# Traffic and Grid-Based Parking Lot Allocation for PEVs Considering Driver Behavioral Model

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***Abstract*- In this study, optimal parking lots (PLs) for plug-in electric vehicles (PEVs) fleet are allocated on a feeder of a given electrical distribution network to minimize the total cost of the local distribution company (DISCO) considering driving patterns of the PEVs' drivers and their behavioral model in respect to the value of incentive (discount on charging fee) and the distance from the PL. The cost terms include investment cost for installing the PLs, maintenance cost of the PLs, the expense of incentive provided to the PEVs' drivers, the energy loss cost of the feeder, and the expected energy not supplied (EENS) cost over the operation period. In order to achieve realistic results, economic factors such as yearly inflation and interest rates and technical factors including hourly and daily variations of the load demand, yearly load growth of the feeder, and yearly growth rate of PEVs' application are considered in the PL allocation planning problem. The optimization problem is solved applying quantum-inspired simulated annealing algorithm (QSA). We demonstrate that the behavioral model of the drivers and their driving patterns can remarkably affect the outcomes of the problem.**

***Index Terms*- Behavioral models, driving patterns, expected energy not supplied (EENS), plug-in electric vehicle (PEV), power loss, traffic and grid-based parking lots (PLs) allocation.**

## I. Introduction

A recent study demonstrates that almost 27% of total energy consumption and 33% of greenhouse gas emissions in the world are related to the transportation sector [1]. Replacing internal combustion based vehicles with plug-in electric vehicles (PEVs) is a promising strategy to mitigate the energy security and environmental issues, since PEVs can be charged by electricity generated by renewables as the free and clean sources of energy [2]. Based on the study presented in [3], PEVs utilization is being increased rapidly in some developed countries because of the advancement in battery technology.

In [4], the economic and technical characteristics of the PEVs fleet have been discussed. Different objective functions in the literature have been considered for the parking lot (PL) placement problem that include minimum energy and power losses [5-8], maximum reliability [9-10], maximum voltage stability [11-12], and spinning reserve supply in power market [13]. However, in these studies, the behavior of PEVs' drivers and their driving patterns reacting to incentives (discount on charging fee of the PEVs) and distance from the PL have not been modeled and investigated in the problem.

In this study, a new approach for the PL placement planning problem is introduced and applied on a case study. In this approach, the traffic of PEVs fleet and the technical and economic aspects of the electrical distribution network are taken into consideration. In other words, the PLs are allocated to the given feeder of the distribution network considering the driving patterns of the PEVs' drivers and the behavioral model of the drivers. Herein, the drivers' behavior are modeled respect to the value of incentive and the amount of average daily distance of the PEVs from the PL. The value of incentive is considered to motivate the drivers to charge their vehicles through the PLs.

We formulate a mixed-integer nonlinear programming (MINLP) problem for the PL allocation planning. The objective function of the planning problem is minimizing the total cost of the local distribution company (DISCO) over the operation period. The cost terms of the objective function include total investment for purchasing and installing PLs in the optimal locations, present worth value of maintenance cost of the installed PLs over the operation period, present worth value of incentive considered for the PEVs' drivers over the operation period, present worth value of energy loss cost over the operation period, and present worth value of expected energy not supplied (EENS) cost over the operation period.

In addition, in order to achieve realistic results, economic and technical factors such as yearly inflation and interest rates, yearly growth rate for application of PEVs, yearly load growth rate, and daily and hourly variations of the load demand are taken into consideration in the planning problem. Moreover, the security constraints of the grid including loading limit of the branches and voltage magnitude limits of the buses are considered over the operation period. Furthermore, quantum-inspired simulated annealing algorithm (QSA) is applied to solve the MINLP problem.

The paper is organized as follows. In Section II, the proposed approach is presented. In Section III, the problem is formulated. In Section IV, the optimization technique is presented. The numerical study is presented in Section V, and finally Section VI concludes the paper.

## II. Proposed Approach

### A. Modeling Driving Patterns of the PEVs Fleet

Fig. 1 shows the synthetic electrical distribution network and feeder 1 that has been designed on the geography of Brookland, Washington D.C., US. The feeder 1 has 28 distribution substations (bus), each of which has a known latitude and longitude. We also synthesize the driving paths of PEVs over time. Herein, in order to figure out the driving pattern of a PEV or a group of PEVs, the position data of PEVs are recorded at every hour of a typical day. By knowing the hourly position data of every PEV, the rout and the driving pattern of the PEV can be determined. Fig. 2 shows the hourly space-time driving patterns of the PEVs (Patterns 1-6) from our synthetic data. As can be seen, at some periods of time (hours 1-7 and 23-24), the PEVs do not move in the space as time goes on, since the PEVs have been parked.

