify the EMHC of power systems to EVs is required to plan for system improvements and ensure maximum utilization of resources. In this work, a method to calculate the EMHC of power systems to EVs is developed based on variable charging/discharging rates. The EMHC is calculated for charging stations at both homes and workplaces. The charging/discharging rates are varied based on daily energy demand and parking durations of EVs and network constraints. The parking duration is calculated based on probability distribution functions (PDFs) of arrival and departure times. The energy required to travel each mile and PDF of daily travel distances are used to calculate the daily energy demand of EVs. The optimization problem to maximize the hosting capacity is formulated using a linearized AC power flow model. The Monte Carlo simulation is used to calculate the EMHC. The proposed method is demonstrated on the modified IEEE 33-bus system. The results show that the daily EMHC of the modified IEEE 33-bus system varies between 20–41 cars for selected nodes.**

***Index Terms*—Electric vehicles, grid-to-vehicle, hosting capacity, power systems, smart charging/discharging, vehicle-to-grid.**

I. Introduction

The sharp increase in the amount of electricity consumption due to rapid growth in the use of electric vehicles (EVs) has led to increasing the challenges of satisfying electricity demand using existing power system infrastructure. For example, from 2013 to 2018, electricity consumption by plug-in EVs in the United States has been increased from 0.3 terawatt-hours to 2.8 terawatt-hours [1]. This high increase reshapes existing load profiles of power systems that requires appropriate countermeasures or allocation of new resources to satisfy network constraints. Also, charging periods of EVs change dynamically due to variation in the daily driving distance, departure time, and arrival time. This dynamic change unevenly reshapes power system load profiles which limits the hosting capacity (HC) of power systems to EVs. Therefore, developing a method to quantify the maximum HC of power systems to EVs is indispensable for system expansion and ensure efficient utilization of resources.

Several charging/discharging strategies are proposed in the literature to reduce negative impacts of EVs on power system operation. In [2], a cooperative strategy is introduced to stimulate EV owners to charge their vehicles during valley load and discharge during peak load, which balances electric loads, reduces power loss, and increases profits of EV owners. In [3], a smart charging/discharging strategy is developed for public charging stations to provide voltage and frequency support to grids. An optimal charging/discharging strategy is proposed in [4] to reduce the impacts of voltage drop due to cloud shade over photovoltaic panels on microgrids. In [5], an online charging/discharging strategy is introduced to consider temporal and spatial coordination of EVs to improve power utilization and avoid overloading. In [6], a two-stage interactive charging/discharging strategy is proposed in which the minimum charging demands of EVs are satisfied first, and then the remaining state of charge (SOC) levels contribute to reducing load fluctuation. In [7], an optimal charging/discharging strategy is developed based on reinforcement-learning to improve power quality. Although the proposed strategies in [2]–[7] are beneficial to increase the penetration levels of EVs, a method to quantify the EMHC still needs to be developed for system planners to handle high EV penetration.

Smart charging/discharging strategies are proposed in [8]–[12] to increase financial benefits of EV charging/discharging process. In [8], a smart charging/discharging strategy is proposed to maximize the number of EVs that are charged up to desired levels as well as financial benefits of both commercial stations and EV owners. An intelligent charging/discharging strategy is proposed in [9] to determine optimal charging/discharging times and rates over 24 hours to maximize the overall profits of an EV parking deck. A game-theory-based smart charging/discharging strategy is proposed in [10] to maximize the financial benefits of commercial buildings through optimizing energy consumption profiles. In [11], an hourly electricity price-based optimal charging/discharging scheme is proposed to maximize the profits of parking lots. An optimal charging/discharging strategy is developed in [12] to charge specific number of EVs at charging stations based on economical benefits. The strategies in [8]–[12] are developed mainly to increase financial benefits of EV owners and charging stations without providing much attention on quantifying the HC of power grids. A voltage constrained-based method to calculate the maximum HC of distribution systems to EVs for both fully controlled and uncontrolled charging is developed in [13]. In [14], the maximum permissible number of EVs that can be penetrated at transmission system buses are quantified using the extra hourly loading capacities. The developed methods in [13], [14] are aimed to determine the maximum HC considering only charging capability of EVs. However, a method to maximize the HC for both charging and discharging is required to ensure maximum utilization of existing resources as well as to determine appropriate times for the allocation of new resources.

