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Optimal Scheduling of Plug-in Electric Vehicle Charging Including Time-of-Use Tariff to Minimize Cost and System Stress

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Abstract: Technological advancement, environmental concerns, and social factors have made plug-in electric vehicles (PEVs) popular and attractive vehicles. Such a trend has caused major impacts to electrical distribution systems in terms of efficiency, stability, and reliability. Moreover, excessive power loss, severe voltage deviation, transformer overload, and system blackouts will happen if PEV charging activities are not coordinated well. This paper presents an optimal charging coordination method for a random arrival of PEVs in a residential distribution network with minimum power loss and voltage deviation. The method also incorporates capacitor switching and on-load tap changer adjustment for further improvement of the voltage profile. The meta-heuristic methods, binary particle swarm optimization (BPSO) and binary grey wolf optimization (BGWO), are employed in this paper. The proposed method considers a time-of-use (ToU) electricity tariff such that PEV users will get more benefits. The random PEV arrival is considered based on the driving pattern of four different regions. To demonstrate the effectiveness of the proposed method, comprehensive analysis is conducted using a modified of IEEE 31 bus system with three different PEV penetrations. The results indicate a promising outcome in terms of cost and the distribution system stress minimization.

Keywords: plug-in electric vehicle; charging coordination; optimization; time-of-use tariff

1. Introduction

Plug-in electric vehicles (PEVs) are promising low emission vehicle that have gained popularity in recent years [1]. The PEVs are driven by an electric motor energized by a rechargeable battery. For a variety of reasons, including technological advances in electrical motors and drives, and environmental concerns, the PEV market is expanding around the world. Reduction in oil reserves and an increase in its price has driven the application of PEV in the transportation sector [2]. Furthermore, PEVs are a cost-effective vehicle with a low maintenance cost [3]. From the technical point of view, electrification in the transportation sector has improved energy conversion efficiency from electricity to motor rotation. In electric vehicles, 59–62% of electrical energy drawn from the power grid [4] can be converted into the driving force of the wheels, whereas for a conventional vehicle, 17–21% of gasoline energy can be converted into the driving force [4]. From the environmental point of view, PEV able to reduce dependency on the fossil fuel transportation sector, with lower carbon, sound, and heat emission [5].

Basically, PEVs utilize a large battery capacity that requires frequent charging to provide sufficient energy for the high power-rated motors [6]. The batteries of a PEV can be charged at home or any other commercial location through the standard electrical power outlets. The PEV is considered as an extra electric load on the distribution system. The PEV charging activities cause significant potential risk to the network such as severe voltage fluctuations, excessive power loss, and substation transformer overloading [7]. Consequently, the overall performance of the system is degraded and could lead to major system blackout if charging activities are not managed well [8]. Moreover, too large a voltage deviation also causes power quality issues that need to be avoided in the distribution system. Adding to this problem is the unpredictable time and duration of PEV charging activities that depend on PEV users. This increases the risk of overloading the distribution system and power quality issues at any time. Thus, an effective coordination charging strategy is crucially needed. Previous studies, such as in [5], have proven that the coordinated PEV charging scheme provides more benefits to the customers and distribution network operators.

In general, two main PEV charging coordination strategies can be found: centralized and decentralized coordination [1]. There are various decentralized coordination strategies that have been proposed in the literature. In [6], a non-cooperative game theory approach for building a decentralized approach is proposed to minimize the PEV charging cost and reduce the load fluctuation. In this solution, the building controller sends the total load data of the building to each PEV customer. Then, the PEV customer selects the charging timeslot and charge amount in order to pay as little as possible. This procedure is repeated until convergence is reached. A game theoretic approach has been applied in by Sheikhi, A. et al. [9] to minimize the overall charging cost of PEVs. In this research, the PEV users' driving pattern was considered in the charging schedule. Meanwhile, a multi-level optimization is proposed in [10] to achieve a valley-filling effect using a price signals scheme. In this technique, the objective at the distribution level is to minimize the overall generating costs, while at the user level, the objective is to minimize the charging cost. However, this control scheme has a drawback where congestion of lines and transformers could happen. A decentralized approach is proposed by Ma, Z. et al. [11] to minimize the charging cost considering all the local grid constraints, battery efficiency, and lifetime. This strategy facilitates the tradeoff between the total generation cost and the local cost to solve the large-scale optimization problem. Moreover, an agent-based approach has been proposed to postpone the PEVs charging activities in balancing the fluctuations of renewable energy sources [12]. To develop a PEV charge coordination along with the distributed demand response in a residential distribution network, a congestion pricing approach was proposed in References [12,13]. In this study, PEV user preference was considered, such as charging a tariff in a certain period of time. Based on this, a PEV user that is willing to pay more will get faster charging. The study in [14] presented a random-access framework to schedule the PEV charging to avoid network congestion and voltage drop problems. However, the outcome of decentralized coordination may or may not be optimal, since this coordination depends on local information and signals. Therefore, the final decision is always taken by the PEV users, which never guarantees the optimal solution.

There are also several centralized strategies of coordination of PEV charging that can be found in the literature. Vayá, M.G. et al. [15] proposes a linear optimal solution based on convex optimization to minimize the difference between the demand profile and power demand created by the PEV charging activities. An intelligent charging algorithm based on a meta-heuristic method is proposed by Valentine, K et al. [13] to minimize generation costs. The total operational cost and CO_2 emissions have been reduced using convex optimization to solve the large-scale problem in [15]. Artificial immune systems (AIS) is integrated with a heuristic method to minimize the total power loss considering network constraints. Here, the function of the heuristic method is to avoid overloads and voltage limits violations [16]. The same network constraints are taken into account in [17] to minimize the generation cost associated with power loss and voltage deviation. In this paper, maximum sensitivities selection (MSS) originating from the combination of the heuristic method and the objective function is employed. MSS optimization is employed to investigate the impact of PEV charging on a distribution network, and then charging coordination is prepared for each PEV.

From the reviews, it can be observed that some researchers have considered the minimization of daily power loss and voltage deviation together in the PEV charging coordination. Nevertheless, the studies only focused on a PEV charging schedule. The means of improving the voltage profile of the distribution network during the PEV charge scheduling is yet to be explored. Therefore, it is important to improve the voltage profile in all low voltage feeders when the PEV charging coordination takes place. Power system equipment, such as capacitor and on-load tap changer (OLTC) operation, can be utilized to improve the voltage profile. Furthermore, there are few types of research that consider minimizing energy generation cost during PEV charging coordination. So far, none of them have tried to consider PEV charging cost minimization for the benefit of the PEV customer. Therefore, it is imperative to develop a strategy along with PEV charging coordination to minimize the PEV charging cost.

Considering these limitations, this paper introduces the coordination of PEV charging along with the capacitor switching and OLTC adjustment to reduce the total power loss and voltage deviation simultaneously. Herein, capacitor and OLTC have been utilized for the further improvement of voltage profile in the distribution system during the PEV charging coordination. Since the charger capacity and battery size are becoming larger, increasing the mileage in recent years, higher PEV penetration with the larger capacity of the charger (such as 6.6 kW, 7.2 kW) in the distribution system is considered in this study. Moreover, the time of use (ToU) electrical tariff is included in the proposed method to provide economic benefit for the PEV user by minimizing the charging cost. The meta-heuristic methods used in this paper are binary particle swarm optimization (BPSO) and binary grey wolf optimization (BGWO). Nevertheless, other optimization techniques can also be applied. The proposed approach was coded in MATLAB (R2015a, The MathWorks, Inc, Natick, MA, USA) and tested on a modified 449-node residential distribution system. It consisted of 22 low voltage feeders and each feeder had 19 nodes, where each node represented a residential household. For the wide range of feasibility of the proposed method, different PEV penetration levels (32%, 47%, 63%) were studied.

2. PEV Charging Coordination

In centralized coordination, the utility directly controls the vehicle charging while maintaining all the system constraints. Besides, utility offers economic benefits to the PEV owners by reducing the total electrical tariff. The centralized coordination is also known as direct control where the Distribution System Operator (DSO) manages the charging decision for each PEV within its region. Through the coordination process, the DSO performs demand forecasts based on previous day's data and PEV users' driving behavior. Then, the DSO investigates the demand profile for the safe operation of distribution system. When the PEV is charging, it is considered as an additional load to the distribution system while the regular household loads remain connected in the system. It is found that the effective coordinated charging activities can charge the PEV while mitigating all the distribution system impacts [4]. From the distribution system point of view, reduction of power loss and voltage deviation provides many advantages. These include low operation cost and fewer instances of system overload, which improve the reliability of the system.