By knowing the driving pattern of the PEV, the amount of average daily distance of the PEV from every bus of the feeder

($\overline{\eta_{e,b}}$) can be calculated using the hourly position data of the PEV ($x_{e,t}^{PEV}, y_{e,t}^{PEV}$) and the bus ($x_b^B, y_b^B$), as in (1). The value of $\overline{\eta_{e,b}}$ will be applied for determining the reaction of the PEV respect to the value of incentive ($\xi_{Model}$) introduced to motivate the driver to charge his/her vehicle through the suggested PL.

$$\overline{\eta_{e,b}} = \frac{1}{24} \times \sum_{t=1}^{24} \sqrt{\left(x_{e,t}^{PEV} - x_b^B\right)^2 + \left(y_{e,t}^{PEV} - y_b^B\right)^2}, \quad \forall e \in \{1, \ldots, N_{Tot}^{PEVs}\}, \forall b \in \{1, \ldots, Nb\} \tag{1}$$

In addition, by knowing the driving pattern of the PEV, the state of charge (SOC) of the PEV can be approximated, since the SOC of a PEV has a direct relation with the amount of distance that it travels in a day. The value of SOC of the PEV is used to determine the amount of power and energy demands of the PL. The value of SOC of a PEV at every hour of a day ($t$) can be determined using (2). Herein, $kWh_{km}$is the amount of energy (in kWh) that the PEV needs to travel about 1 km and $C_e^{PEV}$ is the capacity of battery of PEV.

$$SOC_{e,t}^{PEV} = kWh_{km} \times \sum_{t=1}^{t} \sqrt{\left(x_{e,t}^{PEV} - x_{e,t-1}^{PEV}\right)^2 + \left(y_{e,t}^{PEV} - y_{e,t-1}^{PEV}\right)^2} \times \frac{1}{C_e^{PEV}}, \forall e \in \{1, \ldots, N_{Tot}^{PEVs}\}, \forall t \in \{1, \ldots, 24\} \tag{2}$$

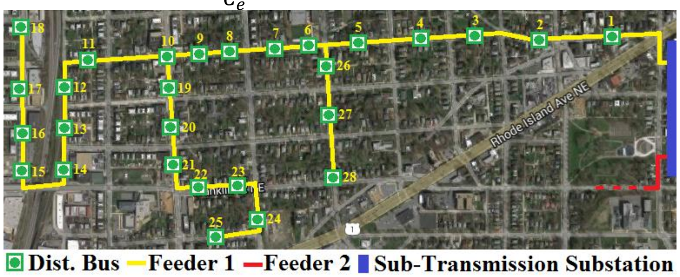


Fig. 1. The synthetic electrical distribution network and feeder 1 that supplies the end-users in Brookland, Washington D.C., US.

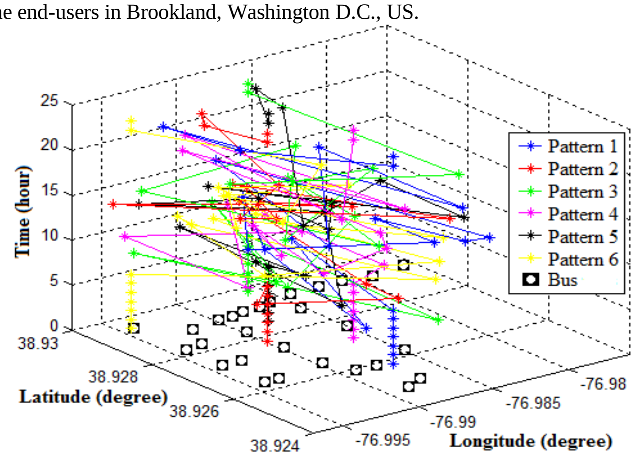


Fig. 2. The hourly space-time driving patterns of the PEVs fleet (Patterns 1-6).

### *B. Modeling Behavior of the Drivers as a Function of Incentive and Distance from the PL*

The percentage of drivers that charge their PEVs through the PL as the mathematical functions of discount on charging fee (%) have been presented in [9]. The work in [9] is mainly for maximizing reliability of network and market participation. Unlike the work in [9], in this study, the behavior of the PEVs' drivers is modeled based on two parameters ($\overline{\eta}, \gamma$). In fact, in addition to the value of discount on charging fee ($\gamma$), the average daily value of distance of the PEV from the location of PL ($\overline{\eta}$) is considered. Herein, a linear function is assumed between $\xi_{Model}$ and $\overline{\eta}$, as can be seen in TABLE I. By considering these two parameters (incentive and distance), $\xi_{Model}$ will be a three-dimensional spatial surface, as can be seen in Fig. 3 ($a_1 = -1/1200, a_2 = 1$). Fig. 3 illustrates the percentage of drivers that charge their PEVs through the PL, where the behavioral models of the drivers have linear relation with the amount of average daily distance (meter) from the PL and Power relation, Logarithmic relation, Linear relation, and Exponential relation with the value of discount on charging fee (%).

