sustainability

MDPI

Article

Multi-Objective Scheduling of Electric Vehicles in Smart Distribution Network

Changhong Deng, Ning Liang *, Jin Tan and Gongchen Wang

School of Electrical Engineering, Wuhan University, Wuhan 430072, China; dengch_whu@163.com (C.D.); tanjin93@163.com (J.T.); wwggchch@163.com (G.W.)

* Correspondence: liangning@whu.edu.cn; Tel.: +86-27-6877-6251

Academic Editor: Shuhui Li

Received: 20 September 2016; Accepted: 23 November 2016; Published: 28 November 2016

Abstract: Due to the energy savings and environmental protection they provide, plug-in electric vehicles (PEVs) are increasing in number quickly. Rapid development of PEVs brings new opportunities and challenges to the electricity distribution network's dispatching. A high number of uncoordinated charging PEVs has significant negative impacts on the secure and economic operation of a distribution network. In this paper, a bi-level programming approach that coordinates PEVs' charging with the network load and electricity price of the open market is presented. The major objective of the upper level model is to minimize the total network costs and the deviation of electric vehicle aggregators' charging power and the equivalent power. The subsequent objective of the lower level model after the upper level decision is to minimize the dispatching deviation of the sum of PEVs' charging power and their optimization charging power under the upper level model. An improved particle swarm optimization algorithm is used to solve the bi-level programming. Numerical studies using a modified IEEE 69-bus distribution test system including six electric vehicle aggregators verify the efficiency of the proposed model.

Keywords: electric vehicles; smart distribution network; bi-level programming; dispatch optimization; coordination

1. Introduction

Owing to environmental degradation, fossil fuel exhaustion and battery technology development, the demand for plug-in electric vehicles (PEVs) has increased, and PEVs have become an important research topic for the improved management of electrical distribution networks [1–4]. However, carbon reductions depend on the way a network generates electricity. For instance, if the electricity is generated from coal, then the carbon reduction that accrues from PEV usage is small. If the electricity is generated from water resources or renewable energy sources, carbon reductions are certain. Thus, if a network contains renewable sources, a large penetration of PEVs could decrease the fossil fuel cost and reduce carbon emissions. However, because PEVs are actually mobile electric loads within a distribution network, their variability and uncontrollability could have harmful effects on the security and reliability of the system [5–9]. These harmful effects include the increases of operation cost, peak load, voltage excursion and distribution network losses.

Compared with traditional loads, PEVs can not only draw energy from the distribution network, and store it in batteries, but also inject energy into the distribution network through vehicle-to-grid technology [10–14]. Reasonable control of PEV charging can increase system security and reliability, while simultaneously providing PEV owners economic benefits. Thus coordinating the control of PEV charging is drawing more and more attention, and some research has been reported on this topic.

Between PEVs and a network, three types of PEV charging management are used: network-dominant, PEV-dominant, and electric vehicle aggregator (EVA)-based schemes. PEVs are regarded as uncertain loads in network-dominant management [15–19]. Zakariazadeh et al. [17] proposed a PEV charging and discharging method for a distribution network that not only reduces operation cost, but also decreases air pollutant emissions. The fast charging of PEVs is a challenging and complex problem for electrical network managers. Bayram et al. [18] examined a network of charging stations equipped with energy storage units, and used the units to mitigate electricity demand fluctuations and protect distribution assets from overloading. Kavousi-Fard et al. [19], addressing the challenge posed by the increasing penetration of PEVs in a grid of the future, presented a distribution feeder reconfiguration strategy to reduce the distribution feeder losses and improve the network security. In PEV-dominant management, the uncontrolled charging of PEVs is considered to be random and unpredictable. Uncontrolled charging can harm network security and power quality, and studies have been conducted to address these issues [20–23]. To utilize an existing network better and increase the penetration of PEVs, Richardson et al. [21], demonstrated how to control the charge rate for each PEV. The technique was based on the PEV charger types (i.e., fast charging and slow charging), pricing, station capacity, customer arrival rates and quality of service targets. Bayram et al. [22] proposed a model that employed pricing mechanisms to control PEV demand. The model provided a charging service with a "best level" quality of service in a large network, while in smaller networks the model determined the minimum amount of resources required to provide specified levels of service quality. Hilshey et al. [23] proposed a new smart PEV charging algorithm, and demonstrated that this model can mitigate the impact of PEV charging. Although a network's characteristics are considered in some cases [24,25], most PEV-dominant management concerns the demand of a single PEV, especially the battery life and PEV's travelled distance, rather than the losses and costs of the grid [26]. To coordinate the PEVs and a network, some researchers developed distributed dispatching optimization methods such as multi-agent-based control [27], decentralized charging control [28], and EVA-based control [29–32]. EVA-based control management of PEV charging is based on coordination and combination of a network and PEVs. The optimal dispatching objectives are to reduce the network losses, improve voltage profiles, decrease damage to the network loads, ensure the electric power demand of PEVs, and subsidize the PEV owners. This approach to controlling PEV charging can increase network security and reduce network losses, while also delivering benefits to PEV owners.

