

Coordinated charging of electric vehicles including customer options for slow or fast charging

Swapna GANAPANENI*^{ORCID}, Srinivasa Varma PINNI^{ORCID}

Department of Electrical and Electronics Engineering, Koneru Lakshmaiah Education Foundation,
Green Fields, Vaddeswaram, Guntur District, A.P., INDIA.

Received: 26.06.2018

Accepted/Published Online: 27.12.2019

Final Version: 28.03.2020

Abstract: Transportation system electrification in the world decreases the gasoline consumption that leads to increase in usage of number of plug in electric vehicles (PEVs). PEV is a bidirectional resource which, while playing the role of a resource, poses challenges in its management. These vehicles are to be charged at a residential standard outlet or in a corporate car charging station. This paper mainly aims to maximize the benefits of a customer who comes to a charging station for charging their vehicle. An incentive-based cost mechanism is introduced to optimally schedule the vehicles; this mechanism minimizes the overall charging cost, considers their random arrival and departure times and maximizes battery energy before they leave the station. As far as we know, there are no studies on minimizing the cost of coordinated optimal charging of electric vehicles at an isolated charging station with different charging modes. This paper presents and solves a linear optimization problem by LINGO, where the vehicles are connected for charging either in slow charging mode or fast charging mode at hourly basis for 6 h. The results are analyzed and validated. A 30-vehicle model is worked out. A 24-h schedule can also be worked on the same lines as given in this paper when the number of incoming vehicles is large.

Key words: Plug in electric vehicles, vehicle charging costs, coordinated charging, linear programming

1. Introduction

Electric vehicles (EVs) are bringing a revolutionary change in the automobile vehicles. They not only reduce the energy storages during peak periods but also solve environmental problems; besides these opportunities, the EVs pose certain challenges in the form of charging facilities at the residential and at the charging stations. The charging of EVs can be a significant load on the grid; therefore, it should be properly managed.

By 2022, as a part of green economy, India, the world's third large energy consumer, planned to have a renewable energy capacity of 175 GW. PEVs have recently emerged as a promising alternative technology to dramatically reduce fleet petroleum consumption, green house emission, and air pollution. By 2030, the government of India is planning to go with all electric in terms of new car sales across India. The Indian government is spending 7 lakh crores of rupees for importing crude oil which is a big matter and needs an immediate substitute which is cost-effective and free from pollution. The first battery charging and swapping station is located at Nagpur. According to a news analysis, it is estimated to have 31 million EVs in India by 2040. There are only 222 community EV charging stations when compared to traditional fuel stations. The Energy Efficiency Services Limited (EESL) is planning nearly 4000 EV charging stations in the National

*Correspondence: ganapaneniswapna@gmail.com

Capital Region. Recent work in this area seems to be analyzing impacts of PEVs on distribution network due to increased loading effects, electricity prices during peak and off-peak periods, time of use of electricity, minimizing the cost of charging electric vehicle, maximizing profit to the customer while charging the PEV, effects of coordinated and uncoordinated charging of PEVs.

The impact of PEVs on the electric power infrastructure has been assessed by several studies [1]. There are different charging strategies that manage the time and frequency of EVs charge as uncontrolled/uncoordinated, controlled/coordinated, delayed, and off-peak charging. A methodology was proposed in [2] to determine the charging rate of each vehicle so that maximum power can be delivered to all vehicles during their charging period without violating the network limits by considering a section of residential distribution network, also included a scenario of high penetration of electric vehicles on the network which is considered and validated.

In [3], the authors investigated decentralized smart charging algorithm for mitigating the impacts of PEVs load on the distribution system by minimizing load variance. The algorithm was also tested with certain uncertainties that happen in the system like random arrival of PEVs, changes in the output of distributed generation, variations in household profiles, etc.