The number of PEVs that charge their vehicles through the PL ($N_{Model}^{PEVs}$), as the size of the PL, is determined using (3) that depends on the percentage of discount on charging fee ($\gamma$), the total number of PEVs in the area ($N_{Tot}^{PEVs}$), and the average daily distance of the PEVs from the locations of PLs ($\overline{\eta}$).

Moreover, the hourly demand of PL ($D_t^{PL}$) in MW is approximated applying (4).

$$N_{Model}^{PEVs} = \xi_{Model} \times N_{Tot}^{PEVs} \tag{3}$$

$$D_t^{PL} = \sum_{e=1}^{N_{Model}^{PEVs}} \left(1 - \frac{SOC_{e,t}^{PEV}}{100}\right) \times \frac{C_e^{PEV}}{1000} \tag{4}$$

TABLE I

THE PERCENTAGE OF DRIVERS THAT CHARGE THEIR PEVS THROUGH THE PL AS THE MATHEMATICAL FUNCTIONS OF DISCOUNT ON CHARGING FEE (%) AND DISTANCE FROM THE PL (METER).

| Model | Percentage of drivers that charge their PEVs through the PL |
|---|---|
| Power model | $\xi_{Pow} = (a_1 \times \overline{\eta} + a_2) \times 100 \times \left(\frac{\gamma}{100}\right)^{0.3}$ |
| Linear model | $\xi_{Lin} = (a_1 \times \overline{\eta} + a_2) \times \gamma$ |
| Logarithmic model | $\xi_{Log} = (a_1 \times \overline{\eta} + a_2) \times 100 \times ln\left(\frac{\gamma}{100} \times (exp(1) - 1) + 1\right)$ |
| Exponential model | $\xi_{Exp} = (a_1 \times \overline{\eta} + a_2) \times 100 \times exp\left(M \times \left(\frac{\gamma}{100} - 1\right)\right), M \gg 1$ |

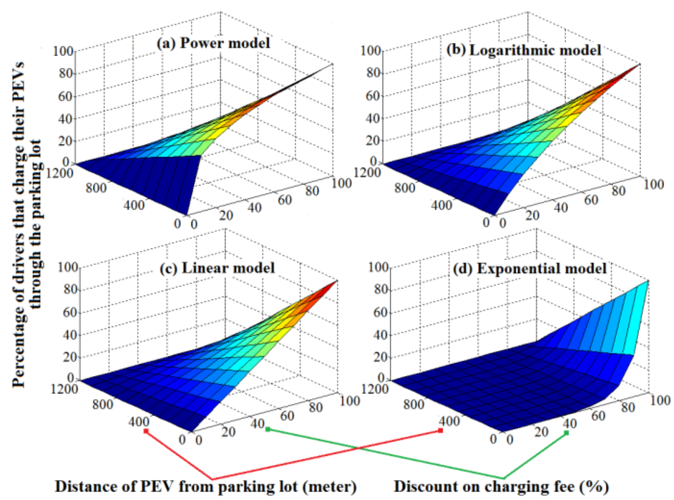


Fig. 3. The percentage of drivers that charge their PEVs through the PL as (a) Power, (b) Logarithmic, (c) Linear, and (d) Exponential functions of discount on charging fee (%) and Linear function of average daily distance (meter) from the PL.

## III. PROBLEM FORMULATION

### *A. Objective Function*

The objective function of problem is minimizing total cost of the local DISCO over the operation period ($Ny$) by installing PLs in the optimal locations of a feeder of the given electrical distribution grid. Herein, the driving patterns of the PEVs' drivers and their behavioral model respect to the value of incentive (discount on charging fee) and the distance from the PL are considered in the planning problem. In addition, several economic and technical factors including yearly inflation and interest rates, hourly and daily variations of the load demand, yearly load growth rate of the feeder, and yearly growth rate of the PEVs' application are taken into consideration.