The economic consideration is one of the major benefits of the charging coordination for the distribution system owner and PEV users. If the PEV charging is not coordinated properly, it will increase the charging cost as well as the energy generation cost considerably. Since the utilities are responsible for the charge of each PEV, the minimization of PEV charging cost is one of the important considerations. However, there are two types of cost associated with the PEV charging coordination: the energy generation cost and PEV charging cost. The energy generation cost includes the price of purchasing or producing electricity and the cost of total energy losses in grid. Therefore, the generation cost can be minimized by reducing the total power loss in the system. On the other hand, the cost of the

PEV charging refers to the cost of energy consumed by the PEV charger. The inclusion of time-of-use (ToU) electricity tariff in the coordination process can minimize the PEV charging cost significantly.

3. Problem Formulation

3.1. Objectives

The main focus of this research was to determine the PEV charging schedule while minimizing power loss and voltage deviation along with the minimum PEV charging cost. Moreover, the capacitor switching and OLTC adjustment was considered to further improve the voltage profile during PEV charging activities. In order to simulate the real-time coordination, the PEV charging coordination approach takes place every 5 minutes (288 timeslots at 24 hours). Due to the constraint in the switching operation of capacitor and OLTC in the distribution system, the proposed method consists of two parts: (i) PEV charging coordination (5-minute interval) and (ii) day ahead capacitor and OLTC switching (1-hour interval). Throughout this whole process, a set of system constraints also needed to be considered. The objective function for the optimization process to carry out the proposed method is:

$$\min f = \sum_{h}^{24} (P_{loss}^{c} + V_d) \tag{1}$$

where P_{loss}^{c} is the ratio of power loss after and before the PEV coordination is made, and V_d is the maximum voltage deviation of the distribution system. Since the power loss and voltage deviation has two different units, the P_{loss}^{c} has been calculated based on the ratio of obtained total system power loss (P_{loss}^{coord}) over total power loss before coordination ($P_{loss}^{uncoord}$).

$$P_{loss}^{c} = P_{loss}^{coord} / P_{loss}^{uncoord} \tag{2}$$

The power loss can be calculated as follows:

$$P_{loss} = \sum_{t=1}^{timeslot} \sum_{j=1}^{n} \left(I_{j,t}^{2} \times R_j \right) \tag{3}$$

where n represents the total branch number of the distribution network.

The voltage deviation (V_d) is calculated through the change of the actual voltage from the rated voltage of the system:

$$V_d = Max_{i=2}^{m} \left(\frac{V_{rated} - V_i}{V_{rated}} \right) \tag{4}$$

V_{rated} is the rated voltage of the system which is 1.0 p.u., V_i is the measured voltage at the ith node, and m denotes the total node number of the distribution system.

The estimated charging cost of PEV can be calculated utilizing the ToU electricity tariff using:

$$Cost_{estd} = \sum_{k=1}^{N_{PEV}} \sum_{t=T_c}^{t+T_r} \left(\frac{RE_k}{(T_r)_k} \right) \times ToU_t \tag{5}$$

where RE_k is the total required energy to get the desired state of charge (SOC) from the current SOC for kth PEV. Tr_k and Tc_k are the required timeslot to reach the desired SOC and current SOC for the kth PEV, respectively. ToU_t represents the electricity tariff for the tth timeslot and N_{PEV} is the number of PEV selected by the optimization to be connected.

The required energy RE_k to achieve the desired SOC for each PEV is calculated considering the charger efficiency is:

$$RE_k = CHG_k \times \left(SOC_{req} - SOC_{int}\right)_k \times \frac{1}{Efficiency} \quad (6)$$

where CHG_k is the charger capacity kth PEV and *Efficiency* is the charging efficiency of the PEV charger when the battery is being charged from the system. SOC_{int} and SOC_{req} are the initial and required state of charge of the battery respectively where SOC_{req} is set based on customer preferences.

3.2. Constraints

The following are the set of constraints that must be fulfilled:

3.2.1. Maximum Capacity

$$P^{\max}_{demand} \geq \sum_{i=2}^{n} P_{load,i} + P_{PEV,i} \quad (7)$$

Here, n represents the branches of the network, $P_{load,i}$ and $P_{PEV,i}$ are the residential and PEV load at the ith node, respectively. P^{max}_{demand} is the maximum capacity of the distribution system.

3.2.2. Bus Voltage

$$0.9 \text{ p.u.} \leq V_i \leq 1.1 \text{ p.u.} \quad (8)$$

Vi is the actual voltage level at node i. Herein, the voltage range is considered within ±10% for this distribution system.

3.2.3. State of Charge (*SOC*)

$$SOC_{int} < SOC_{curr}(t) \leq SOC_{req} \quad (9)$$

SOC_{curr} is the instantaneous state of charge for timeslot t. It is worth mentioning that once a PEV starts to get charged, it continues until it reaches a required state of charge (SOC_{req}).

3.2.4. Daily Switching of Capacitor

The number of capacitor switching (turn on/off) is limited to a specific number. The maximum allowable number of capacitor switching is as follows:

$$\sum_{h=1}^{24} \left(C_{s,h} \otimes C_{s,h-1}\right) \leq C_{sm} \quad (10)$$

where $C_{s,h}$ is the state of the capacitor s at hour h and C_{sm} denotes the maximum allowable switching number for the capacitors in a day. In this research, C_{sm} is set to one time per day [18].

3.2.5. Daily Switching of OLTC

Similarly, as in capacitor switching, on-load tap changer (OLTC) cannot be operated frequently. The maximum number of OLTC operations per day is as follows:

$$\sum_{h=1}^{L} \left|Tap_h - Tap_{h-1}\right| \leq Tap_{\max} \quad (11)$$

Here, L is the number of load level in a day. Since the frequent operation of OLTC may lead to a higher maintenance cost, the maximum number of OLTC operations a day is set to 30 times as suggested in [19]. In this research, the tap changer transformer has 17 tap positions (−8, −7, . . . , 0, 1, 2, . . . , 8), which varies the voltage −5% to +5% [20]. Therefore, the minimum and maximum voltages at the tap changer are 0.95 p.u. and 1.05 p.u., respectively.

4. Proposed Method

The aim of this research was to develop an optimal PEV charging coordination with the consideration of capacitor and OLTC operation. Binary particle swarm optimization (BPSO) and binary grey wolf optimization (BGWO) are employed as the optimization techniques. The proposed method for PEV charging scheduling was analyzed with the dynamic residential load pattern. Moreover, the PEV customer satisfaction was also considered for different PEV penetration levels in the network. The objective function in Equation (1) was applied using the optimization techniques. The series of constraints in Equations (7)–(11) were considered to ensure the safe operation of the distribution network. Furthermore, the ToU electricity tariff was also considered in the process of minimizing PEV charging to provide a minimum charging cost to PEV users.

4.1. Optimal PEV Charging Coordination

The following steps can be used to determine the optimal coordination of PEV charging while minimizing the power loss and voltage deviation simultaneously. All the system constraints were also considered in this stage.

1. All the input data were inserted in the program. This data were network data, bus data, line data, residential load data, and a set of PEV data. The PEV data consisted of the arrival time to the charging point with charger capacity, battery size, battery initial state of charge (SOC), and requested SOC by the users.
2. In the optimization process, the initial population was determined by selecting the random PEV charger to be turned on. In this case, only the arrived PEVs at the charging point were considered. The population represented the status of PEV charger where digit "1" corresponds to a PEV being charged while digit "0" indicated the charging had not started or had already finished.
3. Employing the initial population, a fitness function was calculated using Equation (1). In the fitness function, a backward–forward load flow method was executed to determine the power loss and voltage.
4. The optimization procedure selected the best combination of PEV chargers, which provided the minimum power loss and voltage deviation. This iterative process was continued until the optimal result was obtained.
5. Once the optimization process had converged or the maximum iteration number was reached, it updated each PEV switching status and prepared for the next timeslot.
6. In each Δt timeslot, the algorithm took the input of a new arrival PEV to the charging point. The algorithm always checked the fully charged PEVs and eliminated them from the queue. Only the new arrival PEVs or left over PEVs to be charged were considered in the optimization process.

