Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2020) 28: 1314 – 1330

doi:10.3906/elk-1907-189

Combined analytic hierarchy process and binary particle swarm optimization for multiobjective plug-in electric vehicles charging coordination with time-of-use tariff

Junaid Bin Fakhrul ISLAM[1], **Mir Toufikur RAHMAN**[2], **Hazlie MOKHLIS**[1,*]
Mohamadariff OTHMAN[1], **Tengku Faiz TENGKU MOHMED NOOR IZAM**[1],
Hasmaini MOHAMAD[3]
[1]Department of Electrical Engineering, Faculty of Engineering, University of Malaya, Kuala Lumpur, Malaysia
[2]School of Engineering, RMIT University, Melbourne, Australia
[3]Faculty of Electrical Engineering, University of Technology Mara (UiTM), Shah Alam, Malaysia

Received: 26.07.2019 • **Accepted/Published Online:** 26.10.2019 • **Final Version:** 08.05.2020

Abstract: Plug-in electric vehicles (PEVs) are gaining popularity as an alternative vehicle in the past few years. The charging activities of PEVs impose extra electrical load on residential distribution system as well as increasing operational cost. There are multiple conflicting requirements and constraints during the charging activities. Therefore, this paper presents multiobjective PEV charging coordination based on weighted sum technique to provide simultaneous benefits to the power utilities and PEV users. The optimization problem of the proposed coordination is solved using binary particle swam optimization. The objectives of the coordination are to (i) minimize daily power loss, (ii) maximize power delivery to PEV, and (iii) minimize charging cost of PEV considering time-of-use tariff. In order to determine balance weighting factor for each of these objectives, analytic hierarchy process is applied. By using this approach, the best result of charging coordination can be achieved compared to uncoordinated charging. A 23-kV residential distribution system with 449-nodes is used to test the proposed approach. From the attained results, it is shown that the proposed method is effective in minimizing power loss and cost of charging with safe operation of distribution system.

Key words: Plug-in electric vehicle, charging coordination, analytic hierarchy process, cost minimization, optimization

1. Introduction

Plug-in electric vehicles (PEVs) are environment friendly low-emission vehicles. The depletion of natural sources such as fuel oil reserve and the increase in oil price has contributed to the significant development of PEVs in recent years [1]. Generally, a PEV utilizes a large-capacity battery that needs frequent charging to run high-powered motors [2]. PEVs can be charged at home or at other locations such as shopping complexes and gas stations using the standard electric power outlets. PEVs consume a large amount of electricity in comparison with residential load and regarded as extralarge electrical consumption in the distribution network. The charging activities of PEVs cause significant potential risk such as extreme voltage fluctuations, enormous power loss, and overloading of substation transformers [3]. As a result, the overall performance and efficiency of the system will be degraded. Furthermore, a too large voltage deviation will cause issues on the reliability of the system which must be avoided in order to assure effective operation of electric appliances. Uncoordinated PEV charging raises load peaks that lead to cable and transformer overload, as well as fuse blowouts. In the worst-case

*Correspondence: hazli@um.edu.my

scenario, uncoordinated PEV charging could also cause system blackout. Consequently, the operational cost of the distribution system will increase [4].

To address these issues, recent researches have studied the integration of PEVs in the distribution system using different strategies and optimization methods. Those studies focus on PEV charging coordination that relies on the availability of a two-way smart grid communication infrastructure [5]. A multiagent distribution system operator and aggregator-based PEV charging management are implemented in laboratory microgrid to avoid distribution transformer overloading [6]. The distribution line and transformer overloading are reduced in [7] by employing heuristic methods. Distribution network's energy costs were minimized along with overload limitation in [8] by using the Lyapunov optimization and the Lagrange dual decomposition techniques. As a result of controlling load, voltage profile is increased as well. A comparison of slow and fast charging with the aim of technical and financial benefits is studied in [9]. The authors concluded that fast charging degrades the performance of the system and increases the daily operational cost. However, slow charging takes a long time and vehicles might not be fully charged during the charging period. Considering this, an optimal fixed charge rate coordination strategy in minimizing power loss and voltage deviation is proposed in [10]. Together with the distributed demand and response, a PEV charging is proposed in [11, 12] by employing congestion pricing approach. The authors in [11] employed charging tariff to provide faster charging facility to the consumers who are willing to pay more. After all, the consequence of this coordination strategies may not be advantageous as the coordination relies on local information and signals. Accordingly, a linear programming-based convex optimization is presented in [13] to lessen the gap between the demand profile and demand raised by charging activities of PEV. Real-time PEV charging coordination is proposed in [14–16] employing different metaheuristic optimization. Water filling algorithm is used in [14] to reduce peak demand. Generation cost is reduced by minimizing the cost of power loss using maximum sensitivities selection in [16]. In [2] quadratic and dynamic programming are analyzed where quadratic programming is found to be more accurate for PEV charging coordination in terms of minimizing power loss and voltage deviations simultaneously.

Besides the above-mentioned coordination techniques, several researches focused on PEV charging cost minimization in distribution network. A PEV charging control strategy was proposed in [17] using noncooperative game theoretic approach to minimize the charging cost. A multilevel optimization was carried out in [18] using price signal scheme where electricity generation cost is minimized in one level and cost of charge is minimized in other level of optimization. A PEV charging coordination with aggregator was developed in [19]; however, the authors put an option to select the charging period by user to reduce the waiting time that may impose congestion of line. To handle the extra load of PEVs within the existing distribution network, smart charging coordination was proposed in [9]. Charging cost of PEVs is also reduced in this research. A long-term hybrid planning approach based on cost benefit analysis is proposed in [20]. In this work, the authors developed two different charging strategies considering economic and technical benefits separately. Minimization of charging cost approach has been taken as objective function in [21] where PEV users are allowed to participate in demand side management.