The cost terms of the objective function include total investment cost for installing the PLs in the optimal locations ($Cost^{INV}$), present worth value of maintenance cost of the installed PLs over the operation period ($\widetilde{Cost_{Ny}^{MAINT}}$), present worth value of cost of discount on charging fee of the PEVs over the operation period ($\widetilde{Cost_{Ny}^{INC}}$), present worth value of energy loss cost of the feeder over the operation period ($\widetilde{Cost_{Ny}^{EL}}$), and present worth value of EENS cost of the feeder over the operation period ($\widetilde{Cost_{Ny}^{EENS}}$), as can be seen in (5).

$$OF_{Ny} = min\left\{Cost^{INV} + \widetilde{Cost_{Ny}^{MAINT}} + \widetilde{Cost_{Ny}^{INC}} + \widetilde{Cost_{Ny}^{EL}} + \widetilde{Cost_{Ny}^{EENS}}\right\} \quad (5)$$

## B. Cost Terms

### 1) Investment cost

The total investment cost for purchasing and installing the equipment of the PLs in the optimal locations of the feeder is presented in (6). Herein, $C^{INV}$ is the amount of investment for equipping the PL for one PEV.

$$Cost^{INV} = C^{INV} \times N_{Model}^{PEVs} \quad (6)$$

### 2) Maintenance cost

The present worth value of maintenance cost of the PL over the operation period is given in (7). Herein, $C^{MAINT}$ is the amount of yearly maintenance cost of the PL for one PEV.

$$\widetilde{Cost_{Ny}^{MAINT}} = \sum_{y=1}^{Ny} C^{MAINT} \times N_{Model}^{PEVs} \times (F^{PWV})^{y}, F^{PWV} = \frac{1 + IFR/100}{1 + ITR/100} \quad (7)$$

### 3) Incentive cost

The present worth value of cost of discount on charging fee of the PEVs over the operation period is presented in (8). Herein, $\gamma$ and $\pi^{E}$ are the percentage of discount on charging fee and the price of electricity in Cents per kWh, respectively. Also, the value of $D_{t}^{PL}$ has been presented in (4).

$$\widetilde{Cost_{Ny}^{INC}} = \sum_{y=1}^{Ny}\sum_{d=1}^{365}\sum_{t=1}^{24} D_{t,d,y}^{PL} \times \frac{\gamma}{100} \times \pi^{E} \times 10 \times (F^{PWV})^{y} \quad (8)$$

### 4) Energy loss cost

The value of energy loss of the feeder over the planning horizon is presented in (9). Moreover, the present worth value of energy loss cost of the feeder over the operation period is given in (10). Herein, $R$ is the value of resistance of the branch of the feeder, $|I|$ is the magnitude of current flowing through the branch, and $MVA^{BASE}$ is the value of base power in per unit system.

$$EL_{Ny} = \sum_{y=1}^{Ny}\sum_{d=1}^{365}\sum_{t=1}^{24}\sum_{br=1}^{Nbr} R_{br} \times \left|I_{y,d,t,br}\right|^{2} \times MVA^{BASE} \quad (9)$$

$$\widetilde{Cost_{Ny}^{EL}} = \sum_{y=1}^{Ny}\sum_{d=1}^{365}\sum_{t=1}^{24}\sum_{br=1}^{Nbr} R_{br} \times \left|I_{y,d,t,br}\right|^{2} \times MVA^{BASE} \times \pi^{E} \times 10 \times (F^{PWV})^{y} \quad (10)$$

### 5) EENS cost

The value of EENS of the feeder over the operation period is determined using (11) [14]. As can be seen, this value, as the reliability index or risk level of the system, depends on the failure rate of the branches of the feeder ($\lambda$), failure locating duration ($\tau^{FL}$), and failure repairing duration ($\tau^{FR}$). Herein, $LNS^{FL}$ is the value of load not supplied during locating the fault and $LNS^{FR}$ is the value of load not supplied during repairing the fault.

The present worth value of the EENS cost of the feeder over the operation period is presented in (12). Herein, $\pi^{ENS}$ is the value of cost of EENS of the customers in cents per kWh.

$$EENS_{Ny} = \sum_{y=1}^{Ny}\sum_{br=1}^{Nbr} \lambda_{br} \times \left(\tau^{FL}\sum_{b=1}^{Nb} LNS_{y}^{FL} + \tau^{FR}\sum_{b=1}^{Nb} LNS_{y}^{FR}\right) \quad (11)$$

$$\widetilde{Cost_{Ny}^{EENS}} = \sum_{y=1}^{Ny}\sum_{br=1}^{Nbr} \lambda_{br} \times \left(\tau^{FL}\sum_{b=1}^{Nb} LNS_{y,b}^{FL} + \tau^{FR}\sum_{b=1}^{Nb} LNS_{y,b}^{FR}\right) \times \pi^{ENS} \times (F^{PWV})^{y} \quad (12)$$