PEVs will develop rapidly in the future, and some networks will have a large number of PEVs. Based on EVA-based control management, coordination of each PEV and network will lead to a high dimensionality optimization problem. Dispatching each PEV directly and achieving the global optimum is a huge challenge, and can also cause great impact on the communication network between each PEV and the network control center. In recent years, bi-level programming for coordinated dispatching of PEVs has been proposed [33,34]. Momber et al. [33] proposed a bi-level optimization problem with equilibrium constraints optimizing the aggregator's decisions. In the upper level (UL) optimization, the objective was to maximize profits that aggregator agencies obtained from the charging of PEVs, and the lower level (LL) objective was to minimize the cost of PEV charging. Yao et al. [34] presented a hierarchical architecture for dispatching PEVs. The optimization objective of the UL routine was to minimize the total cost of system operation by joining EVAs. The optimization objective of the LL routine was to assure each individual PEV followed the EVA constraint and dispatching instructions of the UL charging strategies.

This purpose of this paper is not to challenge existing approaches to PEV charging management. Instead, it is intended to be a support that can provide a distribution network operator and PEV owners with additional choice. The paper presents a bi-level programming approach that coordinates PEVs' charging with the network load and electricity price on the open market. The major objective of the UL model is to minimize the total network costs and the deviation of EVAs' charging power and the equivalent power. The objective of the LL model subsequent to the UL decision is to minimize the dispatching deviation of the sum of PEVs' charging power and its optimization charging power as determined by the UL model. An improved particle swarm optimization (IPSO) algorithm is used to solve the proposed dispatch model. The proposed model is tested using a modified IEEE 69-bus distribution test system.

2. Hierarchical Dispatching Architecture via EVAs in Smart Distribution Network

Due to a large number of PEVs plugging into a distribution network, it is difficult to dispatch every PEV directly. This difficulty causes many dispatching problems. For example, it is challenging for a system operator to dispatch every PEV directly and obtain optimized results. In addition, the communication network is challenged to accommodate the large amount of interactive information that is exchanged between each PEV and the smart distribution network control center. To achieve optimized results and reduce the burden on the communication network, a bi-level programming approach illustrated in Figure 1 is employed. In this programming strategy, PEVs are managed by one EVA in a region, and the smart distribution network operator will dispatch EVAs rather than each PEV directly. Thus, EVAs should obtain the required information from PEVs to carry out the dispatch strategies. The PEV owners will get some financial incentives by dispatching their PEVs.