In [4] the authors developed a coordinated smart charging schema for both ac and dc distribution system for optimal charging of PEVs by taking real time pricing into consideration, maintaining network within the limits, prioritizing utmost satisfaction of PEVs owners for minimizing the charging cost.

Price of electricity, battery state of charge (SoC), time needed to reach remaining SoC of battery as the real-time constraints, statistical data were considered and a real-time scenario was studied using estimation of distribution algorithm analyzed in [5] which schedules the electrical energy efficiently to the electric vehicles connected to the grid.

In order to eliminate distribution grid congestion and to maintain electricity grid constraints such as voltage and power within the limits, a new method is proposed for optimal charge plan of PEVs while meeting individual requirements of each EV and is tested on the electricity grid addressed in [6].

All EVs when connected during off-peak nighttime may lead to overloading of transformers in distribution substation. Therefore, taking the thermal constraints of the transformer into consideration which is serving a small fleet of EVs are scheduled based on decentralized incentive-based PEV charging algorithm proposed by the authors in [7] which follows the dual ascent approach.

All EV owners are habituated to charge their EVs at their homes or at a car park lot, due to this distribution grid may experience voltage variations and power losses when all are plugged in at a time or after a fixed time lapse. Therefore, authors in [8] proposed a coordinated charging algorithm in order to develop optimal charging schedule of PEV by minimizing power losses.

Concept of noncooperative games was introduced by the authors in [9] for decentralized optimal charging of PEVs so that cost would be minimized in a region with a large population of PEVs and it was assumed that non-PEV load is deterministic while not giving preference to customer's time constraints and health of the battery.

Large scale integration of PEVs along with the domestic load may have a bad impact on distribution system, so Monte Carlo simulation was used in [10] to estimate the load of PEVs as a function of time with different penetration levels based on probabilistic characteristics of domestic car usage data provided by UKTUS. In [11], authors discussed several existing optimal scheduling methods of PEVs including linear, nonlinear, dynamic, and quadratic models which are solved easily in the powerful software packages like GAMS, CPLEX

etc. However, keeping PEV owners and EV aggregator interests in mind there is a need to propose multiobjective formulations which would satisfy their needs such as maximizing profit, minimizing the charging time etc.

Table 1 shows the comparison of computational methods for PEV scheduling in terms of problem, solution approach, merits, and demerits. To account the stochastic nature of PEVs, a new method was proposed to calculate the PEVs charging load, to minimize peak load happening due to charging the PEVs, daily load fluctuations, and finally cost-benefit analysis of a PEV charging and discharging respectively was done by using a mixed integer programming in [12]. Considering level I and level II charging scenarios, different charging times of a day and evaluation of various factors on the distribution system like demand factor, utilization factor, price of electricity, load factors due to PEVs is proposed by authors in [13].

Charge plan infrastructure of PEVs based on hybrid particle swarm optimization gravitational search algorithm is proposed in [14] by considering the constraints as charging time, present SoC, and price of the energy for the maximization of state of charge so that maximum power can be allocated.

Monte Carlo simulation and Krill Herd algorithm were used by authors in [15] to estimate the stochastic charging behavior of PEVs by considering the uncertainties like energy prices, network loading which ensures the secured operation of the system and reduces the expected cost of charging.

Both quadratic and dynamic programming methods were applied to a residential distribution grid in [16] in order to achieve cost and losses minimization, storage requirements with a proper coordinated schedule among PEVs by applying day and night tariff structure, the effect of voltage controller embedded in the PEV. In [17] a centralized PEV recharging scheduling system is proposed in order to maximize the revenue of parking area and to fulfill the needs of PEV owners to the maximum extent by considering different mobility patterns of vehicles in real time.