This paper proposes a smart charging/discharging-based method to calculate the EMHC of power systems to EVs. A smart charging/discharging strategy for EVs and a system architecture to implement the strategy are also proposed. The smart charging/discharging strategy is developed based on the daily energy demand and parking duration of EVs. Probability distribution functions (PDFs) of arrival and departure times are used to calculate the parking duration. The daily energy demand is calculated based on the energy required to travel each mile and PDF of daily travel distances. An optimization problem to maximize the HC is formulated based on network constraints (e.g., voltage limits, generation and line capacities, and loads), charging/discharging limits of smart chargers, and daily energy demand and parking durations of EVs. To relieve the computational burden, a linearized AC power flow model is leveraged to capture the nonlinear characteristics of network constraints. The EMHC for charging stations at both homes and workplaces are calculated using the Monte Carlo simulation.

The rest of the paper is organized as follows. Section II provides a description of smart charging/discharging strategy and explains the problem formulation. Section III provides the algorithm to calculate the EMHC. Numerical results based on a modified IEEE 33-bus system are given in section IV. Section V provides several concluding remarks.

II. Smart Charging/Discharging Strategy to Maximize the Hosting Capacity

In the proposed smart charging/discharging strategy, the rates are controlled by a central controller based on network constraints and provided inputs (e.g., departure time, next travel distance, and type of vehicle) to smart chargers. This section illustrates the overall system architecture for the proposed framework and describes the formulation of the optimization problem to maximize the HC of power systems to EVs.

A. System Architecture

We introduce a smart charging/discharging architecture which is composed of smart chargers, a communication layer, and a central controller. The smart chargers have input panels in which EV owners provide their departure time, next travel distance, and type of vehicle. Also, it is assumed that the EV owners plug in their vehicles immediately after arrival. The smart chargers can read arrival times and initial SOCs of EVs and calculate parking duration by taking the difference between arrival and departure times. Different types of EVs (e.g., sedan, mid-sedan, SUV, and mid-SUV) have different energy consumption per mile. The smart chargers are also capable of determining the energy required to travel each mile based on vehicle type. Moreover, the smart chargers calculate the required charging energy as follows,

$$\mathcal{E} = \mathcal{D} \times \eta_{\mathcal{E}}, \tag{1}$$

where $\mathcal{D}$ is the expected travel distance by an EV; $\eta_{\mathcal{E}}$ is the required energy for the EV to travel each mile; and $\mathcal{E}$ is the total energy demand of the EV.

The departure time, calculated parking duration, and energy demand are fed as inputs to the central controller by smart chargers using a communication channel. Also, the central controller gathers network information such as voltage levels, hourly generation capacities, line capacities, and loads. These information are used to control charging/discharging rates without violating network constraints. Each day of a year is divided into 24 time-intervals to control charging/discharging rates. However, the time-intervals can be adjusted based on the requirements. The total number of intervals that are suitable for charging and discharging depends on the arrival and departure times. The charging and discharging of an EV cannot occur simultaneously within a time interval and charging/discharging power during a time interval remain unchanged.

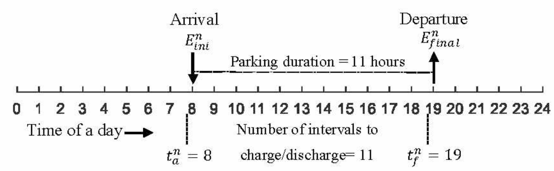


Fig. 1. Charging/discharging period

Fig. 1 shows an example for the timeline of charging and discharging periods. From Fig. 1, we can see that the arrival time, t_a^n, departure time, t_f^n, and parking duration of the n^{th} EV are 8, 19, and 11 respectively. Therefore, the total number of time intervals for charging/discharging is 11. The initial and desired final energy levels are E_{ini}^n and E_{final}^n, respectively. The value of E_{final}^n has to be less than or equal to the maximum energy limit of the EV battery. If the network has additional capacity after satisfying its existing demand (without EV), then the EV is charged. On the other hand, if the network fails to satisfy its existing demand (without EV), then the EV is discharged. The charging/discharging rate during an entire interval remains constant which is determined by the optimization model described in Section II-B and Section II-C, respectively. This procedure is repeated for all possible time intervals. Also, in the proposed smart charging/discharging strategy, it is ensured that the EV battery will achieve the desired final energy level at the time of departure. A schematic diagram of the proposed smart charging/discharging strategy for a microgrid is shown in Fig. 2.