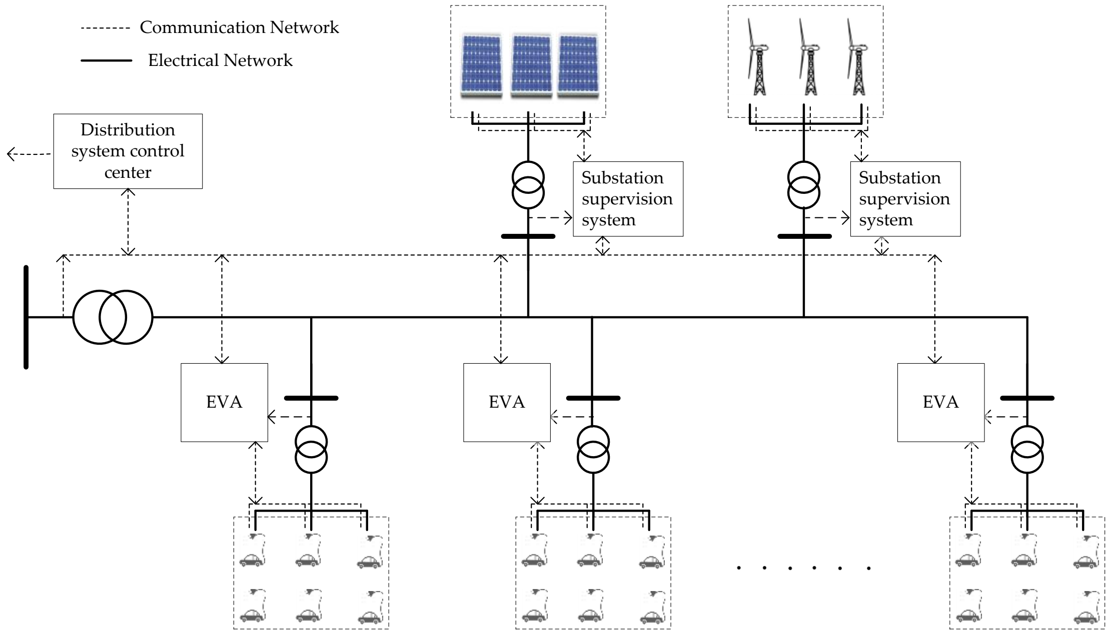

Figure 1. Coordinated control architecture of plug-in electric vehicles (PEVs) in smart distribution network. These six dots are the ellipsis representing lots of EVAs which were omitted.

3. Electric Vehicles Model

In a smart distribution network, PEV charging is schedulable and controllable. Therefore, formulas can be used for calculating the daily travel mileage of PEVs, as well as the times when PEVs plug into and plug out of the distribution network. This optimization dispatching research covers a 24-h period. During one dispatching period, PEVs are characterized by driving patterns such as the time that the first trip starts, the time that the last trip ends, and the travel distance.

In 2009, a survey [35] of American travel behavior was released by the USA. Department of Transportation Federal Highway Administration. The results were analyzed using a probability method. The survey characterized daily personal travel patterns throughout America, and has become the nation's authoritative source of such data. In the current study, normal distributions are used to describe the "first trip starts and last trip ends" time model, while the logarithmic normal distributions are used to describe the daily travel distance model. Equations (1) and (2) denote the probability density for the time that the first trip starts and last trip ends, respectively, while Equation (3) represents the probability density of the daily travel distance of PEVs. The equality constraints of electric quantity for a PEV's battery are described by Equation (4). Equation (5) represents the number of PEVs in the ith EVA.

$$f_s(x) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma_s}\exp(-\frac{(x-\mu_s)^2}{2\sigma_s^2}) & 0 < x \le \mu_s + 12 \\ \frac{1}{\sqrt{2\pi}\sigma_s}\exp(-\frac{(x-24-\mu_s)^2}{2\sigma_s^2}) & \mu_s + 12 < x \le 24 \end{cases} \tag{1}$$

$$f_e(x) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma_e}\exp(-\frac{(x+24-\mu_e)^2}{2\sigma_e^2}) & 0 < x \le \mu_e - 12 \\ \frac{1}{\sqrt{2\pi}\sigma_e}\exp(-\frac{(x-\mu_e)^2}{2\sigma_e^2}) & \mu_e - 12 < x \le 24 \end{cases} \tag{2}$$

$$f_m(x) = \frac{1}{\sqrt{2\pi}\sigma_m x}\exp(-\frac{(\ln x - \mu_m)^2}{2\sigma_m^2}) \tag{3}$$

where μ_s = 8.92; σ_s = 3.24; μ_e = 17.47; σ_e = 3.41; μ_m = 2.98; and σ_m = 1.14.

$$E_i(t) = (1-\lambda_\text{b})E_i(t-1) + (\eta_c P_i^c(t) - \frac{P_i^d(t)}{\eta_d})\Delta t \tag{4}$$

where $E_i(t)$ is the electricity quantity of PEV i in period t; λ_b is battery self-discharge rate; η_c and η_d are the battery charging and discharging efficiency factors, respectively; Δt is the time step; and P_i^c (t) and P_i^d (t) are the ith PEV charging and discharging power, respectively, in period t.

$$N_\text{Dis}^i(t) = N_\text{Dis}^i(t-1) + N_\text{s}^i(t) - N_\text{e}^i(t) \tag{5}$$

where $N_\text{Dis}^i(t)$ is the number of PEVs in ith EVA in time period t; and $N_\text{s}^i(t)$ and $N_\text{e}^i(t)$ are the numbers of PEVs when the first trip starts and last trip ends, respectively.