So far, most of the research has focused on the PEV charging coordination either on technical benefits of utility such as minimizing power loss and voltage deviation, load flattening, peak load shaving, and overload avoiding or financial benefit such as minimizing charging cost and operational cost separately. In previous work, it was found that a lower number of PEVs can be connected through the coordination strategy if the objective function only considers minimization of cost. In contrast, more PEVs can be connected in the charging coordination which apply objective of technical benefit though in this strategy charging cost is increased [9]. Therefore, it is imperative to develop an optimal coordination strategy which takes into account the objective of technical and financial benefit simultaneously when maximum number of PEVs will take charge. In addition, time-of-use tariff can be used for optimal charging cost. Practical scenario such as different charger capacities, battery sizes are also needed to be considered.

To address these research gaps, this paper proposes a multiobjective PEV charging coordination strategy in near real-time duration (5 min interval). The main contributions of this paper are to (i) minimize power loss and charging cost of PEVs, (ii) maximize distribution system capacity by charging maximum number of PEV during charging period while maintaining all system constraints, and (iii) analytic hierarchy process (AHP) is used as the decision making method. In this research, binary particle swarm optimization (BPSO) is employed as the optimization algorithm and weighting factors for each objective function is determined through AHP. The algorithm minimizes the daily power loss and cost of charge while it maximizes the distribution system capacity. At the same time, it also managed to maintain the system constraints such as voltage limit and no overload in the system. Simulations are performed on 449-node residential smart grid and the results are discussed in detail, confirm its effectiveness with and without considering charging cost as objective function.

The organization of this paper is as follows. Section 2 presents the mathematical formulation of the proposed PEV charging coordination and the power system constraints. Section 3 discusses the proposed PEV charging coordination where BPSO and AHP are used as the optimization technique and weightage calculation technique for the multiobjective optimization. Section 4 describes the system condition, case studies, and test network. Results of different case studies are discussed and analyzed in Section 5, and Section 6 concludes this paper.

2. Mathematical formulation and constraints

The objective function (F) of the coordination is constructed based on three factors as in (1):

$$F = min(w_1 * f_1 + w_2 * (\frac{1}{f_2}) + w_3 * f_3), \tag{1}$$

where w_1, w_2, and w_3 are the weighting factors for each of the objective function. The total daily power loss and the charging cost for each PEV should be minimized while the distribution system capacity is maximized. The values of all the objective functions are transformed into the same range: [0,1].

The first objective function (f_1) is to minimize the daily power loss (P_{loss}) which can be represented by Equation (2).

$$f_1 = \sum_{i=1}^{\text{timeslot}} (I_{b,i}^2 * R_b), \tag{2}$$

where $I_{b,i}$ is b^{th} branch current at timeslot i and R_b is branch resistance.

The second objective (f_2) is to maximize the power delivery to the PEV. The maximization of power delivery can be done by connecting maximum number of PEVs at time t while the maximum demand constraint is strongly maintained. f_2 is represented by Equation (3).

$$f_2 = P_{DS}^{max} / (P_{PEVque} - P_{PEVconn}), \tag{3}$$

$$P_{PEVque} = \sum_{k=1}^{N} (\frac{RE_k}{RTS_k})_i, \tag{4}$$

$$P_{PEVconn} = \sum_{k=1}^{N_{PEV}} (\frac{RE_k}{RTS_k})_i, \tag{5}$$

where P_{DS}^{max} is the maximum distribution system capacity. P_{PEVque} is the total required power for the PEV which are waiting to get charged at i^{th} timeslot. $P_{PEVconn}$ is the total power required by the PEV which is selected through the optimization to connect at i^{th} timeslot. RE_k is the required energy and RTS_k is the required time to obtain full charge for k^{th} PEV. N is the total number of PEVs and N_{PEV} is the number of PEVs that are selected for charging at i^{th} timeslot.

The third objective (f_3) is to minimize the charging cost for all PEVs connected to the distribution system. The cost minimization is forecasted based on time-of-use (ToU) tariff while the total required charging cost is forecasted for each PEV and calculate total cost for entire system. f_3 is represented by Equation (4).

$$f_3 = \sum_{k=1}^{N_{PEV}} \sum_{i=CTS}^{i+RTS} (\frac{RE_k}{RTS_k}) * ToU_i, \tag{6}$$

where RE_k is the total amount of energy and RTS_k are the required number of timeslots (5 min each) to achieve the expected state of charge from the initial state of charge for K^{th} PEV respectively. CTS_k is the timeslot when PEV starts to get charged. ToU_i is the electrical tariff at i^{th} timeslot and N_{PEV} represents the number of PEVs that is selected through the optimization to connect at the respective timeslot.

The total energy (RE_k) needed for each PEV is determined by considering each PEV charger efficiency which is presented as:

$$RE_k = CHG_k * (SOC_{req} - SOC_{int})_k * \frac{1}{\text{Charger efficiency}}, \tag{7}$$

where CHG_k is the capacity of K^{th} PEV charger and 'charger efficiency' is the PEV charger charging efficiency when battery of PEVs are being charged. SOC_{int} and SOC_{req} are the primary and required states of charge, respectively.