## C. Security Constraints

### 1) Loading limit of the branches

The loading constraint of each branch, as its thermal limit, is presented in (13). As can be seen, magnitude of the apparent power flowing through the branch must be less than the allowable magnitude of the apparent power of the branch.

$$|MVA_{br}| \le |\overline{MVA}_{br}|, \forall br \in \{1, \dots, Nbr\} \quad (13)$$

### 2) Voltage magnitude limits of the buses

Magnitude of voltage of each bus must be within the allowable minimum and maximum limits.

$$(1 - \sigma^{V}/100) \times |\bar{V}_{b}| \le |V_{b}| \le (1 + \sigma^{V}/100) \times |\bar{V}_{b}|, \forall b \in \{1, \dots, Nb\} \quad (14)$$

# IV. Optimization Technique

In this study, quantum computation concept is applied in the simulated annealing algorithm (SA) to design the quantum-inspired SA algorithm (QSA) and solve the optimization problem [8], [15], which is a mixed-integer nonlinear programming (MINLP) problem. Other optimization algorithms could be used in this problem; however, quantum parallelism, as the superiority of the quantum computation, which originates from the uncertainty of quantum states, is the advantage compared to the other algorithms [15].

The Q-bit matrix of the problem variables ($\mathbb{Q}$ matrix) includes the Q-bits related to the location of PLs and the value of incentive, as can be seen in (15). Herein, every bus of the feeder ($\forall b \in \{1, \dots, Nb\}$) is considered as a candidate for installing a PL. Therefore, the $b^{th}$ bus has a PL with the probability amplitude about $(\beta_{b}^{PL})^{2}$.

In addition, the value of incentive is changed from 0% (or 0) to 100% (or 10) with the 10% (or 1) steps. Thus, the minimum number of needed Q-bits for indicating the value of incentive is 4, since $2^3<10<2^4$. Based on this, 0% discount and 100% discount can be indicated by the states $|0000\rangle$ and $|1010\rangle$ that have probability amplitude about $(\alpha_{1}^{INC})^{2} \times (\alpha_{2}^{INC})^{2} \times (\alpha_{3}^{INC})^{2} \times (\alpha_{4}^{INC})^{2}$ and $(\beta_{1}^{INC})^{2} \times (\alpha_{2}^{INC})^{2} \times (\beta_{3}^{INC})^{2} \times (\alpha_{4}^{INC})^{2}$, respectively.

$$\mathbb{Q} = \left[\begin{pmatrix}\alpha_{1}^{PL}\\ \beta_{1}^{PL}\end{pmatrix} \cdots \begin{pmatrix}\alpha_{b}^{PL}\\ \beta_{b}^{PL}\end{pmatrix} \cdots \begin{pmatrix}\alpha_{Nb}^{PL}\\ \beta_{Nb}^{PL}\end{pmatrix} \middle| \begin{pmatrix}\alpha_{1}^{INC}\\ \beta_{1}^{INC}\end{pmatrix} \cdots \begin{pmatrix}\alpha_{4}^{INC}\\ \beta_{4}^{INC}\end{pmatrix}\right] \quad (15)$$

Herein, the value of objective function of the problem is defined as the value of internal energy of the molten metal ($\varepsilon$) and then it is tried to minimize the amount of this energy. The different steps for applying QSA algorithm in the problem have been presented and described in [8].

## V. Numerical Study

### A. Primary Data of the Grid and Problem

The technical data of different types of PEVs are presented in TABLE II [16]. In simulation results part (Part B), the type of PEVs is considered to be Nissan Leaf BEV; however, in the sensitivity analyses part (Part C), other types of the PEVs are considered in the problem. TABLE III presents the value of parameters of the grid and problem. The hourly power demand of feeder 1 throughout a day (p.u.), the daily power demand of the feeder throughout a year (p.u.) related to March 1st at 17 pm, and the value of other parameters are presented in [8].

TABLE II
The technical data of the PEVs [16].

| - | Nissan Leaf BEV | Chevy Volt 2012 PHV | Toyota Prius 2012 PHV |
|---|---|---|---|
| Performance (kWh/km) | 0.21 | 0.17 | 0.18 |
| Battery capacity (kWh) | 24 | 16 | 4.5 |
| Charging voltage (V) | 240 | 240 | 240 |

TABLE III
The value of parameters of the grid and problem.