It is worth mentioning that once a PEV started to be charged, it will not be considered in the optimization process for the next timeslot. Also, once a PEV had started to be charged, it continued until it reached the required SOC. However, if any PEV moved out during the charging process, it was considered as newly arrived PEV and could only be charged in the next timeslot.

4.2. Optimal Capacitor and OLTC Operation

In order to ensure the voltage performed well and within allowable limits during the PEV charging activities, capacitor switching and OLTC operation were considered. The following steps were used for the capacitor and OLTC adjustment:

1. All the input data were inserted in the program. The data were the size of the capacitor, their locations, bus data, and line data. The numbers of tap changer position with their respective voltages were taken as input as well. A residential load data was also considered over 24 h integrating the PEV load of the previous day from the historical data.
2. The algorithm initialized the random population by selecting when the capacitor turned on and off. The population represented the status of capacitor operation where digit "1" corresponded to a capacitor being turned on while digit "0" indicated the capacitor was turned off. Moreover, the tap position of the OLTC was set to "0" as the initialization.
3. The fitness function was calculated based on the initial population using Equation (1). Here, backward–forward load flow was employed to determine the total power loss and voltage at each bus.
4. The tap changer operation took place simultaneously with the capacitor switching. The optimum tap changer position was determined based on the fitness function. For instance, 1.0499 p.u. was adjusted to 1.05 p.u.
5. The optimization continued the iterative process until it converged or reached the maximum iteration number.

4.3. Cost Minimization Including ToU Electricity Tariff

A method was also designed to utilize the different electricity tariff in PEV charging cost minimization while coordination PEV charging is made. The following steps were used to minimize the PEV charging cost utilizing the ToU electricity tariff:

1. All the input data were inserted in the program. The data were PEV charger capacity, battery current and required state of charge, and electricity tariff at each time slot.
2. The required energy and timeslot to reach the required *SOC* of the arrived PEV in the charge points were calculated. Then, a queue table of the PEV base was developed for the time required to get the required state of charge.
3. The queue table was categorized into three sub-sections: which PEV need (i) more than 60 timeslots, (ii) less than 12 timeslots, and (iii) timeslots in between 12 and 60.
4. PEVs that needed more than 60 timeslots were considered in the optimization process immediately when arriving at the charging point.
5. Then, the PEVs that needed less than 12 timeslots were postponed; they were considered in the optimization process when the tariff was lowest.
6. During the moderate rate of electricity tariff, only those PEVs that needed 12 to 60 timeslots were considered for charging.

Figure 1 is the flowchart of the overall proposed method:

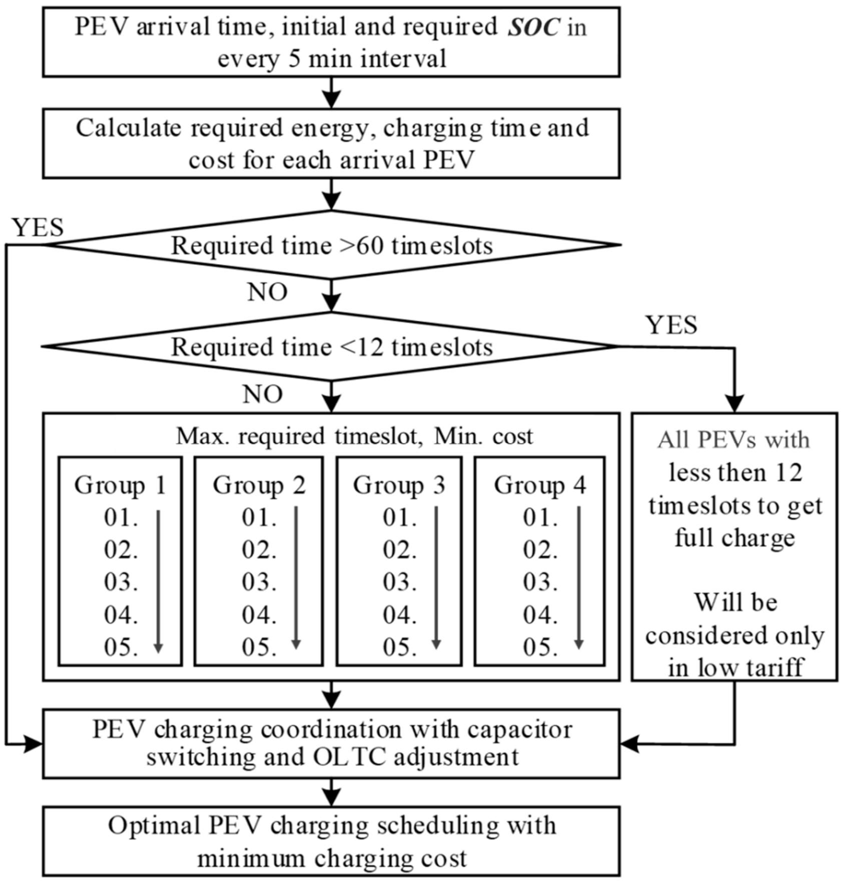


Figure 1. Flowchart of the proposed PEV charging cost minimization strategy.

5. Algorithms and Implementation

5.1. Binary Particle Swarm Optimization (BPSO)

Binary particle swarm optimization (BPSO) introduced in [21] was applied to solve the proposed PEV charging method. The major difference between the binary and continuous version of PSO is only in the particle position change equation. However, the velocity equation for each particle is presented in Equation (12) and the position change equation for each particle is Equation (13). All the particles move in d-dimensional space.

$$vel_{i,d}^{t} = w^{t} vel_{i,d}^{t} + c_1 r_1 [pbest_{i,d}^{t} - x_{i,d}^{t}] + c_2 r_2 [gbest_{i,d}^{t} - x_{i,d}^{t}] \quad (12)$$

Here $vel_{i,d}^{t}$ and $x_{i,d}^{t}$ are the velocity vector and position vector of particle i in dimension d at time t, respectively. r_1 and r_2 are two random numbers from a uniform distribution at time t. The value of c_1 (cognitive component) and c_2 (social component) are set to 1.4 and 1.8, respectively.

$$x_{i,d}^{t+1} = \begin{matrix} 0 & rand() \geq sig\left(vel_{i,d}\right) \\ 1 & rand() < sig\left(vel_{i,d}\right) \end{matrix} \quad (13)$$

$$sig\left(vel_{i,d}\right) = \frac{1}{1 + e^{-vel_{i,d}}} \quad (14)$$

Here, $sig\left(vel_{i,d}\right)$ is a logistic function transformation and $rand()$ is a random number between "0" and "1". The BPSO is chosen in this research due to the nature of the required solution. BPSO provides the final solution in the form of a binary "1" or "0", which indicates the charging and off-charging, respectively. Moreover, it is well known that BPSO can provide better optimal solutions in a short timespan over other optimization techniques [22].

5.2. Binary Grey Wolves Optimization (BGWO)

The binary grey wolf optimization (BGWO) is an evolutionary algorithm that follows the leadership hierarchy of grey wolves in the hunting and searching process of prey [23]. Generally, grey wolves live in a pack and it has a strict social dominant hierarchy. In a pack, the leaders make the decision for hunting and finding place to sleep. These kinds of wolves are known as alphas (α). The second level of hierarchy is defined as the betas (β), which help the alpha (α) in making the decision for the various pack activities. Finally, the least ranking grey wolves are known as omegas (ω) and maintain the dominance structure in the pack. Other than these three wolves, the rest of the wolves are known as delta (δ) and dominate the omegas in the pack. This hierarchy process of grey wolves is strictly maintained in the group hunting and this phenomenon is utilized in the modeling of BGWO to perform optimization. However, BGWO was chosen in this research since the required solution is in binary form. The binary value directly states the status of a PEV charger and capacitor switching. It is found that BGWO provides better convergence in real-time application [23]. The main position updating equation can be formulated as follows:

$$X_i^{t+1} = Crossover(x_1, x_2, x_3) \tag{15}$$

where:

$$x_1 = \begin{cases} 1 & x_\alpha + equation(14) \\ 0 & otherwise \end{cases} \quad x_2 = \begin{cases} 1 & x_\beta + equation(14) \\ 0 & otherwise \end{cases} \quad x_3 = \begin{cases} 1 & x_\delta + equation(14) \\ 0 & otherwise \end{cases}$$

Equation (14) refers to the sigmoid function for transforming the encircling behavior of prey to the probability of position where x_1, x_2, and x_3 make up a binary vector representing the effect of wolf movements for the alpha, beta, and delta wolves.