In the literature there are several methods proposed in a decentralized system to obtain coordinated charging of PEVs by satisfying various constraints such as minimizing voltage deviations, power losses, maintaining distribution system within the limits, operating distribution transformer in a secured way etc. Similarly, various optimal scheduling methods have been suggested to minimize the overall charging cost of PEVs, maximization of SoC in residential areas or in a microgrid region. The novelty of this paper is that at a single charging station, the station owner gives priority to customer preferences like normal charging or fast charging mode and generates optimal scheduling for charging PEVs to minimize the overall charging cost based on incentive pricing mechanism, considering their arrival and departure times and maximizes their energy before it leaves the station without deviating the power constraints on the station.

To our knowledge, there are no studies on minimizing the cost of coordinated optimal charging of electric vehicles at an isolated charging station with different charging modes. Our objective is to solve a linear optimization problem that gives coordinated optimal schedule with minimal charging cost of PEVs, even in a charging station without deviating the power constraints on the station following incentive price mechanism. With both normal and fast charging modes available at station, this provides each customer a chance to meet his needs satisfactorily.

This paper is organized as follows: Section 2 formulates the problem of EV charging in a coordinated way. Section 3 gives the algorithm for solution, Section 4 gives the results of investigation and discussion.

2. Problem formulation

Usually all charging stations try to earn more revenue from customers by charging the Evs and there may be competition among various charging stations to attract more customers. In order to deal with such a situation in

Table 1. Comparison for computational methods for PEV scheduling.

Authors	Problem	Solution approach	Merits	Demerits
[2]	Determined optimal charging rate for each electric vehicle in order to maximize power delivered to each EV	Linear programming	Does not require large amount of data from distribution System operator. Computation is easy. Does not need large historical data.	The ability of the EV battery and vehicle to grid support are not considered.
[8]	Coordinated charging is proposed to minimize power losses and maximize grid load factor.	Quadratic and dynamic programming	Stochastic approach is used to determine error in the forecasted data. Charging during peak load can be avoided. Quadratic programming is more accurate, requires less storage and computational time than dynamic programming.	Voltage control, reactive power control etc. are not considered.
[9]	Coordinated charging of autonomous PEVs using noncooperative games.	Game theory	The methodology proved to be more suitable for large PEV penetration changes significantly the electricity patterns with PEVs charging. Nash equilibrium occurs very quickly where centralized control is not possible. Strategy improved PEV market penetration especially in the centralized system.	Time constraints, battery state of health were not considered. Stochastic nature of demand was not considered.
[12]	Investigated optimal strategies for PEVs coordination with cost benefit analysis.	Linear mixed integer programming	Calculated PEV charging pattern Coordination strategy for peak shaving and valley filling. Analyzes the benefits and costs of a coordinated charging strategy.	Although random variables are considered, linear integer programming problems are deterministic optimization problems.
[13]	Impact of PEVs charging on distribution system was studied.	Demand response programs	Evaluated impact of demand factor, load factor, utilization factor for different pricing options of charging PEVs on distribution system.	Power flow from vehicle to grid is not involved.
[14]	Optimizing smart charging of PEVs by maximizing their SOC.	Hybrid particle swarm optimization gravitational search algorithm.	Easy to implement and yields good performance. Price of electricity, initial SOC, charging duration are considered for optimal allocation of power.	Assumption made that PEV arrives at the station only once for charging in a day.
[17]	Maximizing the revenue of parking lot and fulfilling the needs of all EVs.	Proposed a system parking lot recharge scheduling (PLRS)	Executed on realistic vehicular mobility and proved to be best compared with basic scheduling mechanisms.	V2G aspects not considered, local generation, direct energy transfer between vehicle to vehicle.

various EV charging stations, a charging station can choose its own pricing mechanism to maximize the benefits of EV owner by minimizing the overall charging cost of EV in different charging modes. Therefore, in this section an objective function is formulated to solve the aforementioned problem by assuming that a charging station of capacity P MW with K number of charging sockets available some of which are normal charging and the rest are meant for fast charging, it is further taken into consideration that all EVs that arrive at the station

are equipped with a battery management system which gives information about state of charge and state of health on arrival. The vehicle charging duration depends on the state of charge of the arriving vehicle; this can be anywhere between 20% and 95% charging. The charging schedule depends on the owner's options, like the period of charge; if the vehicle is to be charged fast, then the charging price will be higher than the normal.