| Parameter | Value | Unit | Symbol |
|---|---|---|---|
| Operation period | 30 | Year | $Ny$ |
| Load growth rate | 0.6 | %/year | - |
| PEV application growth rate | 5 | %/year | - |
| Inflation rate | 10 | %/year | $IFR$ |
| Interest rate | 5 | %/year | $ITR$ |
| Investment cost for PL [16] | 2200 | $/PEV | $C^{INV}$ |
| Maintenance cost for PL | 1 | %/year | $C^{MAINT}$ |
| Electricity price [17] | 10 | Cent/kWh | $\pi^{E}$ |
| EENS cost | 50 | Cent/kWh | $\pi^{ENS}$ |
| Failure rate of a branch | 3 | Fault/year | $\lambda$ |
| Locating duration of a fault place | 1 | Hour | $\tau^{FL}$ |
| Repairing duration of a defective branch | 3 | Hour | $\tau^{FR}$ |
| Acceptable voltage tolerance | 5 | % | $\sigma^{V}$ |
| Base power in per unit system | 10 | MVA | $MVA^{BASE}$ |

### B. Simulation Results

Before the allocation of PLs to the feeder 1, the value of energy loss and EENS of the feeder over the operation period are about 2.9173 and 0.1349 Million MWh, respectively. In addition, the value of energy loss cost and EENS cost over the operation period are about 620.26 and 143.41 Million Dollars, respectively. After solving the problem, it is observed that just one PL is allocated to the feeder considering every behavioral model of the PEVs. TABLE IV presents the detailed results of the problem simulations. As can be seen, power model and exponential model are the most and the least desirable behavioral models for the PEVs fleet, since the total profit of the local DISCO are the most and the least, respectively. Regarding the power model, by installing a PL with the size of 756 PEVs in bus 26 and considering 30% discount on the charging fee of the PEVs, the energy loss and EENS of the feeder are decreased about 142,800 and 700 MWh over the operation period, respectively.

It should be noticed that although the exponential model has the least value of energy loss and EENS (and accordingly cost of energy loss and cost of EENS), these models are not the most favorable model because minimizing the total cost of the local DISCO is the objective function of the problem.

By investigating the results presented in TABLE IV, it is observed that the optimal value of discount on charging fee, the optimal location of PL, and the optimal size of PL are not the same for every behavioral model of the PEVs fleet. In other words, the predetermined value of incentive and default size and location of the PL will not result in maximum profit for the local DISCO.

TABLE IV
The detailed results of optimal PL allocation considering different behavioral models for the PEVs fleet.

| - | Pow. | Log. | Lin. | Exp. |
|---|---|---|---|---|
| Optimal discount (%) | 30 | 70 | 90 | 100 |
| Optimal bus for PL | 26 | 3 | 3 | 2 |
| Optimal size of PL | 756 | 542 | 617 | 686 |
| Energy loss (Million MWh) | 2.7745 | 2.7772 | 2.7592 | 2.7432 |
| EENS (Million MWh) | 0.1342 | 0.1344 | 0.1343 | 0.1342 |
| Investment cost (Million $) | 1.6636 | 1.1928 | 1.3593 | 1.5104 |
| Maintenance cost (Million $) | 1.0612 | 0.7608 | 0.8670 | 0.9634 |
| Cost of discount (Million $) | 6.346 | 10.617 | 15.557 | 19.206 |
| Energy loss cost (Million $) | 589.91 | 590.48 | 586.66 | 583.26 |
| EENS cost (Million $) | 142.73 | 142.87 | 142.80 | 142.73 |
| Maximum profit (Million $) | 21.963 | 17.755 | 16.433 | 16.002 |

### C. Sensitivity Analyses

*1) Sensitivity analysis for the value of incentive*

Herein, it is assumed that the PL has been placed in the optimal bus of the feeder for every model of the drivers' behavior, and then the total benefit of the local DISCO is investigated based on different values of incentive. Fig. 4 shows the total profit of the local DISCO over the operation period (Million $) respect to the value of discount on charging fee (%) considering Power model (optimal bus is 26), Logarithmic model (optimal bus is 3), Linear model (optimal bus is 3), and Exponential model (optimal bus is 2) for the PEVs behavior. As can be seen, the presented data in TABLE IV regarding the optimal value of discount on charging fee is approved by Fig. 4.

*2) Sensitivity analysis for the location of PL*

In this part, it is assumed that the optimal value of incentive for every model of the drivers' behavior is determined, and then the optimal bus of the feeder for installing one PL is probed. Fig. 5 illustrates the total profit of the local DISCO over the operation period (Million $) respect to the location of PL considering Power model (with optimal discount equal to 30%), Logarithmic model (with optimal discount equal to 70%), Linear model (with optimal discount equal to 90%), and Exponential model (with optimal discount equal to 100%) for the PEVs behavior. As can be seen, Fig. 5 agrees with the presented data in TABLE IV regarding the optimal location of the PL.