Subject to the following constraints:

a. Distribution system capacity

$$(\sum_{d=2}^{m} (P_{load} + P_{PEV})_d + P_{loss})_d \leq P_{DS}^{max}, \tag{8}$$

where m represents the number of nodes in the system. $P_{load,d}$ specifies the residential load and $P_{PEV,d}$ is the load of PEV on d^{th} node and P_{DS}^{max} denotes the maximum distribution system capacity in 24 h.

b. Bus voltage

$$V_{min} \leq V_m \leq V_{max}. \tag{9}$$

V_{min} and V_{max} stand for the lowest and highest permissible voltages respectively. For this charging scheme, the voltage differences are defined as $\pm$ 10% (deemed to be 0.9 pu to 1.1 pu).

c. State of charge (SOC)

$$SOC_{int} < SOC_{curr} < SOC_{req}. \tag{10}$$

Here SOC_{curr} is the charge status after particular Δt timeslot. This equation means that once a PEV is connected to charger, it will continue charging until reaching the required level of SOC as defined by the users.

3. Proposed method

The proposed strategy aims to simultaneously reduce power loss during the PEV charging operation and charging cost of PEV while the distribution system capacity is maximized. In this work, the real-time PEV charging coordination is developed by employing BPSO, and AHP is employed to find out the suitable weighting factors for each objective function in (1). The proposed PEV charging coordination can be implemented in smart distribution grid system as illustrated in Figure 1. The system equipped with communication architecture to control the charging activities.

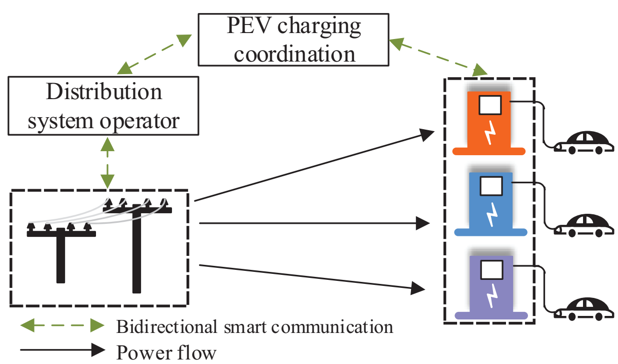


Figure 1. Plug-in electric vehicle charging coordination system architecture in smart distribution grid.

3.1. Binary particle swarm optimization (BPSO)

BPSO, initiated in [22], was employed to solve the proposed PEV charging coordination strategy. The fundamental concepts of binary PSO and PSO are identical. The only difference is in the equation of particle position change. BPSO has been chosen for this work due to the nature of the solution of EV charging scheduling that required binary form; "1" refers to charging while "0" indicates off-charging status respectively. Moreover, it is proven that with respect to other optimization techniques, BPSO offers better optimal solutions with limited number of parameters [23].

Each particle velocity and position in d-dimensional space can be expressed by Equations (11) to (13) respectively.

$$Vel_d^{t+1} = W * Vel_d^t + C_1 * r_1 * (P_d^t - X_d^t) + C_2 * r_2 * (G_d^t - X_d^t), \tag{11}$$

where r_1 and r_2 are two distinct random values, W is the inertia weight, C_1 and C_2 are two acceleration coefficients. vel_d^t and x_d^t are the particle velocity and position respectively at time t. P_d^t and G_d^t are the best particle positions in one single iteration and among all the iterations respectively. Each vel_d^t indicates the probability of new position of particle x_d^{t+1} that is bounded within $[Vel_{min}, Vel_{max}]$.

$$Sig(Vel_d^{t+1}) = \frac{1}{1+e^{-Vel_d^{t+1}}}, \tag{12}$$

$$X_d^{t+1} = \begin{cases} 1 & \phi < Sig(Vel_d^{t+1}) \\ 0 & \phi > Sig(Vel_d^{t+1}) \end{cases}, \tag{13}$$

where $sig(Vel_d^{t+1})$ is a logistic function transformation and ϕ is a quasirandom number between '0' and '1'.

3.2. Analytic hierarchy process

AHP is a systematic multicriteria decision-making technique formulated by Saaty [24]. The AHP decision-making process has been employed in this research because of its ability to structure a complex, multiattribute, and multiperson problem hierarchically. Moreover, it possesses the ability to solve the differently scaled unit objective function theoretically [25]. The precise weighted factors can be determined through a pair-wise qualitative comparison of criteria systematically. In this paper, three levels of AHP are adopted in the decision-making process. The first level of hierarchy is to determine the best combination of PEV chargers while the second level is to select the criteria. In this work, power loss, maximizing distribution capacity, and cost of charging are considered as the criteria. It is worth to mention that the sum of criteria weight value is '1'. In the third level, the available alternatives which depend on the number of population in the optimization are analyzed. Moreover, the sum of alternative weight value is '1'. The calculation of weighting factor for each criterion using AHP is as follows:

A pair-wise comparison judgement matrix $(PM_{criteria})$ is represented in Equation (14). It is derived for criteria based on power loss C_{ploss}, distribution capacity $C_{Mcapacity}$, and cost of charging C_{cost}.

$$PM_{criteria} = \begin{array}{c} \begin{array}{ccc} P_{loss} & \text{DS Capacity} & Cost \end{array} \\ \begin{bmatrix} 1 & \frac{C_{Ploss}}{C_{Mcapacity}} & \frac{C_{Ploss}}{C_{Cost}} \\ \frac{C_{Mcapacity}}{C_{Ploss}} & 1 & \frac{C_{Mcapacity}}{C_{Ploss}} \\ \frac{C_{Cost}}{C_{Ploss}} & \frac{C_{Cost}}{C_{Mcapacity}} & 1 \end{bmatrix} \end{array} \begin{array}{c} P_{loss} \\ \text{DS Capacity} \\ Cost \end{array} \tag{14}$$