B. Objective Function

The objective employed in this paper maximizes the HC of power systems to EVs, which is expressed as follows.

$$\mathcal{H}^{ev,\max} = \max\left(\sum_{n\in N} \mathcal{E}^{n,d}\right), \quad \forall d \tag{2}$$

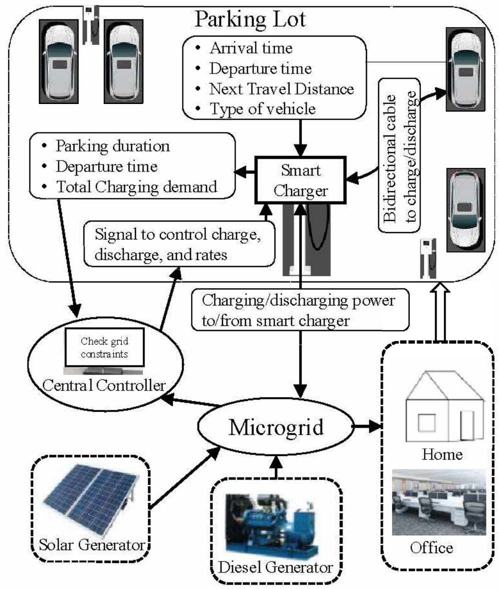


Fig. 2. Smart charging/discharging architecture for a microgrid

where d is the index for days of a year, running from 1 to 365; N is the set for all candidate EVs to be charged/discharged; $\mathcal{E}^{n,d}$ is the required energy of the n^{th} EV on the d^{th} day; and $\mathcal{H}_m^{ev,\max}$ is the maximum HC of a power system to EVs.

C. Network Constraints

We leverage the linearized AC power flow model proposed in [15] to describe the network constraints.

Power balance equations,

$$\begin{aligned} &B'^{t,d}\theta^{t,d} - G^{t,d}V^{t,d} + P_g^{t,d} + P_{dis}^{t,d} = P_{ch}^{t,d} + P_l^{t,d}, \ \forall t, \forall d \\ &G'^{t,d}\theta^{t,d} + B^{t,d}V^{t,d} + Q_g^{t,d} = Q_l^{t,d}, \quad \forall t, \forall d \end{aligned} \tag{3}$$

where t is the index for hours of a day, running from 1 to 24; $B'^{t,d}$ and $G'^{t,d}$ are the modified susceptance and conductance matrices [15] at time t on day d, respectively; $B^{t,d}$ and $G^{t,d}$ are the conventional susceptance and conductance matrices at time t on day d, respectively; $\theta^{t,d}$ and $V^{t,d}$ are the vectors of nodal voltage angles and magnitudes at time t on day d, respectively; $P_g^{t,d}$ and $Q_g^{t,d}$ are the vectors of real and reactive power generations at time t on day d, respectively; $P_{dis}^{t,d}$ and $P_{ch}^{t,d}$ are the vectors for discharging and charging power of EVs at time t on day d, respectively; and $P_l^{t,d}$ and $Q_l^{t,d}$ are the vectors of real and reactive power demand (without EVs) at time t on day d, respectively.