*3) Sensitivity analysis for the model of driving pattern*

In this part, the problem is investigated considering different driving patterns for the PEVs and the results are compared with consequences of the default case, that is, 100 PEVs for each driving pattern (Patterns 1-6). Herein, the power model is considered for the drivers' behavior. As can be seen in TABLE V, the value of optimal discount on charging fee, the optimal location of the PL, and maximum profit of the local DISCO are affected by the driving pattern of the PEVs fleet. This phenomenon indicates the necessity for realistically determining the driving pattern of the PEVs fleet in the traffic and grid-driven PL allocation problem.

*4) Sensitivity analysis for the types of PEVs*

Herein, the problem is investigated for other types of the PEVs, that is, *Chevy Volt 2012 PHV* and *Toyota Prius 2012*

*PHV* and the outcomes are compared with the results of default case (*Nissan Leaf BEV*). As can be seen in TABLE VI, different types of the PEVs change some of outcomes of the problem. Thus, the type of PEVs fleet must be identified in the optimal PL allocation problem.

The reason for achieving lower profit with *Chevy Volt 2012 PHV* and *Toyota Prius 2012 PHV* is related to their smaller battery capacity, and also their better performance (lower value for kWh per km) compared to *Nissan Leaf BEV*. In other words, *Nissan Leaf BEV* has the biggest battery capacity and high value of kWh per km (more energy consumption), thus this vehicle has more daily energy demand and PL placement for this type of PEV will result in more profit.

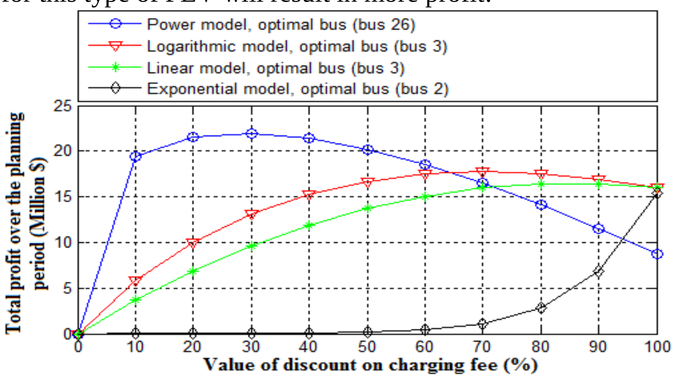


Fig. 4. Total profit over the operation period (Million $) respect to the value of discount on charging fee (%).

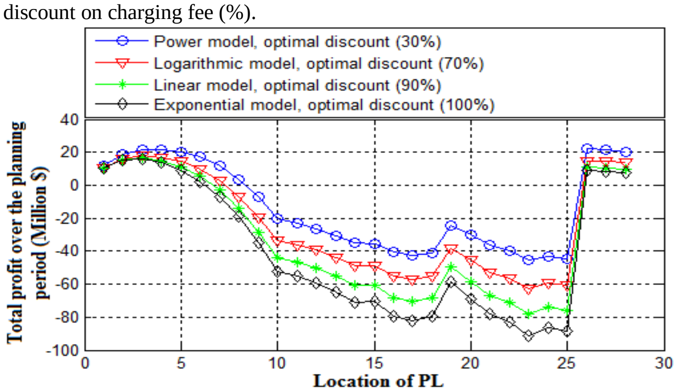


Fig. 5. Total profit over the operation period (Million $) respect to the location of PL.

TABLE V

THE RESULTS OF OPTIMAL PL ALLOCATION CONSIDERING DIFFERENT DRIVING PATTERNS FOR THE PEVS (DRIVERS' BEHAVIOR MODEL IS POWER MODEL).

| Driving pattern of the PEVs | Optimal discount (%) | Optimal bus for PL | Maximum profit (Million $) |
|---|---|---|---|
| Default (100 PEVs for each pattern) | 30 | 26 | 21.963 |
| All PEVs have pattern 1 | 40 | 3 | 23.772 |
| All PEVs have pattern 2 | 30 | 26 | 16.427 |
| All PEVs have pattern 3 | 40 | 3 | 39.864 |
| All PEVs have pattern 4 | 30 | 26 | 16.914 |
| All PEVs have pattern 5 | 40 | 3 | 21.956 |
| All PEVs have pattern 6 | 30 | 5 | 18.567 |

TABLE VI

THE RESULTS OF OPTIMAL PL ALLOCATION CONSIDERING DIFFERENT TYPE FOR THE PEV (DRIVERS' BEHAVIOR MODEL IS LINEAR MODEL).