6. System Modelling

6.1. Test System

To demonstrate the proposed methodology, a smart grid test system topology was developed by adopting PEVs charging activities. The studied test system is a modification of an IEEE 31 bus 23 kV distribution system. It had 22 low voltage (415 V) feeders, as shown in Figure 2. Each of the feeders had 19 nodes, each representing a customer household, and with some the nodes assigned for PEV charging. The residential load at each node was assumed to be 2 kW and 0.97 kVAR. In this research, a practical domestic load curve (Western Australia) recorded from a distribution transformer was utilized. It was recorded that the maximum consumption of one house was around 2 kW with a power factor of 0.9 [17].

6.2. Capacitor

In this proposed method, one of the important tasks was to determine the number of capacitors, their location in the system, and capacitor size. There were different proposed methods that can be categorized into analytical methods, numerical programming methods, heuristic methods, and artificial intelligence methods [24]. In this research, the number of capacitors, their corresponding location, and capacitances were taken from [25]. The system was also comprised of five capacitors at bus numbers 4, 14, 16, 20, and 27.

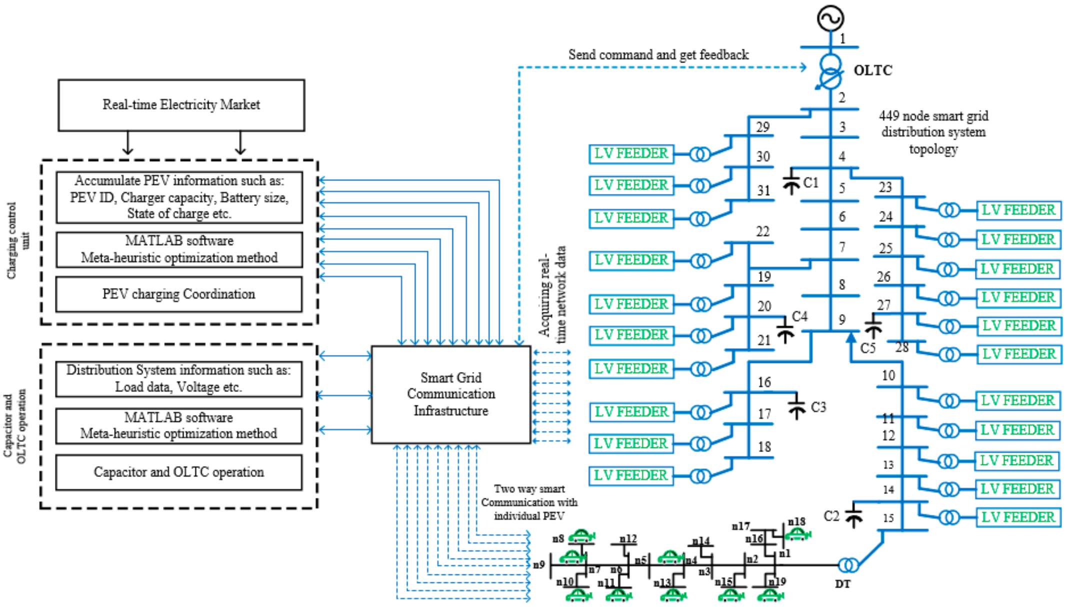


Figure 2. The functional diagram of PEV charging coordination in smart grid.

6.3. Online Tap Changer

In this test system, the OLTC had 17 tap positions, which could change the voltage −5% to +5%. Each tap position was presented in terms of predefined voltage, as presented in the previous section, which corresponded to a specific tap position.

6.4. PEV Charger and Battery

Generally, the charger capacity must be high enough to charge the PEV batteries within a reasonable timespan. Although the charger has some technical losses of its own, for simplicity in the simulation, it was assumed that the charger efficiency was 100%. Three distinct types of PEV chargers were found based on their charging power as follows:

- Level 1: Generally, an electric outlet in a residential house is 115 VAC, 15 A or 230 VAC, 6A single-phase. This connection can deliver around 1.5 kW, and the charge time varies between 7 and 30 h based on battery size.
- Level 2: A mid-sized PEV can be charged in 4–5 h through a 230 VAC, 30 A with two poles. This type of chargers is mostly used at home and public charging stations. It delivers 7 kW to feed the 6.6 kW onboard PEV charger.
- Level 3: The ultra-fast PEV charging utilizes 400–600 VDC, up to a 300 A connection. The onboard charger is bypassed and feeds the power directly to the battery. It produces up to 120 kW to charge a Li-ion battery to 80% in about 30 minutes.

In this paper, level 2 category 3.3 kW, 6.6 kW, and 7.2 kW chargers were selected considering the limitation in the wiring capacity of the household. These types of chargers are commonly used in single-phase residential houses without having to change its wiring system. Generally, PEV battery capacities are found ranging from a few kWh to over 50 kWh [26]. Some of the latest PEV battery sizes are presented in [27]. In this research, 6 kWh, 16 kWh, and 19.2 kWh battery capacities were considered since they are commonly available in the market.

6.5. Smart Grid Communication Infrastructure

In the real-time PEV charging coordination process, the distribution system operator (DSO) must obtain data from PEVs such as PEV identification (ID), charger capacity, battery size, batter state, and user's preferences. This data is then used in algorithm of the proposed method. A smart grid communication infrastructure is important for the PEV charging coordination process. The communication infrastructure provides the smart metering, monitoring, and management services in the smart grid that establishes an automated system. Many recent innovations in information technology can be applied in smart grid automation such as interoperability of data exchanges and the integration of existing future devices and systems [28]. In recent years, the smart grid is becoming more flexible and automated with the introduction of the wireless technology communication infrastructure [29]. Figure 3 illustrates the proposed PEV charging activities facilitated by the smart grid infrastructure.

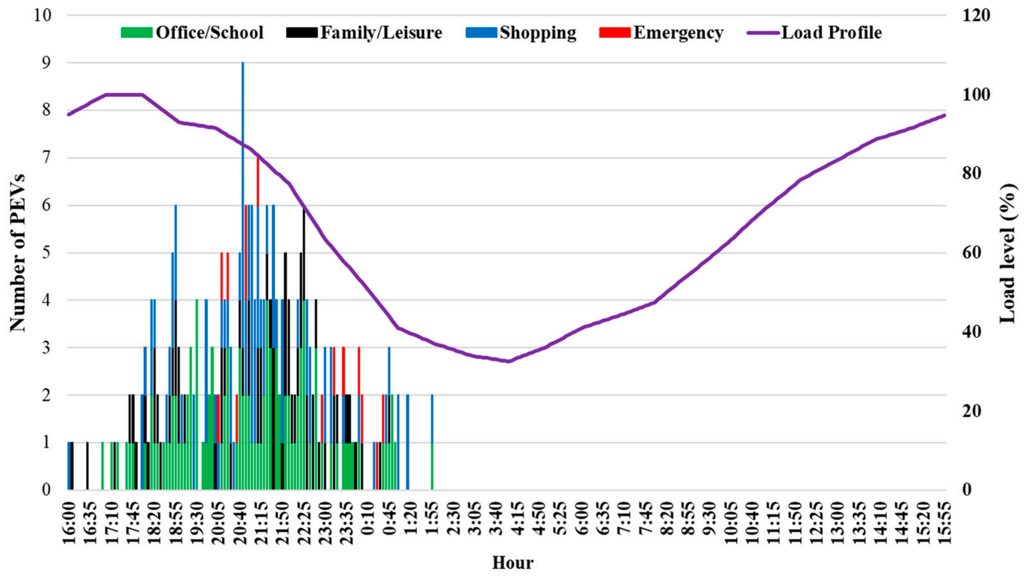


Figure 3. Daily load profile and PEVs arrival at charge point at 63% penetration.