EV energy level at each hour for charging/discharging,

$$\mathcal{E}^{n,t,d} + \frac{1}{\eta_{dis}} P_{dis}^{n,t,d}\Delta t - \eta_{ch} P_{ch}^{n,t,d}\Delta t = \mathcal{E}^{n,t-1}, \quad \forall t, \forall d \tag{4}$$

where Δt is the duration of each time interval; η_{ch} and η_{dis} are the efficiency coefficients of charging and discharging, respectively; $P_{dis}^{n,t,d}$ and $P_{ch}^{n,t,d}$ are the discharging and charging power of n^{th} EV at time interval t on day d, respectively; and $\mathcal{E}^{n,t-1,d}$ and $\mathcal{E}^{n,t,d}$ are the energy level of n^{th} EV at time $t-1$ and t on day d, respectively.

Daily EV energy demand constraints,

$$\begin{aligned} &\sum_{t=t_a^{n,d}}^{t_f^{n,d}} \left(\frac{1}{\eta_{dis}} P_{dis}^{n,t,d}\Delta t - \eta_{ch} P_{ch}^{n,t,d}\Delta t\right) \geq \mathcal{E}^{n,d}, \quad \forall d \\ &\mathcal{E}^{n,\min} \leq \mathcal{E}^{n,d} \leq \mathcal{E}^{n,\max}, \quad \forall d \end{aligned} \tag{5}$$

where $t_a^{n,d}$ and $t_f^{n,d}$ are the arrival and departure times of the n^{th} EV on the d^{th} day, respectively; $\mathcal{E}^{n,\min}$ and $\mathcal{E}^{n,\max}$ are the minimum and maximum battery capacity of the n^{th} EV, respectively.

Charging/discharging constraints,

$$\begin{aligned} &0 \leq P_{ch}^{n,t,d} \leq P_{ch}^{\max}, \quad \forall t, \forall d \\ &0 \leq P_{dis}^{n,t,d} \leq P_{dis}^{\max}, \quad \forall t, \forall d \end{aligned} \tag{6}$$

where $P_{ch}^{\max}$ and $P_{dis}^{\max}$ are the maximum charging and discharging rates of smart chargers, respectively.

Real and reactive power generations constraints,

$$\begin{aligned} &P_g^{\min} \leq P_g^{t,d} \leq P_g^{\max}, \quad \forall t, \forall d \\ &Q_g^{\min} \leq Q_g^{t,d} \leq Q_g^{\max}, \quad \forall t, \forall d \end{aligned} \tag{7}$$

where $P_g^{\min}$ and $P_g^{\max}$ are the vectors of minimum and maximum real power generation, respectively; and $Q_g^{\min}$ and $Q_g^{\max}$ are the vectors of minimum and maximum reactive power generation, respectively.

Feeder capacity constraints,

$$\begin{aligned} &S_F^{t,d} \leq S_F^{\max}, \quad \forall t, \forall d \\ &-S_R^{t,d} \leq S_R^{\max}, \quad \forall t, \forall d \end{aligned} \tag{8}$$

where $S_F^{\max}$ and $S_R^{\max}$ are the vectors of maximum forward and reverse feeder flow capacities, respectively; and $S_F^{t,d}$ and $S_R^{t,d}$ are the vectors of forward and reverse feeder flows at time t on day d, respectively.

Voltage constraints,

$$V^{\min} \leq V^{t,d} \leq V^{\max}, \quad \forall t, \forall d \tag{9}$$

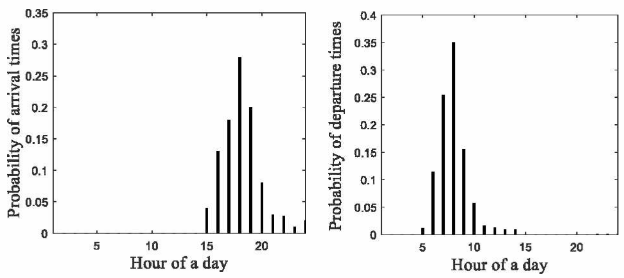
where $V^{\min}$ and $V^{\max}$ are the vectors of minimum and maximum bus voltage magnitudes, respectively.