To calculate the weights for each criteria, the approximate method is applied instead of the exact method due to its simplicity [26]. The normalization matrix$(NM_{criteria})$ is derived from the comparison matrix from (15) and (16):

$$criteria_{column} = \left[\sum column_1 \quad \sum column_2 \quad \sum column_3\right] \tag{15}$$

$$NM_{criteria} = \left[\frac{(PM_{criteria})_1}{\sum column_1} \quad \frac{(PM_{criteria})_2}{\sum column_2} \quad \frac{(PM_{criteria})_3}{\sum column_3}\right] \tag{16}$$

where i=1, 2, 3 represents the number of criteria in rows. From this normalized matrix, the weighting factors $(w_1, w_2$ and $w_3)$ are calculated by averaging value of each row using the following equation.

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} = \begin{bmatrix} \sum (NM_{criteria})_j / no.\ of\ criteria \\ \sum (NM_{criteria})_j / no.\ of\ criteria \\ \sum (NM_{criteria})_j / no.\ of\ criteria \end{bmatrix} \tag{17}$$

where j=1, 2, 3 is the number of criteria in row.

Once the weighing factors are calculated, it is imperative to check the consistency of pair-wise comparison judgement matrix. The procedure to check the consistency ratio (CR) is described in [26]. It is worth to mention that CR=0.10 or less than that is acceptable to continue the AHP analysis.

3.3. Proposed computational procedure using BPSO and AHP

The proposed PEV charging coordination has the following steps:

Step 1: Initialize the required input data such as distribution network, line data, bus data including PEV location, battery and charger capacity. The BPSO parameters such as range of inertia weight, acceleration coefficients, convergence accuracy, number of population and maximum iteration are also defined. The weighting factor for each objective function is determined using AHP in (14)–(17).

Step 2: Set the timeslot t=1 and generate initial random particle in binary number for each arrived PEV where digit “1” corresponds to a PEV being charged while digit “0” indicates that the charging has not been initiated or already finished.

Step 3: Execute backward forward load flow analysis to find the power loss and voltage level of each node. Estimate the required energy and charging cost for those PEV considering charger efficiency in (7), those are being selected to be charged. Calculate each objective function using (2)–(6). Then, evaluate the fitness function (1) considering the weighted value.

Step 4: The initial pbest and gbest are determined based on the minimum fitness generated from the initial PEV charging decision. The gbest represents the best combination of PEV chargers at timeslot t. Throughout this stage all the constraints in (8)–(10) are checked.

Step 5: Change the velocity of each particle using (11) and determine the updated status for each PEV charging status. To determine the new state of PEV charger sigmoid transformation, (12) and (13) are used to convert the continuous number to binary number.

Step 6: In this step, execute Step 3 with the updated particle position and check all the constraints. Record the new pbest and gbest, and compare them with the outcomes of previous iteration.

Step 7: Steps 3-6 are repeated until all the PEV charger switching combinations provide the same fitness value. The optimization process stops when it reaches the predefined maximum iteration number.

Step 8: Finally, the charging decision is sent to each PEV through the smart grid communication infrastructure. Now set the timeslot t=2 and sort out those PEVs which failed to connect and arrived in the current timeslot.

The proposed PEV charging coordination steps are summarized in flow chart of Figure 2.

It is worth to mention that once the PEV starts to charge from the grid, it will continue until it reaches the required level of SOC. However, if the total residential load reaches to the maximum distribution system capacity in any timeslot, the PEV charger that is used will be disconnected. Then, these PEVs are prioritized for reconnection charging once the residential load becomes lower than the maximum distribution system capacity.

4. Assumption and system conditions

The proposed PEV charging coordination approach has been simulated in MATLAB and the following assumptions and case studies are considered.

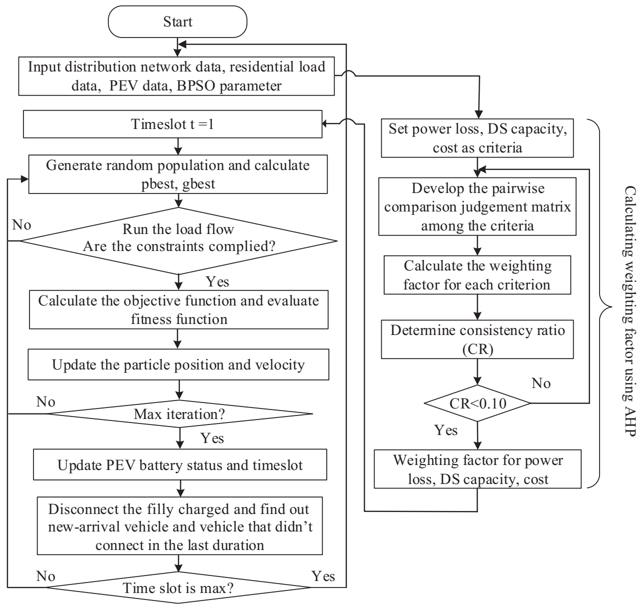


Figure 2. Flowchart of the proposed charging coordination.