| Type of PEV | Optimal discount (%) | Optimal bus for PL | Maximum profit (Million $) |
|---|---|---|---|
| Default (Nissan Leaf BEV) | 90 | 3 | 16.433 |
| Chevy Volt 2012 PHV | 80 | 3 | 11.470 |
| Toyota Prius 2012 PHV | 60 | 3 | 1.947 |

## VI. CONCLUSION

This paper studies the optimal PL allocation planning problem for plug-in PEVs fleet on a feeder of a given electrical distribution network to minimize the total cost of DISCO. It was noticed that the drivers' behavioral model, drivers' driving patterns, and even the type of PEVs can remarkably affect the outcomes of the planning problem including the optimal size and location of the PLs, optimal value of incentive, and maximum profit of the local DISCO. However, previous works for this problem fail to consider these factors. In this work, we consider these factors in solving the problem. Our numerical study confirmed the influence of these factors and the effectiveness of our approach.

## ACKNOWLEDGMENTS

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## REFERENCES

[1] Tie, S.F., Tan, C.W.: 'A review of energy sources and energy management system in electric vehicles', *Renewable and Sustain Energy Reviews*, 2013, 20, pp. 82-102.

[2] Kempton, W., et al.: 'A test of vehicle-to-grid (V2G) for energy storage and frequency regulation in the PJM system', Newark, DE: Univ. Delaware, 2008.

[3] According to BC Hydro's Draft Integrated Resource Plan, Appendix 2A–2011 Electric Load Forecast. [Online]. Available: <https://www.bchydro.com/content/dam/hydro/medialib/internet/documents/environment/EVcharging_infrastructure_guidelines09.pdf>

[4] Ferreira, J.C., et al.: 'Vehicle-to-anything application (V2Anything App) for electric vehicles', *IEEE Trans Ind Informat* 2014, 10, pp. 1927–1937.

[5] Oliveira, D. Q., Zambroni de Souza, A.C., Delboni, L.F.N.: 'Optimal plug-in hybrid electric vehicles recharge in distribution power systems', *Elect Power Syst Res*, 2013, 98, pp. 77– 85.

[6] Liu, Z., Wen, F., Ledwich, G.: 'Optimal planning of electric-vehicle charging stations in distribution systems. *IEEE Trans Power Del*, 2013, 28, pp. 102-110.

[7] Sortomme, E., Hindi, M., MacPherson, S., Venkata, S.: 'Coordinated charging of plugin hybrid electric vehicles to minimize distribution system losses', *IEEE Trans Smart Grid*, 2011, 2, pp. 198–205.

[8] M. Rahmani-andebili, "Optimal power factor for optimally located and sized solar parking lots applying quantum annealing," *IET Gener. Transm. Distrib.*, 2016, DOI: 10.1049/iet-gtd.2015.1553.

[9] Rahmani-andebili, M., Venayagamoorthy, G.K. 'SmartPark placement and operation for improving system reliability and market participation, *Elect. Power Syst. Res.*, 2015, 123, pp. 21-30.

[10] Chen, C., Duan, S.. 'Optimal integration of plug-in hybrid electric vehicles in microgrids', *IEEE Trans Ind Informat.*, 2014, 10, pp. 1917–1926.

[11] Leemput, N., Geth, F., Roy, J.V., Büscher, J., Driesen, J.: 'Reactive power support in residential LV distribution grids through electric vehicle charging', *Sustainable Energy, Grids and Networks*, 2015, 3, pp. 24–35.

[12] Guo, S., Zhao, H.: 'Optimal site selection of electric vehicle charging station by using fuzzy TOPSIS based on sustainability perspective, *Applied Energy*, 2015, 158, pp. 390–402.

[13] Rahmani-andebili M.: 'Spinning reserve supply with presence of plug-in electric vehicles aggregator considering compromise between cost and reliability', *IET Gener Trans Distrib.*, 2013, 7, pp. 1442-1452.

[14] IEEE Guide for Electric Power Distribution Reliability Indices, IEEE Std., pp. 1366–2003, 2004.

[15] Chen Z., Luo, P.: 'Incorporating quantum computation into simulated annealing for optimization problems', *IEEE Congress on Evolutionary Computation (CEC)*, New Orleans, LA, 2011.

[16] D. Newbery, "The Economics of Electric Vehicles," EPRG and Imperial College London, E&E Seminar, Cambridge, Jan. 2013. [Online]. Available: http://www.eprg.group.cam.ac.uk/wp-content/uploads/2013/01/EEJan13_EconomicsEVs.pdf.

[17] U.S. energy information administration (EIA), [Online]. Available: http://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_5_6_a, Accessed Jun. 2015.