Angle constraints,

$$-\pi \leq \theta^{t,d}, \leq \pi \quad \forall t, \forall d \tag{10}$$

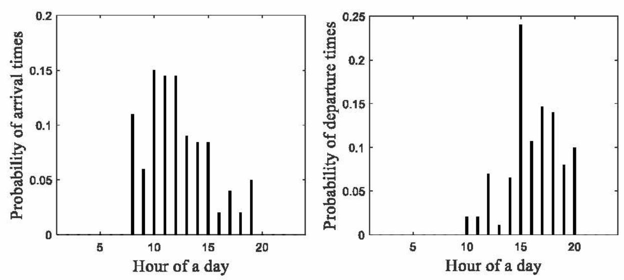
III. Calculation of the EMHC

The proposed algorithm to calculate the EMHC of power systems to EVs follows an iterative process, which starts with computing the maximum HC at each day of a year. To determine the HC at each day, we assume that there are enough number of smart chargers deployed at both homes and workplaces to plug in EVs immediately after arrival. Then, the arrival times, departure times, and next travel distances on the first day of a year for an initial number of EVs for both homes and workplaces are determined. The arrival and departure times are determined based on the PDFs provided in Fig. 3 and Fig. 4. The PDFs for arrival and departure times at homes are developed using the survey data for conventional cars provided in [16], [17]. The PDFs for arrival and departure times at workplaces are developed using the survey data [18]. The next travel distances are calculated based on the PDF of daily travel distances for conventional cars shown in Fig. 5, which is developed using the survey data provided in [17].



(a) (b)

Fig. 3. PDFs of (a) arrival times at homes and (b) departure times from homes.



(a) (b)

Fig. 4. PDFs of (a) arrival times at workplaces and (b) departure times from workplaces.

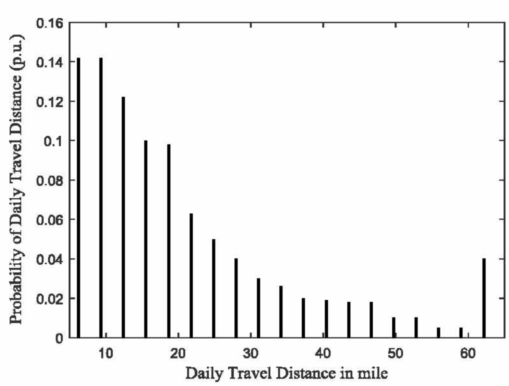


Fig. 5. PDF of daily travel distances of EVs

In the next step, parking duration, required charging energy, and initial SOC level for each EV are determined. The parking duration is calculated by taking the difference between arrival and departure times. The required charging energy is calculated using (1). The initial SOC level is determined randomly between 10% to 30% of the maximum battery capacity. The hourly demand for existing loads (without EVs) is calculated using data tables provided in [19]. Then, the optimization problem described in Section II is solved by using linear programming (LP) solver. The number of EVs is updated until the obtained solution for the optimization problem is infeasible. The final number of EVs is the maximum HC on first day of the year. The above procedure is repeated 365 times to calculate the maximum HC for each day of a year. A flowchart to calculate the maximum HC at each day is provided in Fig. 6.