4.1. PEV battery and chargers

Generally, PEVs use large-capacity batteries ranging from a few kilowatt hours to 50 kWh to enhance the travelling mileage [27]. The rate of charge depletion of each PEV battery depends on the battery manufacturer's design and the efficiency of the electric drive. For the deep cycle battery, the depth of discharge (DOD) is assumed to be 80% of the rated battery capacity [28]. For instance, a 16-kWh PEV battery can provide maximum 12.8 kWh during the discharging time.

In practical, PEV battery chargers should be sufficiently large to charge a sizable battery within an acceptable time. The power delivered to the PEV battery in each hour is the maximum allowable charging capacity of the charger. It is assumed all the battery will get the required level of SOC at the end of the charging period. In this study, all the PEV chargers are considered as a standard single-phase 240 V keeping in mind the household wiring limitation. However, the PEV charger efficiency is considered 88% since it has its own power losses [29]. Therefore, the energy requirement from the grid to charge a battery is larger than the calculated energy at the battery. For instance, a 6.6-kWh single-phase charger requires 14.4 kWh from the grid to charge a 16-kWh battery (DOD=80%).

4.2. PEV Penetration Level

In this research, three different levels of PEV penetrations (32%, 47%, and 63%) are studied to cover all the reasonable PEV charging scenarios in near future. The penetration levels are determined based on the ratio of number of nodes with PEV and total number of nodes. It is assumed that one household can have maximum one PEV. The selection of nodes with PEV is done based on random distribution in the low voltage feeder. Therefore, the total number of PEVs are 132, 198, and 264 for the penetration levels of 32%, 47%, and 63% respectively. The random arrival of PEV is also shown in Figure 3. At 32% penetration, 132 PEVs have arrived which is shown in green color. For 47% penetration, the remaining 32% (198-132=66) PEVs are marked in blue color. Finally, for 63% penetration, the remaining 47% (264-198=66) PEVs have arrived and marked as red color in Figure 3.

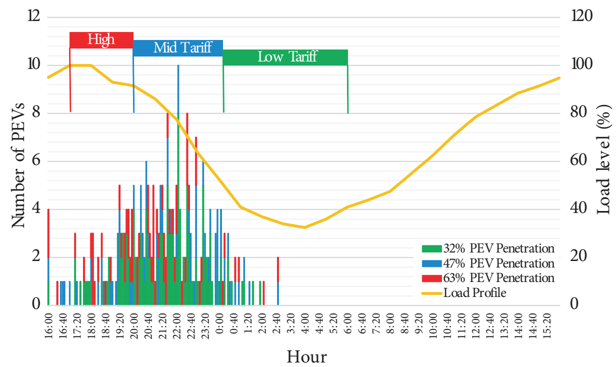


Figure 3. Everyday residential load profile and ToU tariff with random arrival of PEVs at three penetration levels.

4.3. Case studies

To evaluate the efficacy of the proposed technique, three case studies are carried out with different considerations as follows:

Case 1: Random charging. PEV starts to get charged immediately after arriving at home ignoring the system constraints. There is no control over charging decision in this case.

Case 2: Two objective functions on minimizing daily power loss and maximizing distribution system capacity are considered with all system constraints.

Case 3: All three objective functions on minimizing daily power loss, maximizing distribution system capacity and minimizing total daily charging cost are considered with all system constraints.

It is important to mention that, in all case studies, all of the PEV data including random arrival time, charger capacities, battery sizes, and initial and required levels of SOC remain the same.

4.4. Test system

A 449-node smartgrid consisting of modified IEEE 31-bus 23-kV distribution network shown in Figure 4 is used in this study where the number of low voltage (415 V) feeder is 22. The system is assumed to have smart grid two-way communication infrastructure facilities to receive and send data from/to individual PEVs. The low voltage feeder consists of 19 nodes which represent customer's household load and for PEV some selected nodes are assigned. The daily load profile with the maximum load (2 kW and 0.9 kVAR) in each household is presented in Figure 3. The maximum distribution system capacity is 840 kW. The time-of-use electrical tariff (1st January 2018 to 31st January 2018) is obtained from Australian market[1] and illustrated in Figure 3 after splitting into four partitions. The charging cost is calculated in Australian Dollar (AUD).

5. Results and discussion

Three case studies have been carried out in MATLAB simulation environment. The obtained results are discussed elaborately in the following subsections.

5.1. Case 1: Uncoordinated PEV charging

Figures 5a and 5b and Table 1 present the impact of uncoordinated charging activities on residential distribution system in terms of power loss, system overload, voltage deviation, and charging cost. From Table 1, at 63% PEV

[1] AEMO (2018). Australian Energy Market Operator [online]. Website https://www.aemo.com.au [Acessed 05-02-2018]