The charging cost at any time slot j is a quadratic function of the per unit power to be provided for charging [18]. This per unit power is

$$P_{net,j} = \frac{(P_{base,j} + P_{ref,j})}{P_{o,j}} \tag{1}$$

So the cost of charging at time j is

$$C_j = C_{ks} * C_{o,j}(P_{net,j})^2 \tag{2}$$

As the number of vehicles for charging increases, charging price increases too.

$P_{base,j}$ is the inelastic base load at time j .

$P_{ref,j}$ is the total charging power of the entire fleet at the time slot j .

$C_{o,j}$ and $P_{o,j}$ are both taken as constant, $C_{o,j}$ is the cost function of $P_{o,j}$.

C_{ks} is the adjustable coefficient which can be used to take care of the vehicle owner's options.

The objective is to minimize the daily charging cost of all EVs as given in eq. (3)

$$Minimize \ EV \ cost = \sum_{j=1}^{24} \sum_{i=1}^n C_j A_{ij} X_{ij}^{nor} + \sum_{j=1}^{24} \sum_{i=1}^n \alpha C_j A_{ij} Y_{ij}^{fast} \tag{3}$$

where n is the fixed number of EVs parked in the grid.

j is the charging time slot.

A_{ij} is the factor to indicate the availability of i^{th} vehicle at time slot j .

X_{ij}^{nor} and Y_{ij}^{fast} are the charging power of the i^{th} EV connected for normal charging and fast charging respectively at the time slot j .

α is the cost factor for the vehicles which are connected in fast charging mode. It is considered as 2 in our work, which means that fast charging price is twice that of slow charging. However, α depends on the time of day at which the vehicle is connected. The function in eq. (3) is a linear function for 24 h charging. The function can be handled for any number of hours and not necessarily for 24 h. In this paper a period of 6 h is considered. Each EV has its own charging power and the energy constraints which must be properly taken into consideration during charge. It is well known that Lithium-ion batteries which are usually used in EVs are very sensitive to abuse; any overcharging in the form of kW or kWh may result in explosion of battery.

2.1. Charging power constraints

$$0 \leq X_{ij}^{nor} \leq P_{Ni} \tag{4}$$

$$0 \leq Y_{ij}^{fast} \leq P_{Ni} \tag{5}$$

where P_{Ni} is the rated power of the battery of i^{th} vehicle.

2.2. Energy capacity of the battery

Let the efficiency of battery for charging be η_c . If the power measured at the battery terminals is P_{ij} , then the charging power of the battery is $\eta_c P_{ij}$.

The battery energy constraints are

$$\sum_{j=1}^{24} \eta_c * A_{ij} * X_{ij}^{nor} + soc_i \leq E_{Ni}^{nor} \quad (6)$$

$$\sum_{j=1}^{24} \eta_c * A_{ij} * Y_{ij}^{fast} + soc_i \leq E_{Ni}^{fast} \quad (7)$$

where E_{ni}^{nor} and E_{ni}^{fast} are the expected energy level of the battery of i^{th} vehicle at the time of departure for normal charging and fast charging respectively.

SoC_i is the i^{th} EV's initial energy available while it arrives at the charging station for charging.

The expected energy to which the vehicle can be charged is 0.95 of rated kWh.

Then the charging station has its own constraints that are kW rating of the station.

$$\sum_{i=1}^n (X_{ij}^{nor} + Y_{ij}^{fast}) \leq P_{grid}, \forall j \quad (8)$$

where P_{grid} is the kW rating of the station at any time slot j.

In this paper it is assumed that all the batteries have η_c as 95% and that they are to be charged to the extent of 95% of their energy capacity.