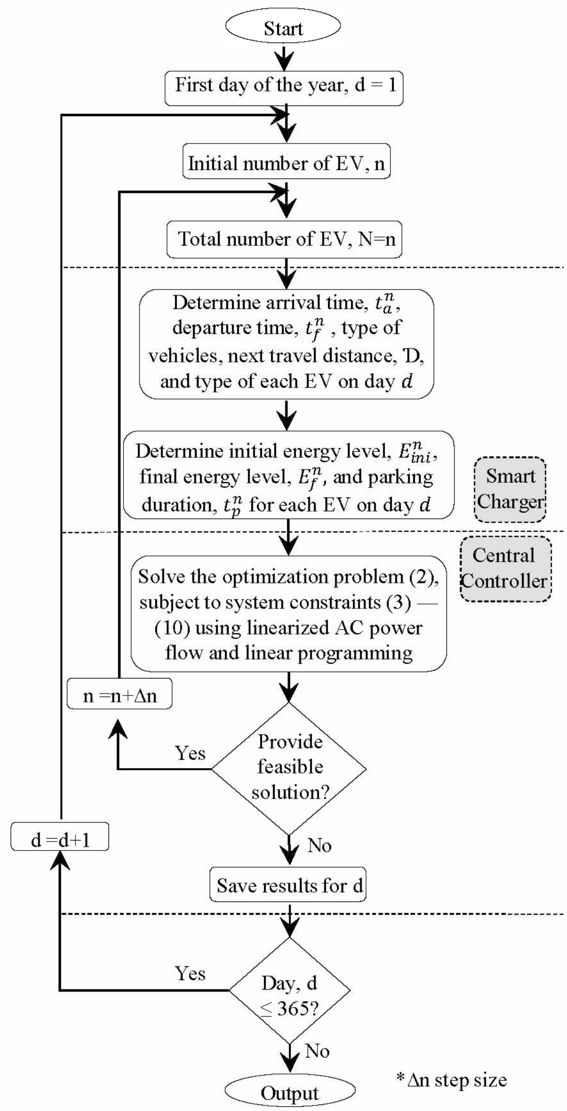


Fig. 6. Algorithm to calculate the daily maximum HC

To calculate the EMHC capacity, the above procedure is repeated for N_y years. Then, the expected maximum hosting capacity at each day of a year is calculated as follows.

$$\xi_m^d = \frac{1}{N_y}\sum_{y=1}^{N_y}\xi_y^d \tag{11}$$

where N_y is the number of simulated years; ξ_y^d is the maximum HC of power systems to EVs on the d^{th} day of y^{th} year; and ξ_m^d is the EMHC on the d^{th} day of a year.

Finally, the EMHC of the power system to EVs is calculated by taking the minimum value of daily EMHC. Following the stopping criterion provided in [20] to evaluate power system reliability using the Monte Carlo simulation, we introduce a stopping criterion based on the coefficient of variance of EMHC as follows.

$$\sigma = \frac{\sqrt{|V(\xi_m)|}}{\xi_m} \tag{12}$$

where ξ_m is the EMHC of power systems to EVs; $V(\xi_m)$ is the variance of the EMHC of power systems to EVs; and σ is the coefficient of variance. Typically, the value for σ to calculate the reliability indices is ≤ 0.2, which is adopted for the proposed algorithm. The variance of EMHC, $V(\xi_m)$, is calculated as follows,

$$V(\xi_m) = \frac{1}{N_y}(\xi_m - \xi_m^2) \tag{13}$$

IV. Numerical Examples

To validate the proposed method, simulations are carried out on the modified IEEE 33-bus distribution system. The 33-bus test system is characterized by 33 nodes, 32 branches, 5 tie-lines, 3 laterals, and operating voltage of 12.66 kV [21]. In the modified IEEE 33-bus system, locations of the generating units and ratings of the photovoltaic (PV) units are selected based on the provided modification in [22]. The total peak demand of the modified 33-bus test system is 2972 kW [22]. The limits of hourly generation amount of the PV units are calculated using PVWatts calculator developed by the National Renewable Energy Laboratory [23].

A specific node of a distribution system may have only home charging stations or only workplace charging stations or both types of charging stations. In this work, we consider that a node contains either only home charging stations or only workplace charging stations. Also, the charging stations can be installed in all or several selected nodes of distribution systems. In this work, we randomly select 10 nodes to install charging stations. The locations of the generating units and charging stations in the modified IEEE 33-bus distribution system are shown in Fig. 7. The ratings of all the generating units are given in Table I.

TABLE I. Ratings of Generators of the Modified IEEE-33 Bus

Types of Generators	Locations (Node No.)	Rating (kW)	Types of Generators	Locations (nod No.)	Rating (kW)
DG	6	1200	PV	12	50
DG	8	400	PV	16	50
DG	14	400	PV	18	100
DG	24	800	PV	24	300
DG	25	800	PV	25	250
DG	30	400	PV	29	100
DG	32	400	PV	30	200
PV	7	100	PV	31	150
PV	10	100	PV	32	50

Typically, two types of chargers—Level 1: charging rate of 1 kW/h and Level 2: charging rate of 6 kW/h—are used at home and work places [24]. Therefore, in this work, we assume that charging/discharging rates of smart chargers vary from 0–6 kW/h.