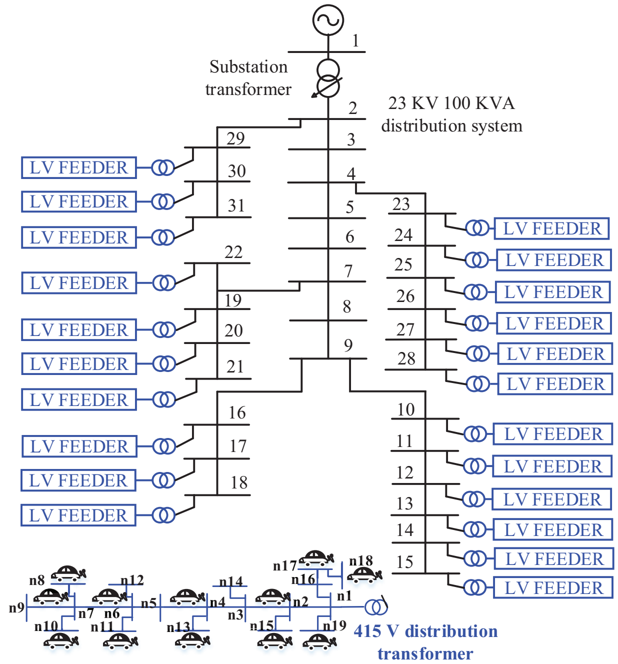
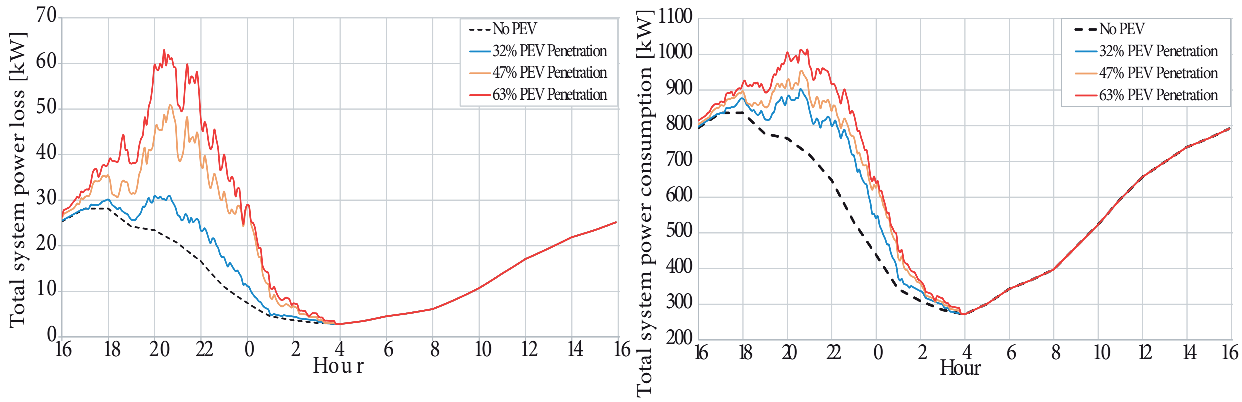


Figure 4. One-line diagram of IEEE modified 31 node 23 KV distribution network along with residential low-voltage feeders and one residential feeder is connected with 63% PEV.

penetration the maximum voltage deviation is found 33.76% and at 47% PEV penetration which is 23.36%. In addition, the power loss of the entire system is shown in Figure 5a, where it is clear that the random PEV charging activities severely increased the power loss during the peak hour of the day. Furthermore, the total power consumption of the distribution system is extremely high at the peak hour. From Figure 5b, it is shown that for 63% and 47% PEV penetration, the distribution system is overloaded in view of system capacity. During lower PEV penetration (32%) the distribution system is also overloaded. Moreover, the total PEV charging cost is found to be unexpectedly high throughout the uncoordinated charging activities. As can be seen in Table 1 column 5, the total PEV charging cost is $1250 at 63% penetration and $941 at 47% penetration which leads the running cost to be extensively high.

5.2. Case 2: PEV charging coordination minimizing power loss and maximizing distribution system capacity

The test results for Case 2 are presented in Table 1. Since the charging tariff is not considered, the optimization problem has only two objective functions. A greater weighting factor w_1=0.7 is assigned for objective function and w_2=0.3 is assigned for objective function to provide more concession to the utility. It has been found that the entire power loss across all penetrations are significantly reduced (Table 1 column 4). For 63% penetration, the power loss is reduced by 23.4% where 18.75% and 8.86% reductions are recorded at 47% and 32% PEV penetration levels respectively. Moreover, by following the maximum demand constraints, the substation transformer is found to be safe since no overload occurs during PEV charging activities. Due to the charging coordination of PEV, the voltage profile is found better as shown in Table 1 column 3. As a consequence of the coordination, the total charging cost is reduced in all penetration levels, even though the charging cost is not considered in optimization fitness function. The total charging cost has been reduced from



(a) Total power loss (b) Total power consumption

Figure 5. Observed distribution system parameter in uncoordinated charging.

Table 1. Overall comparison for three different cases.

Case factor	PEV (%)	ΔV (%)	*Ploss reduction (%)	Chg cost/day ($)	**Chg cost reduction (%)
	0	7.38	-	-	-
Case 1	32	8.18	-	666.11	-
	47	23.36	-	941.63	-
	63	33.7	-	1250.54	-
Case 2	32	8.96	8.6	612.30	8.07
	47	9.95	18.75	849.55	9.77
	63	10.0	23.40	1082.24	13.45
Case 3	32	9.90	6.3	559.99	15.93
	47	9.91	15.98	738.05	21.61
	63	10.0	18.43	970.15	22.42