The vehicles are provided with battery chargers which display the current SoC before they are connected for charging. From the battery name plate details, the power and the energy capacity on hourly basis of the batteries are known.

Given the above data, the problem formulated above can be handled by linear programming which takes care of the objective to minimize the charging price for the normal charging and fast charging of vehicles along with the linear constraints of the battery's power and energy and also of the power of the charging station.

3. Charging algorithm

As the vehicle arrives at the station for charging, its battery parameters are known: SoC_i , P_{Ni} , E_{Ni} , for all $i(i=1,2,3,\dots,N)$. In this paper, the station capacity is taken as 0.25 MW, which can handle, at any time slot j, 30 vehicles for charging, even if the need is 14 kW. With the available data, the linear objective function formulated when subjected to the constraints determines the coordinated optimal schedule and minimizes the overall charging cost of PEVs show in Figure 1.

4. Results and discussions

The charging schedule is limited to 6 h for the entire fleet of the vehicles. The total number of vehicles that could be handled at the station at any time slot of 6 h is 30. Table 2 shows the results of charging state where 1 and 0 indicate that the vehicle is respectively under charge or idle.

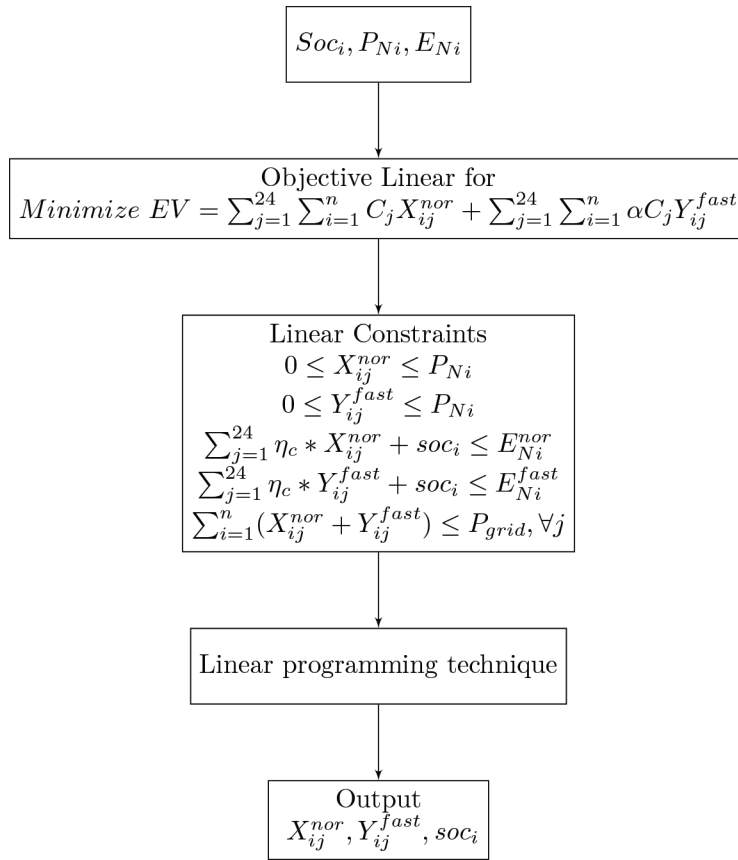


Figure 1. Flow chart for EV scheduling and cost minimization at charging station.

A few of these vehicles can be demand fast charging and others slow charging. The total cost of charging is minimized limited to the EVs’ option for fast or slow charging, and also subject to their power and energy constraints. The linear programming package LINGO [19] is used for scheduling the charging of EVs. LINGO is a comprehensive tool designed to make building and solving linear, nonlinear (convex & nonconvex/Global), quadratic, quadratically constrained, second-order cone, semidefinite, stochastic, and integer optimization models faster, easier, and more efficient. Table 2 indicates the availability of EVs at the charging station to charge their batteries which is randomly considered. It is assumed that all EVs arriving for charging get charged to their full capacity before they leave the station.