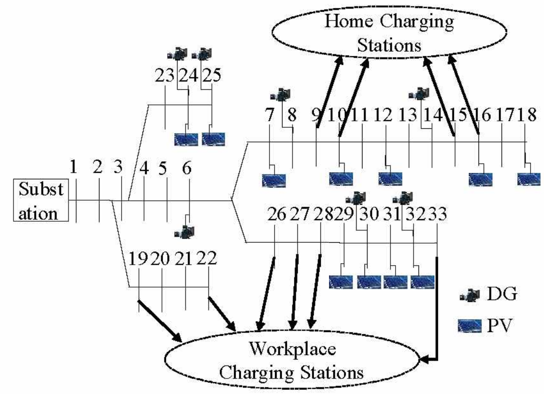


Fig. 7. Modified IEEE 33-bus

The U.S. Department of Energy is welcoming employers to sign the pledge for workplace charging challenges to increase the percentage of charging at workplaces [25]. Also, the employers usually provide free charging to their employees to increase employee satisfaction. Therefore, in this work, we consider that the employees fulfill their entire charging demand at workplaces. The employment rates in the United States at each month of 2019 varied between 60–61% [26]. Thus, the distribution of EVs between homes and workplaces are considered as 40% and 60%, respectively. The distribution ratios of EVs between nodes are same as the distribution ratios of existing loads.

The EMHC at each day of a year is calculated using the algorithm described in section III. The voltage limits to calculate the EMHS are maintained within 5% of base voltage [27]. The value for σ is considered as 0.2. The energy consumption to travel each mile by various types of EVs are provided in [28], which are as follow: full-SUV 0.5075 kWh/mile, mid-SUV 0.4375 kWh/mile, mid-sedan 0.3605 kWh/mile and sedan 0.3225 kWh/mile. In this paper, we assume an average (0.407 kWh/mile) of these energy consumptions per mile as the energy required to travel each mile by an EV. The required number of simulation years to achieve the convergence is 27 years. The calculated daily EMHC of the modified IEEE 33-Bus system is shown in Fig. 8.

From Fig. 8, we can see that the calculated daily EMHC varies between 20–41 cars. Thus, the EMHC of the modified IEEE 33-Bus system is 20 cars. Therefore, it can be deduced that the power system planners can use the proposed method to calculate the EMHC of power systems to EVs for the allocation of resources.

V. Conclusion

This paper has proposed a smart charging/discharging-based method to calculate the EMHC of power systems to EVs. In the proposed method, the charging/discharging rates are controlled based on network constraints, charging/discharging

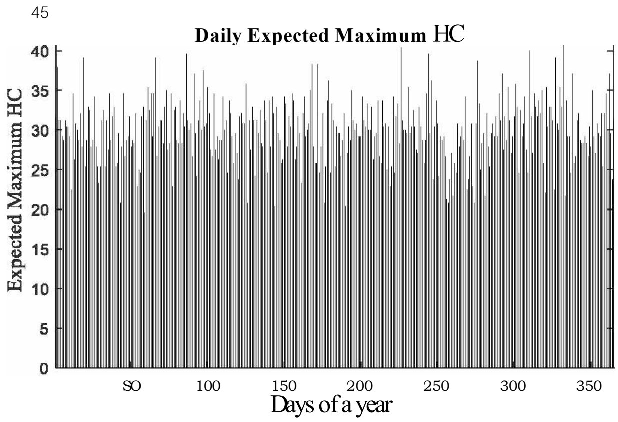


Fig. 8. EMHC of the modified IEEE 33-bus for selected nodes

limits of smart chargers, and daily energy demand and parking durations of EVs. The parking durations are calculated based on the PDFs of arrival and departure times. The daily energy demand is calculated based on energy required to travel each mile and PDF of daily travel distances. The optimization problem to maximize the HC is formulated using linearized AC power flow and solved by LP solver. The EMHC is calculated for charging stations at both homes and workplaces. The proposed method was demonstrated on the modified IEEE 33-bus system as a power system. The results showed that the daily EMHC of modified IEEE 33-bus system varied between 20-41 cars for selected nodes.

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