6.6. Time-of-Use Electricity Tariff

Time-of-use (ToU) pricing is well known in most of the developed countries, e.g. Australia, USA, U.K., Italy, and Spain [30]. The main feature of ToU pricing is to offer time-differentiated electricity prices to the end-users; for example, having two or three predefined price levels per day, i.e., peak and off-peak and shoulder price. Hence, the consumers have the option to shift their flexible loads from hours with the high demands (high tariff) to hours with lower demand (low tariff). In [31], the authors concluded that effective pricing mechanisms to change consumers' behavior is one of the most important factors that affects the success of ToU rates. The results of studies concerning varying numbers of consumers in different countries show that ToU pricing potentially reduces peak demand by 8% to 13%. As ToU prices are static and price rates do not vary dramatically, less communication infrastructure is required, and this is suitable for developing countries. Since the PEV charging load can be managed through the coordination approach, the inclusion of the ToU pricing of electricity is able to reduce the charging cost.

6.7. Electric Vehicle Driving Pattern

For the PEV charging coordination, predicting the PEV arrival time is one of the major challenges because the mobility behavior of PEV depends on each PEV [32]. Therefore, it is important to develop a model for the PEVs' arrival to create a load profile along with the PEV load demand. Generally, this PEV arrival model helps the aggregator to determine the possible scheduling for each individual PEV.

In this study, the survey results of electric vehicle user behavior carried out in [33] was utilized. About a 75.1% response was received from the survey participants. Respondents were selected from the four major states in Malaysia as the State of Selangor, the Federal Territories (Kuala Lumpur and

Putrajaya), Johor, and Penang. These areas were chosen due to the high number of the private vehicle users. The study was carried out considering the following factors: age group, gender, monthly income, and current locality. From this study, the driving behavior of these areas can be categorized into four groups: driving to/from office and school; driving to/from friend, family, or leisure; driving to/from emergency work; and driving to/from shopping. It was assumed that 40% of the PEV was prioritized for the office and school use, 25% for family and friend use, 30% for the shopping use, and final 5% for the emergency work. In order to get the PEV arrival in this paper, the study in [33] was employed and developed, as shown in Figure 3 for the 63% PEV penetration. A similar method was employed to get the arrival time at 47% and 32% PEV penetration.

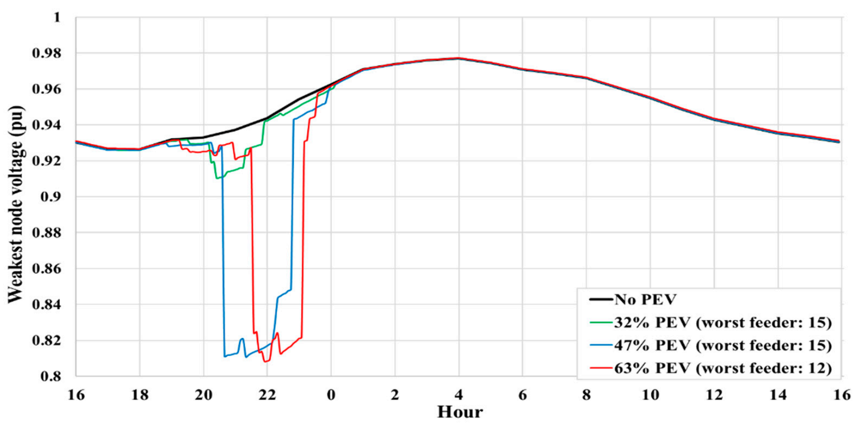
7. Analysis and Discussion

In this paper, there were 30% PEV with a 3.3 kW charger, 40% PEV with a 6.6 kW charger, and 30% PEV with a 7.2 kW charger. The three different battery sizes were 6kWh, 16kWh, and 19.2 kWh, selected with 3.3 kW, 6.6 kW, and 7.2 kW charger capacities, respectively. For instance, charger capacity, battery size, initial SOC, and its corresponding requested SOC are provided in Table 1.

Table 1. An example of detailed input parameter of PEVs from a feeder.

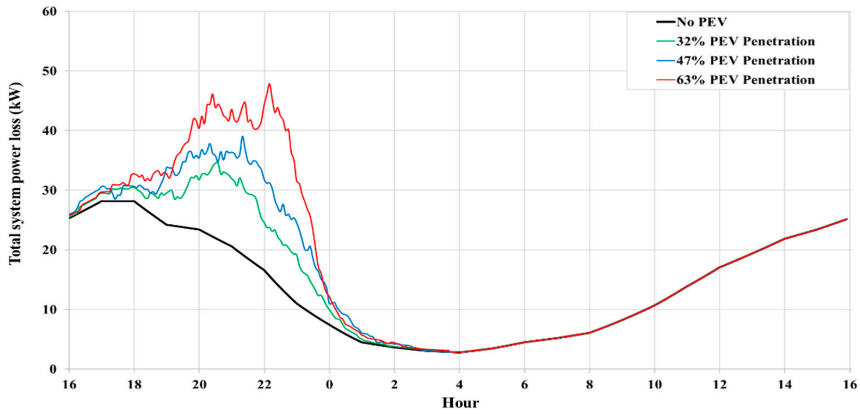
Node Number	n2	n4	n6	n7	n8	n10	n11	n13	n15	n17	n18	n19
Charger capacity (kW)	3.3	7.2	7.2	3.3	6.6	3.3	7.2	7.2	3.3	6.6	7.2	6.6
Battery size (kWh)	6	19.2	19.2	6	16	6	19.2	19.2	6	16	19.2	16
Initial SOC (%)	42	36	39	45	33	29	41	33	52	25	31	37
Requested SOC (%)	69	60	61	80	55	74	68	82	86	65	71	75

The uncoordinated and random PEV charging on the distribution system is shown in Figure 4. This charging process increased distribution system stress, causing overloading, excessive power loss, and high voltage deviation. From Figure 4a, at 63% PEV penetration, the weakest node voltage magnitude was 0.81 p.u., which was the worst voltage drop. At 47% PEV penetration, the voltage in the weakest node was below 0.82 p.u. However, with 32% PEV penetration, the voltage was within allowable limits. The total system power loss is presented in Figure 4b. It was found that the random PEV charging process raised the power loss to extremely high levels during the peak hour. In addition, the total power consumption of the distribution system was immensely high during the peak hour. As shown in Figure 4c, for 63% and 47% PEV penetration, the distribution system was overloaded in terms of system capacity. Moreover, the distribution system was also overloaded during the lower PEV penetration (32%).

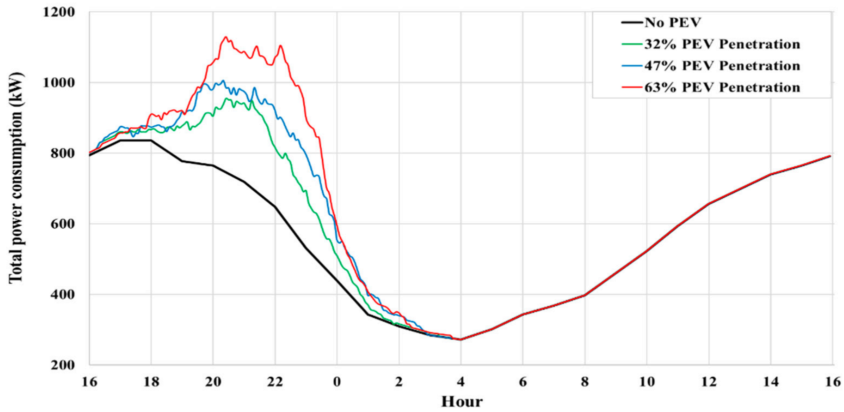


(a)

Figure 4. *Cont.*



(**b**)



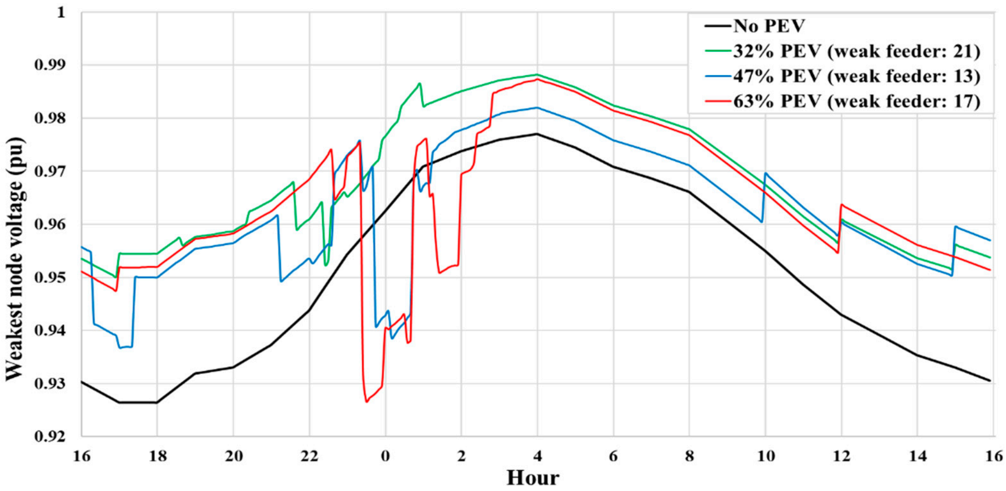
(**c**)

Figure 4. (**a**) Voltage deviation, (**b**) power loss, and (**c**) total power consumption during the uncoordinated PEV charging.