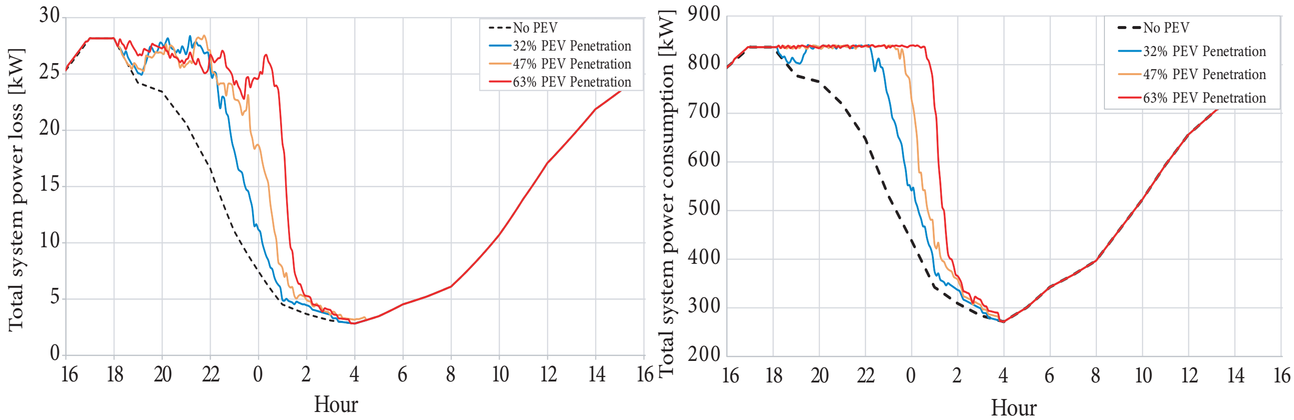
*Ploss reduction compared to respective uncoordinated charging

**Chg cost reduction compared to respective uncoordinated charging

the uncoordinated scenario. In Table 1 column 5, the total charging cost for one day in the studied system is presented for each penetration level. As can be seen, the optimization algorithm has decreased the total charging cost. For instance, in 63% PEV penetration, the charging cost is from $1250.54 to $1082.24, that is, 13.45% reduction.

5.3. Case 3: PEV charging coordination to minimize power loss and charging cost of PEV while maximizing distribution system capacity

In Case 3, all three objective functions are considered. Since there are three different objective functions in the optimization procedure, it is important to determine the weighting factors for each objective function. In this paper, AHP decision-making method was employed to determine suitable weighting factors using Equations (14–17). Simulations are carried out and the test results for Case 3 are presented in Figures 6a and 6b and Table 1.



(a) Total power loss

(b) Total power consumption

Figure 6. Observed distribution system parameter in coordinated charging.

The weighting factor for each objective function is determined as w_1 =0.6196, w_2=0.1560, and w_3=0.2243. Prior to that the pair-wise comparison judgment matrix based on the Saaty's pair-wise comparison scale [26] for three criteria are determined and presented as follows:

$$PM_{criteria} = \begin{array}{c} \begin{array}{ccc} P_{loss} & \text{DS Capacity} & Cost \end{array} \\ \begin{bmatrix} 1 & 3 & 4 \\ 1/3 & 1 & 1/2 \\ 1/4 & 2 & 1 \end{bmatrix} \\ . \end{array} \begin{array}{c} P_{loss} \\ \text{DS Capacity} \\ Cost \end{array}$$

The consistency of the pair-wise comparison judgement matrix is checked following the process described in [26]. Finally the value of CR is found as 0.0942. Since the value of CR is less than 0.1 there is no inconsistency in the pair-wise comparison judgment matrix. Therefore, this overall analysis of AHP is acceptable.

In order to proof the suitability of the chosen weighting factors from AHP method, a comparison is conducted with randomly chosen weighting factor w_1=0.5000, w_2=0.2500, and w_3=0.2500 and equal weighting factor, which is w_1=0.3333, w_2=0.3333, and w_3=0.3333. The compared results are presented in Table 2. From Table 2, it is found that the PEV charging cost is less although the power loss is higher when all weighting factors are equal. In the case of random weighting factor, power loss is reduced a little bit but charging cost is high. On the other hand, when AHP is applied, minimization of power loss has the maximum weight and it reduced power loss significantly. However, the PEV charging cost is found to be a little higher while minimization of power loss gets priority.

In Case 3, power loss is slightly increased compared to Case 2, since this case focuses on PEV charging cost (Table 1 column 3). For instance, at 63% PEV penetration, the power loss is reduced by 18.43%, although the reduction was 23.4% in Case 2 compared to Case 1. For 32% and 47% PEV penetration, loss reduction is found as 6.3% and 15.98% respectively which are low compared to Case 2 as well. In terms of voltage, the proposed approach is able to keep all node voltages in the allowable limit. Moreover, no substation overload is found during the PEV charging activities. In Figure 7 the time span, starting time, and ending time of PEV charging activities in each feeder for Case 3 are illustrated. It is observed that all the PEVs get the required

Table 2. Comparison of considering different weighting factors.

Weight factor	PEV (%)	ΔV (%)	*Ploss reduction (%)	Chg cost/day ($)	**Chg cost reduction (%)
All three are equal	32	9.89	3.9	502.01	24.63
	47	9.90	12.01	695.30	26.16
	63	10.0	14.43	920.11	26.42
w_1=0.5000, w_2=0.2500, w_3=0.2500	32	9.69	5.9	570	8.89
	47	9.90	12.59	760.5	13.30
	63	9.40	14.82	1012.2	12.98
AHP	32	9.90	6.3	559	15.93
	47	9.91	18.98	738	21.61
	63	10.0	18.43	970.15	22.42

level of charge by the morning of the next day. The total charging cost for one day is reduced significantly compared to the other two cases. For instance, at 63% PEV penetration, the total PEV charging cost for one day is reduced from $1250.54 to $970.15 (22.42% reduction compared to Case 1 and 8.97% reduction compared to Case 2). Moreover, significant cost reduction is recorded (21.61% and 15.93%) for 32% and 47% PEV penetration compared to Case 1. The results show the potential for further economic benefits for the PEV customer. Alternatively, from the utility perspective, power loss reduction with utilization of the system in maximum capacity offer maximum profit for the utility.