4. Coordinated Dispatching Model

In 1973, Bracken and McGill first proposed multilevel programming [36]. In many applications, this programming technique is used to solve multilevel optimization problems. The technique is suitable for solving PEV dispatching problems also. Bi-level programming is a special case of multilevel programming, and it is used in this paper to solve the PEV dispatching problems. As suggested by its name, bi-level programming consists of two levels, the UL and the LL. In the UL, the dispatching problems for the EVAs are formulated. In the LL, the PEV charging problem is described. The proposed UL problem is based on the UL decisions in wholesale day-ahead markets. The problem is considered as a basis for analyzing the strategic interactions in a leader-follower game in which the UL problem models the leader while the LL problem models the followers. In this approach, the UL model will affect the LL's strategies and their objective values; conversely, the LL's strategies and objectives can affect the UL's decision. The full mathematical formulation of the bi-level program is described in the following sections.

4.1. Upper Level Model

As Figure 1 shows, the smart distribution network's dispatching problems that are described in this paper consist of two levels. In the smart distribution network environment, distributed generators (DGs) and EVAs can submit their demands to the distribution system control center and be dispatched. Under this premise, the distribution control center establishes the UL problem model and formulates the optimal dispatching instruction for the electricity obtained from the main grid and DGs, and EVAs' charging power, respectively, so that the smart distribution network's operating cost is minimized. Under these structures, the objective function of the UL model can be calculated as Equations (6)–(8). These functions represent the cost of energy obtained from the main grid and the DGs, network loss, and the EVAs' charging coordination model, respectively. Among these functions, the first part of Equation (6) represents the cost of obtaining energy from the main grid; the second part represents the cost of purchasing power from DGs. Equation (7) represents the cost of network losses, it is calculated by the power flow of the network. If PEVs obey the coordination dispatching law, the PEV owners will be compensated in proportion to the charging power obtained from the smart distribution network. In this way, PEV owners will have economic incentives to obey the coordination dispatching law. Accordingly, the first part of Equation (8) represents the model that describes PEVs' charging coordination with the equivalent power which is computed by the network load and the electricity price on the open market; the second part represents the economic incentives for PEV owners.

$$\text{Min } F_1(X) = \sum_{t=1}^{T} [\lambda_{\text{grid}}(t) P_{\text{grid}}(t) + \sum_{i=1}^{N_{\text{N}}} \lambda^i_{\text{DG}}(t) P^i_{\text{DG}}(t)] \quad \forall t \in [1, T] \tag{6}$$

$$\text{Min } F_2(X) = \sum_{t=1}^{T} \sum_{i=1}^{N_{\text{L}}} [\lambda_{\text{loss}}(t) \times P^i_{\text{loss}}(t)] \quad \forall t \in [1, T] \tag{7}$$

$$\text{Min } F_3(X) = \sum_{t=0}^{T} \sqrt{\left\{ \sum_{i=0}^{N_{\text{E}}} [P^i_{\text{EVA}}(t)] - kC_{\text{C}}(t) \right\}^2} + \sum_{t=0}^{T} \sum_{i=0}^{N_{\text{E}}} \alpha P^i_{\text{EVA}}(t) \quad \forall t \in [1, T] \tag{8}$$

where $\lambda_{\text{grid}}(t)$ and $\lambda^i_{\text{DG}}(t)$ are the price of power obtained from the main grid and DGs in period t, respectively; $P_{\text{grid}}(t)$ and $P^i_{\text{DG}}(t)$ are the power obtained from the main grid and DGs in period t, respectively; $\lambda_{\text{loss}}(t)$ is the loss price in period t; T is the total number of periods; N_{N} is the total number of nodes; N_{L} is the total number of lines; N_{E} is the number of EVAs; $P^i_{\text{loss}}(t)$ is the network loss of the ith branch in period t; k is the coordination coefficient; $P^i_{\text{EVA}}(t)$ is the total charging power of the ith EVA in period t; and α is the incentives coefficient. In Equation (8), $C_{\text{C}}(t)$ and $P^i_{\text{EVA}}(t)$ can be expressed as Equations (9) and (10), respectively.