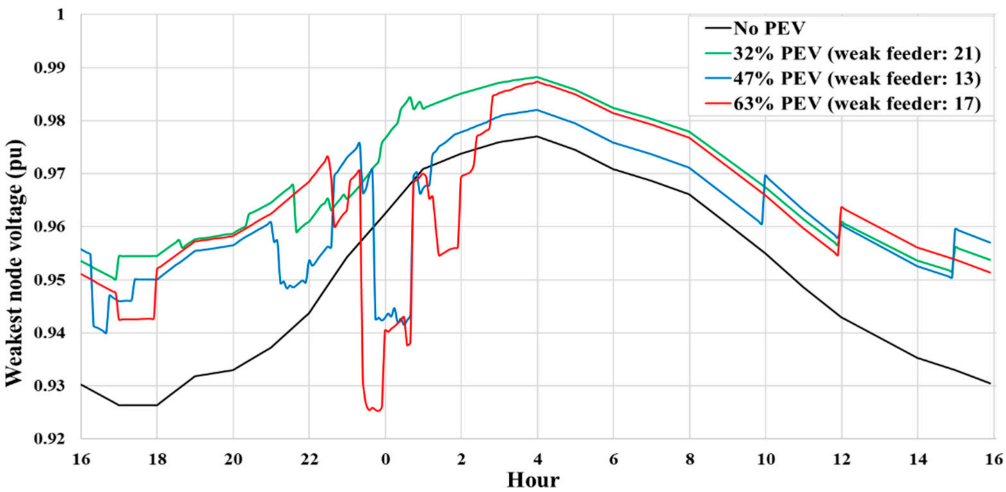
7.1. Further Improvements in System Performances

The capacitor switching OLTC adjustment was conducted for every hour to further improve the voltage. It was observed that the weakest node voltage profile was improved after using the capacitor switching and OLTC operation, as shown in Figure 5a,b by employing BPSO and BGWO, respectively. In Figure 5a, the minimum voltage was 0.920 p.u. and 0.918 p.u. for 47% and 63% PEV penetration, respectively. The voltage profile of the weakest node with the lower PEV penetration (32%) was further improved due to simultaneous activities of a capacitor and OLTC.

The proposed method reduced the total system power loss during the PEV charging. From Figure 6, it is observed that the total power loss in every timeslot was not excessive as in uncoordinated PEV charging activities. The maximum power loss was found for 63% PEV penetration with 35.12 kW at time 23:10, which was acceptable since all the PEV charged. For 32% and 47% PEV penetration, the maximum power loss recorded was 28.16 kW, which was equal to the power loss with no PEV in the network. Therefore, the impact of PEV charging activities in the distribution network can be optimized by using capacitor and OLTC operation during the PEV charging coordination. Moreover, by using the proposed method, there was no transformer overload during the PEV charging in the peak hour, as shown in Figure 6c,d.



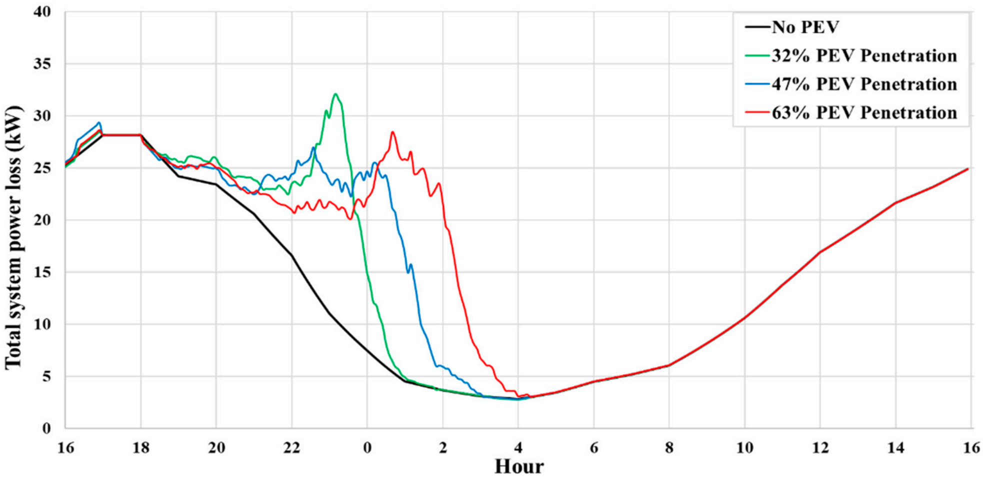
(**a**)



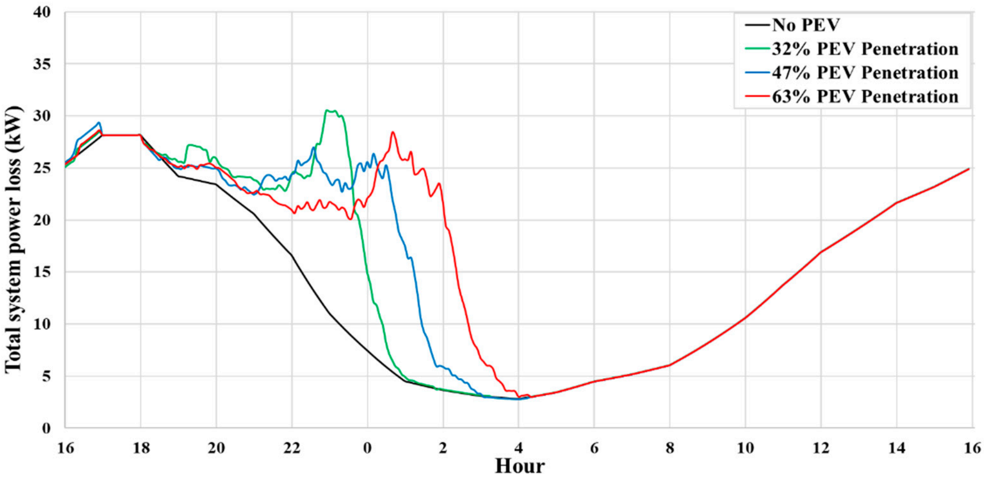
(**b**)

Figure 5. Profile for the weakest node with capacitor switching and OLTC adjustment during PEV charging coordination using (**a**) BPSO and (**b**) BGWO.

Figure 7a,b show the SOC at 63% PEV penetration for the weakest feeder using BPSO and BGWO, respectively. All the PEVs were charged to their respective required SOC by time 3:50 at the weakest feeder. On the other hand, the PEVs in the best feeder were charged in a faster time. The simulation results considering capacitor and OLTC operation during the PEV charging coordination using BPSO and BGWO are summarized in Table 2. It is observed that the PEV user's satisfaction was 100% for all the PEV penetration levels when the capacitor and OLTC operation were considered during the PEV charging coordination. The PEV user's satisfaction was calculated based on how many PEVs get the required charge in a specific low voltage feeder. It was also observed that the overall voltage profile of the network was improved significantly. Moreover, in terms of power loss, the network performed better. The proposed method with the combination of capacitor and OLTC with the PEV charging coordination offered minimum power loss and voltage deviation while satisfying all the PEV users.