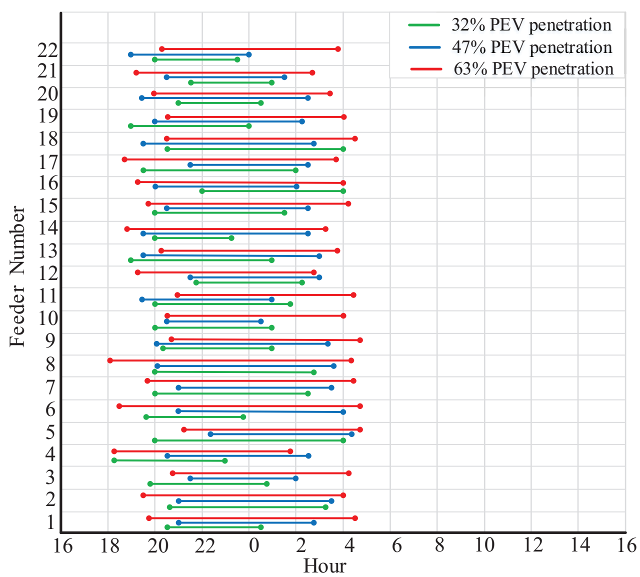


Figure 7. Duration of PEV charging activities for Case 3 at three different penetrations.

In this research, the proposed algorithm is executed in every timeslot consisting of 5 min (total 288 timeslot in a day). In every timeslot, when the algorithm detects any fully charged PEV, that PEV will be disconnected. Then, any new-arrival PEV will be considered by the algorithm. Thus, the number of PEV (particle) is not consistent in every timeslot. To analyze the convergence characteristic of the proposed algorithm in charging for one timeslot, the fitness value presented in Figure 8. This Figure shows three different scenarios; red line is the convergence curve for high number of PEV (63%), blue line for medium number of PEV (47%) and green line represent low number of PEV (32%). Each of the convergence characteristic is based on different timeslot. For high number of PEVs, the timeslot is 50, medium PEV at 25^{th} timeslot and low at 10^{th} timeslot. It can be observed that when the number of PEVs is less (32%), the algorithm is converged fast with less number of iterations. On the other hand, high number of PEV (63%) caused slow convergence.

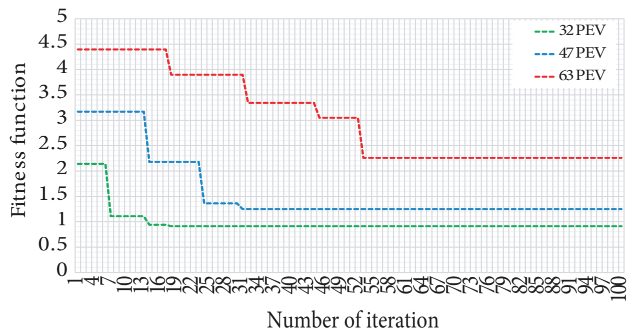


Figure 8. Convergence curve of the optimization process.

5.4. Comparison with other methods

Since different studies in the literature used different test systems with various conditions, it is not possible to conduct direct comparison in terms of their performance as compared to the proposed method. Thus, only the features of the methods can be analyzed and compared. The following Table 3 summarizes the features of different PEV coordination methods and the proposed method. In general, the proposed method considered technical, financial benefits, different charger capacities, and suitable weightage for multiobjective optimization. With these considerations, the proposed method produced more realistic results that not only optimize charging coordination, but also benefit the PEV users in terms of minimizing the charging cost.

6. Conclusion

A multiobjective PEV charging coordination is proposed to improve the distribution system performance along with the benefits of PEV customer. The coordination is made in near real-time (5 min interval) of randomly arrival PEV in residential distribution system. The weight for each criterion in multiobjective is determined by using AHP decision making approach. The algorithm determines the timeslot for each PEV charging based on multiobjective functions associated with PEV customer and utilities. During this entire process of coordination, all the system constraints are successfully maintained. Compared to the uncoordinated PEV charging activities, the proposed approach is capable to ensure the safe operation of distribution system in terms of voltage dropping and substation overloading. The total power loss reduction and no overloading in the system are significant improvements from the utility point of view. Furthermore, the charging coordination has ensured the required level of charge for each PEV in the system. The proposed approach is beneficial for PEV customers in terms of charging cost as in this approach charging cost has reduced remarkably. Moreover, the proposed approach in this paper is capable to accommodate the activities of PEV charging without restructuring the existing network to provide privilege to utility and PEV customer simultaneously.

Table 3. Comparison of the proposed approach over different methods.

Ref	Research objective	Applied method	Consider technical and financial benefit together	Different charger and battery size	Using AHP as decision making
[2]	Minimizing power loss	Quadratic programming	No	No	No
[8]	Overload limitation and cost minimization	Lyapunov and Larange dual decomposition	No	No	No
[9]	Minimizing total daily cost and peak average ratio	GA	No	Yes	No
[14]	Peak demand reduction	Water Filling	No	Yes	No
[16]	Minimizing energy generation cost	MSS	No	No	No
Proposed method	Minimizing power loss, maximizing DS capacity, minimizing charging cost	BPSO and AHP	Yes	Yes	Yes

Acknowledgments

The authors thank the University of Malaya and Malaysian government for supporting this work through research grants (grant codes: GPF055A-2018 and RF013A-2018).

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