$$C_{\text{C}}(t) = C_{\text{CB}}(t) + k_{\text{CC}}[1 - \frac{CH(t)}{CH_{\max}}] + k_{\text{LC}}[1 - \frac{P_{\text{L}}(t)}{P_{\text{Lmax}}}] \quad \forall t \in [1, T] \tag{9}$$

$$P^i_{\text{EVA}}(t) = \sum_{j=1}^{N^i_{\text{Dis}}(t)} [P^i_{\text{PEV},\, j}(t)] \quad \forall t \in [1, T] \tag{10}$$

where $C_{\text{CB}}(t)$ is the constant in period t; k_{CC} and k_{LC} are coefficients; $CH_{\max}$ is the maximum price of power obtained from the main grid in the dispatch period; $CH(t)$ is the electricity price of the open market in period t; $P_{\text{L}}(t)$ is the forecasted load in period t; P_{Lmax} is the maximum forecast load during the dispatch period; and $P^i_{\text{PEV},j}(t)$ is the PEV charging power of the jth PEV that is affiliated to the ith EVA.

(1) Power balance constraints are described in Equations (11) and (12).

$$\sum_{i=0}^{N_{\text{N}}} P^i_{\text{L}}(t) + \sum_{i=0}^{N_{\text{E}}} P^i_{\text{EVA}}(t) + \sum_{i=1}^{l} P^i_{\text{loss}}(t) = P_{\text{grid}}(t) + \sum_{i=1}^{l} P^i_{\text{DG}}(t) \tag{11}$$

$$\sum_{i=0}^{N_{\text{N}}} Q^i_{\text{L}}(t) + \sum_{i=0}^{N_{\text{E}}} Q^i_{\text{EVA}}(t) + \sum_{i=1}^{1} Q^i_{\text{loss}}(t) = Q_{\text{grid}}(t) + \sum_{i=1}^{1} Q^i_{\text{DG}}(t) \tag{12}$$

where $P^i_{\text{L}}(t)$ and $Q^i_{\text{L}}(t)$ are the active and reactive loads at node i, respectively; $Q^i_{\text{EVA}}(t)$ is the reactive load of the EVA at node i; $Q^i_{\text{loss}}(t)$ is the reactive power loss of the network on branch i; $Q_{\text{grid}}(t)$ is the reactive power that obtained from the main grid; and $Q^i_{\text{DG}}(t)$ is the reactive power outputs of DGs at node i.

(2) The constraints of minimum and maximum active and reactive power obtained from the main grid are described by Equations (13) and (14).

$$P^{\min}_{\text{grid}} \leq P_{\text{grid}}(t) \leq P^{\max}_{\text{grid}} \tag{13}$$

$$Q_{\text{grid}}^{\min} \leq Q_{\text{grid}}(t) \leq Q_{\text{grid}}^{\max} \tag{14}$$

where $P_{\text{grid}}^{\min}$ and $P_{\text{grid}}^{\max}$ are the minimum and maximum, respectively, of active power that the smart distribution network purchases from the main grid. Likewise, $Q_{\text{grid}}^{\min}$ and $Q_{\text{grid}}^{\max}$ are the minimum and maximum, respectively, of reactive power that the smart distribution network obtains from the main grid.

(3) EVAs' apparent power constraints are:

$$S_{\text{EVA}}^{\min} \leq S_{\text{EVA}}^{i}(t) \leq S_{\text{EVA}}^{\max} \tag{15}$$

$$\sum_{j=1}^{N_{\text{Dis}}^{i}(t)} S_{\min,\,j}^{\text{PEV},\,i} \leq S_{\text{EVA}}^{i}(t) \leq \sum_{j=1}^{N_{\text{Dis}}^{i}(t)} S_{\max,\,j}^{\text{PEV},\,i} \tag{16}$$

The aforementioned UL model could be considered as an optimal power flow based on the minimum and maximum apparent power constraints of EVAs and an EVA's total PEVs, respectively. In Equations (15) and (16), $S_{\text{EVA}}^{\min}$ and $S_{\text{EVA}}^{\max}$ are the minimum and maximum apparent power constraints of EVAs, respectively; $S_{\min,\,j}^{\text{PEV},\,i}$ and $S_{\max,\,j}^{\text{PEV},\,i}$ are the PEV's minimum and maximum apparent power constraints, respectively, of the jth PEV that is affiliated to the ith EVA.