(**a**)



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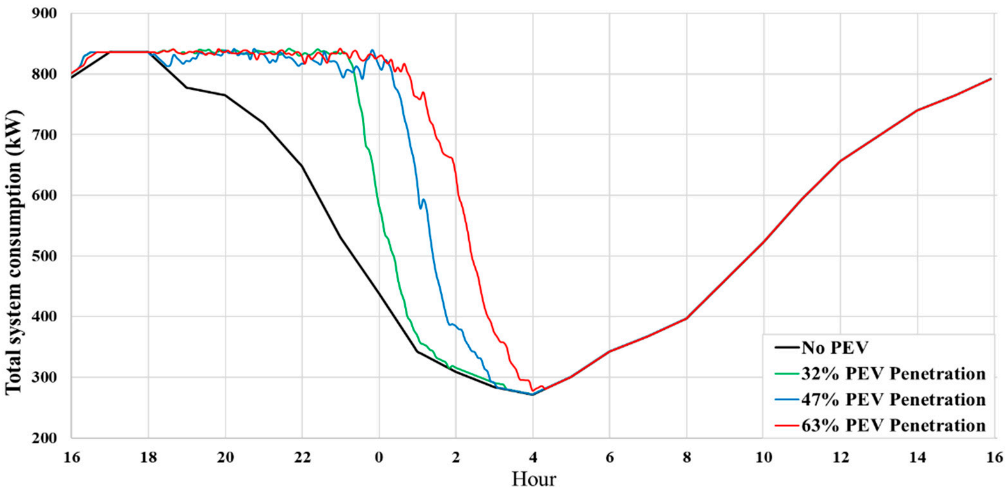
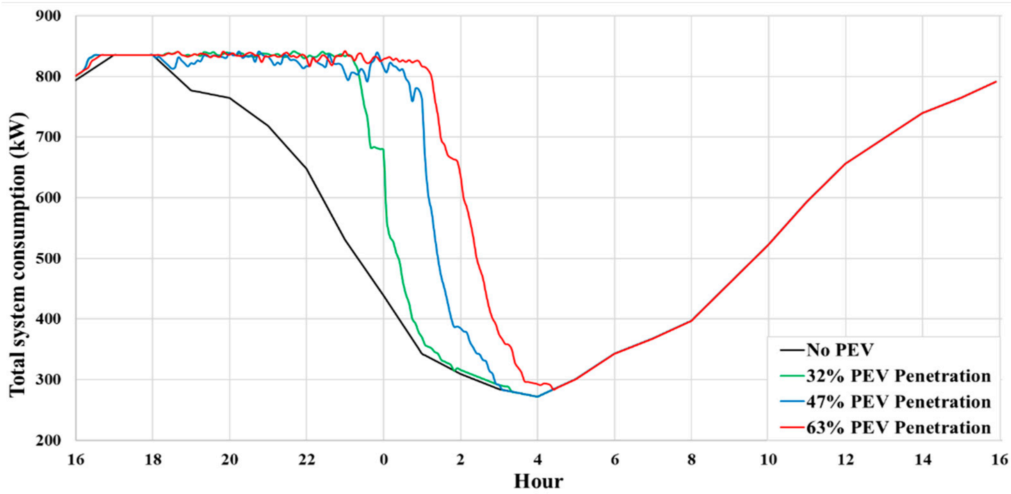


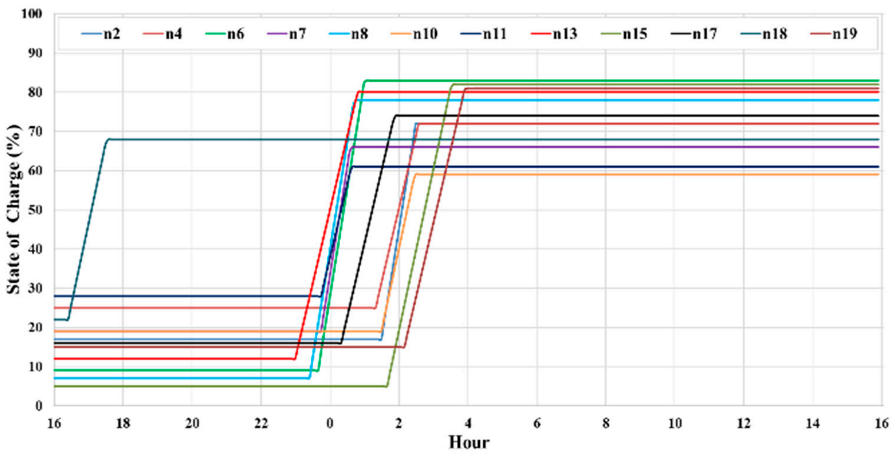
(**c**)

Figure 6. *Cont.*

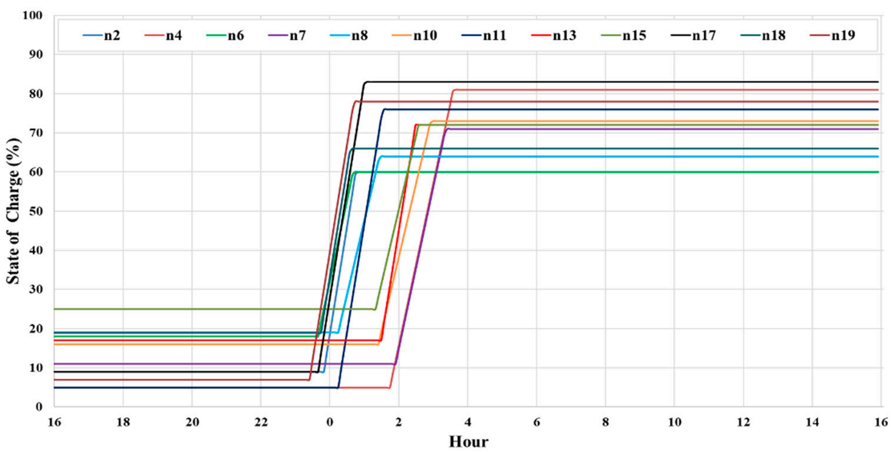


(**d**)

Figure 6. Total system power loss using (**a**) BPSO and (**b**) BGWO, and total power consumption using (**c**) BPSO and (**d**) BGWO with capacitor switching and OLTC adjustment during PEV charging coordination.



(**a**)



(**b**)

Figure 7. SOC for the weakest feeder for 63% penetration with capacitor switching and OLTC adjustment using (**a**) BPSO and (**b**) BGWO.

Table 2. Technical impact of PEV charging in different scenarios on the distribution system.

Scenarios	PEV (%)	ΔV (%)		Increase in Loss * (%)		Satisfaction Ratio **	
No PEV	0	7.35		0		-	
Uncoordinated PEV charging	32 47 63	8.95 17.27 19.16		14.59 23.08 33.85		- - -	
Algorithm		**BPSO**	**BGWO**	**BPSO**	**BGWO**	**BPSO**	**BGWO**
Coordinated PEV charging with the capacitor and OLTC adjustment	32 47 63	4.99 6.32 7.34	4.99 6.51 7.89	11.86 17.28 23.03	11.91 17.32 23.23	22/0 22/0 22/0	22/0 22/0 22/0

* Increase in loss compare to no PEV case. ** Number of satisfied feeders/number of unsatisfied feeders.

7.2. Impacts on Economic

In this research, the minimization of energy cost was done by reducing the energy losses. Table 3 shows the energy generation cost for one day when the PEV were charged in the network since the results were compared with the uncoordinated PEV charging when all the PEV got the required charge. As the PEV penetration increased in the network, the energy consumption also increased. Therefore, the cost of energy loss was reduced in terms of minimizing the daily power loss. The results in Table 3 indicate clearly that the proposed method curtailed the daily energy generation cost significantly. The cost of energy generation was considered to AU$50/MWh [26].

Table 3. The daily cost of energy generation.