If a vehicle is connected at any hour j, then it is indicated as 1 against the vehicle number; otherwise, it is 0. The vehicles ranging from 1 to 20 are connected for slow charging whereas those from 21 to 30 are connected for fast charging. It can also be seen from Table 2 that EVs arriving with poor SoC are kept connected for a long period of time.

For the sake of computation, it is assumed that all EVs connected for slow charging are having their battery capacity as 40 kWh and for fast charging as 64 kWh. Table 3 shows the optimal scheduling of vehicles for the above connections as well as the power taken by each vehicle according to the schedule generated using LINGO. If the vehicle is not scheduled in the given hour, then the power taken by the EV is zero.

As it can be seen from Table 3, at any hour, within the 6 h, the power capacity of the station is not exceeded. For slow mode charging, the charging power is 7 kW and it is 14 kW for fast charging. If the vehicle

Table 2. A 6-h binary availability of vehicles and initial energy present with each EV while arriving at the station.

Vehicle no.	Hour of charging						Initial SoC in kWh
	1	2	3	4	5	6	
1	1	1	1	1	1	1	12
2	1	1	1	1	0	0	18
3	1	1	1	1	1	1	12
4	1	1	1	1	0	0	18
5	1	1	1	1	0	0	18
6	1	1	1	1	1	1	12
7	1	1	1	1	1	1	12
8	1	1	1	1	1	1	12
9	1	1	1	1	0	0	19
10	1	1	1	0	0	0	27
11	0	0	1	1	1	1	27
12	0	0	0	1	1	1	22
13	0	0	1	1	1	0	23
14	0	0	0	1	1	1	23
15	0	1	1	1	1	0	24
16	1	1	1	1	0	0	15
17	1	1	1	1	0	0	19
18	1	1	1	0	0	0	19
19	1	1	1	0	0	0	19
20	1	1	1	1	0	0	19
21	1	1	1	0	0	0	25
22	1	1	1	1	0	0	25
23	1	1	1	1	0	0	16
24	1	1	1	1	0	0	16
25	1	1	1	0	0	0	25
26	1	1	1	0	0	0	25
27	0	0	1	1	1	0	34
28	0	0	1	1	1	0	34
29	1	1	1	0	0	0	34
30	1	1	1	0	0	0	34

is fully charged as indicated by the power and energy ratings of the battery, it is taken out of plug leaving space for another. As formulated earlier, if the number of vehicles connected in an hour is high, the cost of charging the vehicles in that hour is also high. The number of vehicles connected at hours 5 and 6 are lower in Table 2. Therefore, the cost of charging vehicles connected in these hours is less and almost all the vehicles connected in these hours are charged to the rated power of the battery. Moreover, it is observed that a vehicle leaving the charging station is charged in the range of 88% to 95% of its battery capacity.

The power consumed by the vehicles and number of vehicles connected in an hour are shown in Figure 2. It also indicates that the power consumed by the vehicles at any moment has not exceeded the energy capacity of the station. From the above discussion, optimal charge scheduling is developed, which results in cost reduction of both slow charging and fast charging of the connected vehicles. The above function can be implemented for any number of charging stations based on its capacity and for a period of a day.

Table 3. Optimal charging schedule generated during a 6-h period for the EVs that arrived at the station.