(4) An EVA's state of charge (SOC) constraints are described by Equation (17).

$$\sum_{j=1}^{N_{\text{Dis}}^{i}(t)} E_{\min,\,j}^{\text{PEV},\,i} \leq E_{\text{EVA}}^{i}(t) \leq \sum_{j=1}^{N_{\text{Dis}}^{i}(t)} E_{\max,\,j}^{\text{PEV},\,i} \tag{17}$$

where $E_{\min,\,j}^{\text{PEV},\,i}$ and $E_{\max,\,j}^{\text{PEV},\,i}$ are the minimum and maximum magnitudes, respectively, of SOC for the PEV's batteries of the jth PEV that is affiliated to the ith EVA.

(5) DG constraints are expressed by Equation (18).

$$P_{\text{DG,min}}^{i} \leq P_{\text{DG}}^{i}(t) \leq P_{\text{DG,max}}^{i} \tag{18}$$

where $P_{\min}^{i\ \text{DG,}}$ and $P_{\max}^{i\ \text{DG,}}$ are the minimum and maximum constraints of ith DG output power, respectively.

4.2. Lower Level Model

Based on the optimization results from the UL, the final PEV charging schedule of customers is determined by the LL model. Each EVA's objective is to minimize the dispatching deviation between the aggregated charging power of the PEVs and its optimization charging power under UL. The EVA considered the subsidies in the UL model, so the EVA does not consider the subsidies again in the LL model. The objective function of the ith EVA in the LL model can be formulated as Equation (19).

$$\text{Min } f_i(x) = \sum_{t=0}^{\text{T}} [P_{\text{EVA}}^{i}(t) - \sum_{j=0}^{N_{\text{Dis}}^{i}(t)} P_{\text{PEV},\,j}^{i}(t)]^2 \tag{19}$$

The LL objective function in Equation (19) is subject to the following constraints. The security constraint for PEV's SOC is described by Equation (20). When the PEVs plug into the distribution network provided by the EVA, the SOC to satisfy charging equality constraints is defined by Equation (21). Due to the capacity of the PEVs and the charging device, the PEV's charging power is required to satisfy the constraints in Equation (22). To guarantee the PEV can travel enough distance, PEV owners expect that the SOC should be sufficient when the PEV finishes charging. This constraint is calculated as Equation (23).

$$E_{\min,\,j}^{\text{PEV},\,i} \leq E_{\text{PEV},\,j}^{i}(t) \leq E_{\max,\,j}^{\text{PEV},\,i} \tag{20}$$

$$E_j^i(t+1) = E_j^i(t) + \frac{\eta_{\mathrm{ch}} P_{\mathrm{PEV},\,j}^i(t)\Delta t}{\beta_j^i} \tag{21}$$

$$P_{\mathrm{min},\,j}^{\mathrm{PEV},\,i} \le P_{\mathrm{PEV},\,j}^i(t) \le P_{\mathrm{max},\,j}^{\mathrm{PEV},\,i} \tag{22}$$

$$E_{\mathrm{max},\,j}^{\mathrm{PEV},\,i}\varepsilon\% \le E_{\mathrm{PEVL},\,j}^i \tag{23}$$

where $E_{\mathrm{PEV},\,j}^i(t)$ is the SOC of the jth PEV that is affiliated to the ith EVA in period t; η_{ch} is the average charging efficiency of PEVs; β_j^i is the battery capacity of the jth PEV that is affiliated to the ith EVA; $P_{\mathrm{min},\,j}^{\mathrm{PEV},\,i}$ and $P_{\mathrm{max},\,j}^{\mathrm{PEV},\,i}$ are the minimum and maximum charging power of jth PEV, respectively; and $\varepsilon\%$ is the minimum percentage of its total energy that each PEV battery has when the PEV leaves the EVA. For simplicity, in this paper, the PEV that plugs out of the distribution network should be no less than 90%.