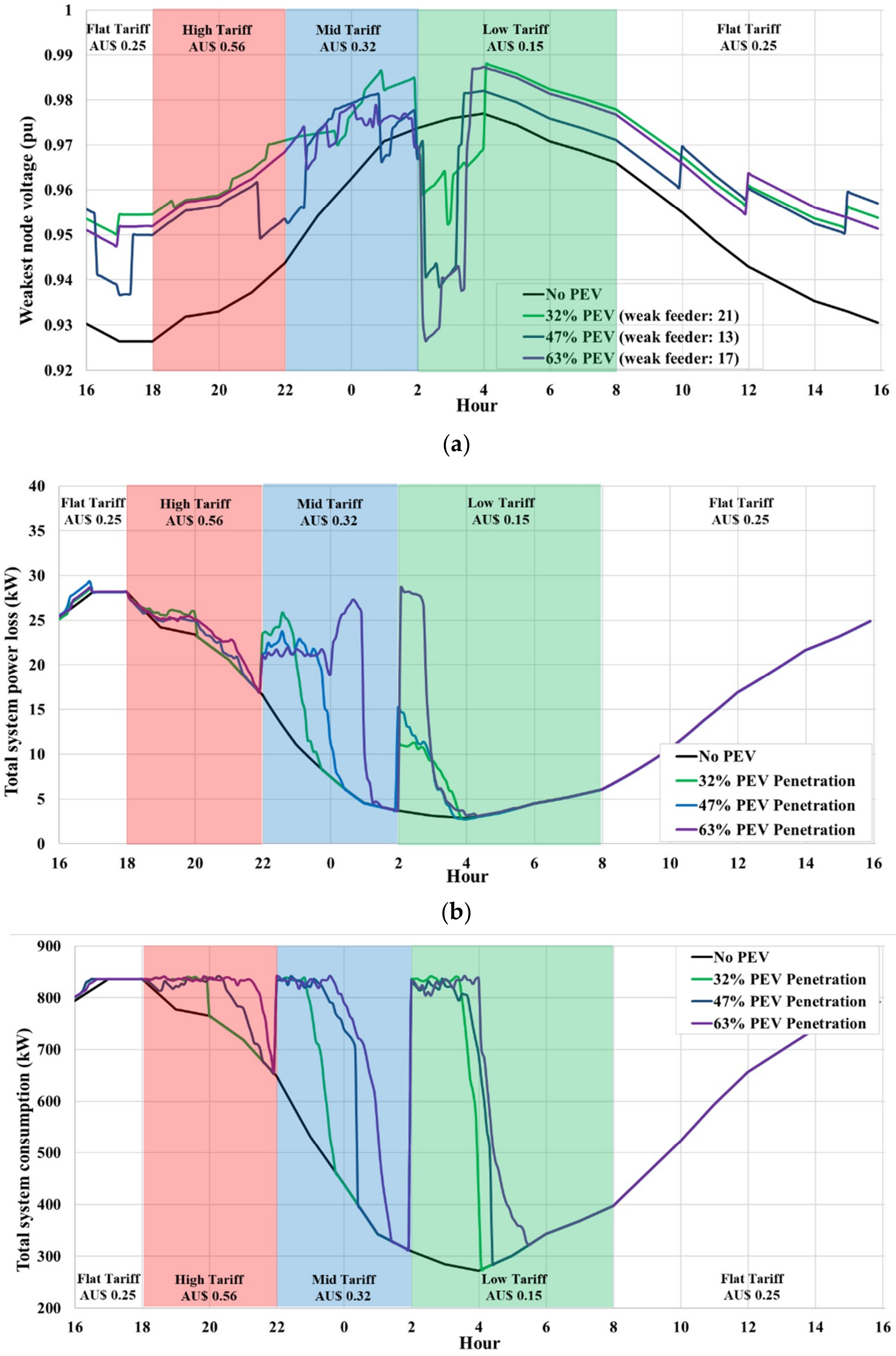
Charging Scenario	PEV (%)	Increase in Power Loss (kW)	Generation Cost/day ($)	Total Cost/day ($)	Increase in Cost (%)
No PEV	0	0	802.5	818.1	-
Uncoordinated charging	32 47 63	14.59 23.08 33.85	927.5 967.5 1008.5	952.4 1008.0 1089.2	16.41 23.21 33.13
Proposed method	32 47 63	11.86 17.28 23.03	909.5 942.5 982.6	922.1 956.1 997.1	12.71 16.86 21.87

Figure 8 presents the impact of PEV charging activities on the distribution network to minimize the PEV charging cost while utilizing an electrical tariff. Figure 8a shows the weakest node voltage profile for all PEV penetration levels. It is observed that the voltage was in the allowable range and the lowest voltages were recorded at midnight when the residential load was lower. Figure 8b,c show the daily power loss and total power consumption, respectively. It is seen that the PEV charging load was distributed over different timeslots based on the electricity tariff.

The changes in charging cost considering different scenarios for different PEV penetration levels are summarized in Table 4. Three different scenarios were studied here since all the PEV customer satisfaction was found to be full. Four different electricity tariffs were considered in this research as AU$0.56 in h 17–22, AU$0.32 in hours 22–02, AU$0.15 in hours 02–08 and AU$0.25 in hours 08–16, as shown in Figure 8. However, after including charging cost minimization after utilizing the ToU tariff, the PEV charging cost was greatly reduced. The total PEV charging cost of 12 PEVs at 63% penetration for a specific feeder is considered in Table 4.

Table 4. PEV charging cost.

Charging Scenario	PEV Penetration (%)	Decrease in PEV Charging Cost (%)
Uncoordinated PEV charging	32 47 63	- - -
Coordinated PEV charging without considering the tariff	32 47 63	3.56 7.14 11.45
Proposed method including the ToU electricity tariff	32 47 63	5.45 9.42 15.89



(c)

Figure 8. Voltage profile, (**b**) total power loss, and (**c**) total power consumption employing the ToU electrical tariff for cost minimization.

8. Conclusions

In the distribution system, uncoordinated and random PEV charging activities impose substantial incremental loading on the distribution transformer, severe voltage deviation, and significantly increased system power losses. As a consequence, the overall operational cost will increase significantly.

Therefore, the main purpose of this research was to develop the optimal charging decision for all PEVs in the distribution system. The proposed PEV charging coordination with the simultaneous operation of capacitor switching and OLTC adjustment gave the minimum power loss and voltage deviation while considering all the system constraints. Furthermore, a ToU electricity tariff was included in the proposed charging coordination to reduce the PEV charging cost. It was found that the power loss and voltage deviation were reduced significantly compared to the uncoordinated PEV charging. At the same time, it was observed that there was no substation overloading. As a result, the power peaks were reduced, and it released the burden of the local distribution system. Furthermore, the inclusion of the ToU electrical tariff in the proposed charging coordination along with the capacitor switching and OLTC adjustment reduced the charging cost significantly. The proposed approach used meta-heuristic techniques—namely, BPSO and BGWO, and both optimization methods were able to provide PEV charging coordination with minimal power loss and voltage deviation. However, it cannot be concluded that BPSO or BGWO performed better since some other arbitrary factors were related to this optimization such as PEV customer satisfaction and the random arrival of PEVs. Moreover, the number of PEVs changed in every timeslot due to their different initial and required *SOC* level.

Author Contributions: H.S. and M.T.R. designed the study, performed all levels of analysis, and developed the scheduling method for investigation and performance validation. They also wrote the first draft of the manuscript. H.M. and H.M. contributed their expertise in the field and verified the obtained results based on theoretical concepts involved. M.O. and H.A.I. reviewed the work critically for important intellectual content. All authors were involved with revising and approving the final manuscript.

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Nomenclature

PEV	Plug-in electric vehicle
SOC	State of charge in percentage
OLTC	On-load tap changer
ToU	Time-of-use electricity tariff in AU$ (Australian dollar)
CHG	Charger capacity in kW
I	Brunch current flow in A
R	Brunch resistance in Ω
RE	Required energy to get desired SOC in kWh
Tr	Total required timeslot to get desired SOC in hour
Tc	Current timeslot when the PEV arrived to get charge
P_{load}	Residential load in kW
P_{PEV}	Load created by PEV
V_{rated}	Node voltage at nominal condition in per unit
V_i	Actual voltage at node in per unit
$C_{s,h}$	Capacitor switching status
C_{sm}	Maximum allowable number of capacitors switching in a day
Tap_h	OLTC tap position
Tap_{max}	Maximum allowable switching operation of OLTC
V_d	Voltage deviation in per unit
P^c_{loss}	Ratio of total power loss of after and before PEV coordination is made
P^{coord}_{loss}	Power loss when the PEV coordination is made in per unit
$P^{uncoord}_{loss}$	Power loss during the uncoordinated PEV charging activities in per unit
$P^{uncoord}_{loss}$	Maximum power demand of the distribution system in kW

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