EV no. i. Power(kW) taken by EV in j	1	2	3	4	5	6	Target E_{Ni} (kWh)
1	0	2.15	0	7	7	7	35.15
2	7	2.84	0	7	0	0	34.84
3	0	2.15	0	7	7	7	35.15
4	7	2.84	0	7	0	0	34.84
5	7	2.84	0	7	0	0	34.84
6	0	2.15	0	7	7	7	35.15
7	0	2.15	0	7	7	7	35.15
8	0	2.15	0	7	7	7	35.15
9	7	2.84	0	7	0	0	35.84
10	7	1.42	0	0	0	0	35.42
11	0	0	0	0	1.42	7	35.42
12	0	0	0	0	6.68	7	35.68
13	0	0	0	5.63	7	0	35.63
14	0	0	0	0	5.63	7	35.63
15	0	0	0	4.57	7	0	35.57
16	7	7	0.05	7	0	0	36.05
17	7	2.84	0	7	0	0	35.84
18	7	7	2.84	0	0	0	35.84
19	7	7	2.84	0	0	0	35.84
20	7	2.84	0	7	0	0	35.84
21	14	14	7.78	0	0	0	60.78
22	14	7.78	0	14	0	0	60.78
23	14	14	2.21	14	0	0	60.21
24	14	14	2.21	14	0	0	60.21
25	14	14	7.78	0	0	0	60.78
26	14	14	7.78	0	0	0	60.78
27	0	0	0	12.31	14	0	60.31
28	0	0	0	12.31	14	0	60.31
29	14	12.31	0	0	0	0	60.31
30	14	12.31	0	0	0	0	60.31

5. Conclusion

This paper proposed an optimization model to minimize the overall charging cost of the PEVs by generating optimal schedule which satisfies the customer options for charging the vehicles. Incentive-based cost mechanism is adopted to decide the price of electricity during that hour and filling their batteries to the full extent before they leave charging station for both slow and fast charging. The methodology is tested and validated for a 6-hour time period using LINGO software. The scheduling can be extended to 24 h too. However, in the future there are many possibilities to extend this work. Stochastic modelling of load profile can be considered

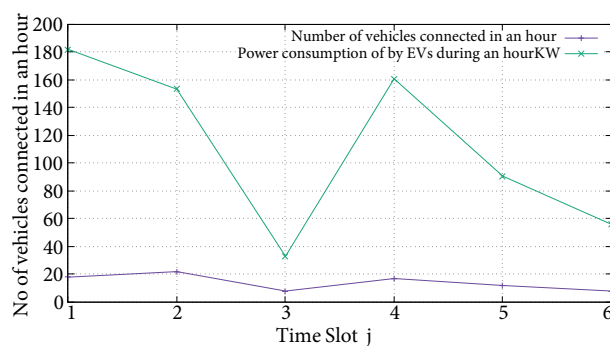


Figure 2. Power consumption by EVs during an hour and number of vehicles connected in an hour.

for a charging station by choosing appropriate probability distribution function; discharging energy from PEV back to the grid i.e. V2G an incentive-based pricing mechanism can be developed to encourage PEV owners to sell energy to the grid; impact of battery charging and discharging cycles on the battery parameters can be considered.

Acknowledgment

We would also like to show our gratitude to Dr. G. Kesava Rao, former professor at IITBHU for sharing his pearls of wisdom with us during the course of this research.

References

- [1] Muratori M. Impact of uncoordinated plug-in electric vehicle charging on residential power demand. *Nature Energy* 2018; 3(3): 193-201. doi: 10.1038/s41560-017-0074-z
- [2] Richardson P, Flynn D, Keane A. Optimal charging of electric vehicles in low-voltage distribution systems. *IEEE Transactions on Power Systems* 2011; 27(1): 268-279. doi: 10.1109/TPWRS.2011.2158247
- [3] Li Q, Cui T, Negi R, Franchetti F, Ilic MD. On-line decentralized charging of plug-in electric vehicles in power systems. arXiv:1106.5063. 2011.
- [4] Shaaban MF, Eajal AA, El-Saadany EF. Coordinated charging of plug-in hybrid electric vehicles in smart hybrid AC/DC distribution systems. *Renewable Energy* 2015; 82:92-9. doi: 10.1016/j.renene.2014.08.012
- [5] Su W, Chow MY. Performance evaluation of an EDA-based large-scale plug-in hybrid electric vehicle charging algorithm. *IEEE Transactions on Smart Grid*. 2011; 3(1): 308-315. doi: 10.1109/TSG.2011.2151888
- [6] Sundstrom O, Binding C. Flexible charging optimization for electric vehicles considering distribution grid constraints. *IEEE Transactions on Smart Grid* 2011 ;3(1):26-37. doi: 10.1109/TSG.2011.2168431
- [7] Hermans R, Almassalkhi M, Hiskens I. Incentive-based coordinated charging control of plug-in electric vehicles at the distribution-transformer level. In: *IEEE American Control Conference (ACC)*; Montreal, Canada; 2012. pp. 264-269. doi: 10.1109/ACC.2012.6315577
- [8] Clement-Nyns K, Haesen E, Driesen J. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *IEEE Transactions on Power Systems*. 2009; 25(1): 371-380. doi: 10.1109/TPWRS.2009.2036481
- [9] Ma Z, Callaway DS, Hiskens IA. Decentralized charging control of large populations of plug-in electric vehicles. *IEEE Transactions on Control Systems Technology* 2011; 21(1): 67-78. doi: 10.1109/TCST.2011.2174059

- [10] Huang S, Infield D. The impact of domestic plug-in hybrid electric vehicles on power distribution system loads. In: IEEE International Conference on Power System Technology; Hangzhou, China; 2010. pp. 1-7. doi: 10.1109/POWERCON.2010.5666513
- [11] Yang Z, Li K, Foley A, Zhang C. Optimal scheduling methods to integrate plug-in electric vehicles with the power system: a review. In: IFAC Proceedings Volumes. 2014; 47(3): 8594-603. doi: 10.3182/20140824-6-ZA-1003.01804
- [12] Luo Z, Hu Z, Song Y, Xu Z, Lu H. Optimal coordination of plug-in electric vehicles in power grids with cost-benefit analysis—Part I: Enabling techniques. IEEE Transactions on Power Systems. 2013; 28(4): 3546-3555. doi: 10.1109/TPWRS.2013.2262318
- [13] Raghavan SS, Khaligh A. Impact of plug-in hybrid electric vehicle charging on a distribution network in a Smart Grid environment. In: IEEE Innovative Smart Grid Technologies (ISGT) 2012. pp. 1-7. doi: 10.1109/ISGT.2012.6175632
- [14] Rahman I, Vasant P, Singh BS, Abdullah-Al-Wadud M. Hybrid swarm intelligence-based optimization for charging plug-in hybrid electric vehicle. In: Springer Asian Conference on Intelligent Information and Database Systems; Bangkok, Thailand; 2015. pp. 22-30. doi: 10.1007/978-3-319-15705-4_3
- [15] Rostami MA, Kavousi-Fard A, Niknam T. Expected cost minimization of smart grids with plug-in hybrid electric vehicles using optimal distribution feeder reconfiguration. IEEE Transactions on Industrial Informatics. 2015; 11(2): 388-397. doi: 10.1109/TII.2015.2395957
- [16] Clement-Nyns K, Haesen E, Driesen J. Analysis of the impact of plug-in hybrid electric vehicles on residential distribution grids by using quadratic and dynamic programming. World Electric Vehicle Journal. 2009; 3(2): 214-224. doi: 10.3390/wevj3020214
- [17] Kuran MŞ, Viana AC, Iannone L, Kofman D, Mermoud G. A smart parking lot management system for scheduling the recharging of electric vehicles. IEEE Transactions on Smart Grid 2015; 6(6): 2942-53. doi: 10.1109/TSG.2015.2403287
- [18] Zhang M, Chen J. The energy management and optimized operation of electric vehicles based on microgrid. IEEE Transactions on Power Delivery 2014; 29(3): 1427-35. doi: 10.1109/TPWRD.2014.2303492+
- [19] Schrage LE, LINDO Systems, Inc. Optimization modeling with LINGO. CA, USA: Duxbury Press, 1997.