5. Approach to Solving the Model

Traditional particle swarm optimization (PSO) was introduced by Kennedy and Eberhartk [37]. In the space of the original PSO, each individual is treated as a particle with velocity vectors and position. In theory, PSO can obtain convergence to the global optimum. In practice, PSO has slow convergence speed and sometimes local optima. Because the proposed bi-level model is highly nonlinear and non-convex, traditional mathematical programming methods would easily be trapped by local optima. To avoid this problem and improve the computational efficiency of traditional PSO, an IPSO algorithm was developed by integrating traditional PSO with the interior point method [38] and is used in the model that coordinates PEVs' charging with the network load and the electricity price on the open market. The interior point method has been widely applied in solving power system dispatching problems because it is highly efficient in searching local optima [39]. This algorithm can not only quickly locate local optima, but also avoid being in local optima. Compared with traditional PSO, this algorithm has a significant advantage. Figure 2 displays the flowchart that is used for solving the bi-level programming model. At the end of each cycle, if the results of LL cannot satisfy the constraints of UL, the UL constraints will be amended in accordance with the LL optimization results, after which a new solution iteration will start.

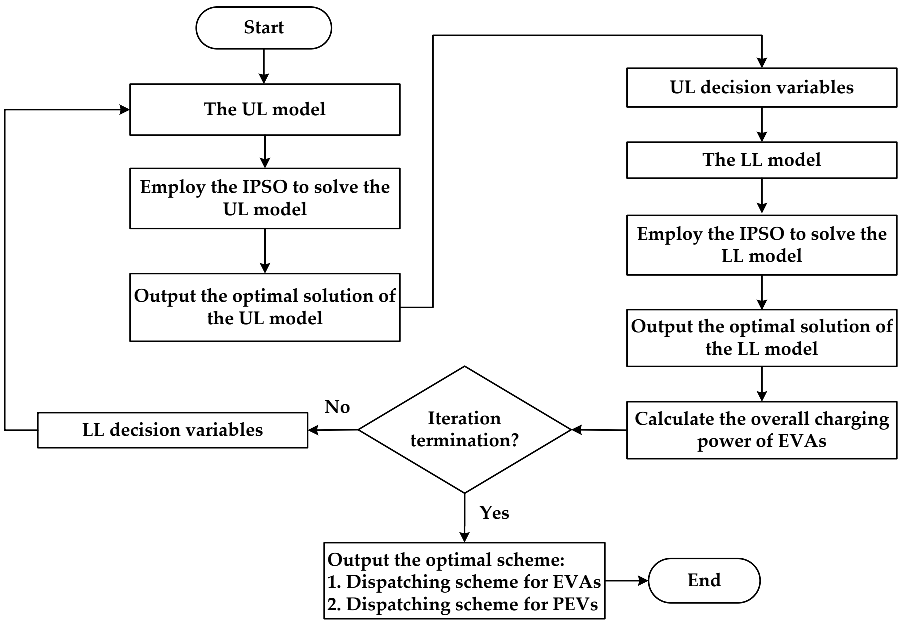

Figure 2. Flowchart for solving the dispatching model.

6. Case Studies

6.1. Case Description

In this paper, a modified IEEE 69-bus distribution test system shown in Figure 3 was adopted to verify the effectiveness of the optimal strategy for a network that contains three wind turbines, two photovoltaic generations and six EVAs. We assumed that either 1100 or 2000 PEVs plug into the smart distribution network while each with a battery capacity of 83.4 kWh. We also assumed that the PEVs' charging power is 6.5 kW under the uncoordinated model, while under the coordinated model, PEVs' charging power is intelligent, and obeys the LL's optimization results. Each PEV's upper limit of charging power is 15.8 kW, and the upper limit of discharging power is also 15.8 kW. The information reported by the PEV owners was simulated using the Monte Carlo simulation method. The time when the PEVs plug into the distribution network, the time when the PEVs plug out of the distribution network and the daily travel distance are generated by sampling from the probability density functions of Equations (1)–(3), respectively. The forecasted outputs of total wind generations and total photovoltaic generation systems are given in Figures 4 and 5, respectively. Three wind turbines are located in the distribution network at nodes 18, 25 and 34. Two photovoltaic generation systems are connected at nodes 18 and 61. Six EVAs are placed in nodes 11, 16, 25, 43, 48 and 61. The share of each bus from hourly demand is given in Table 1, and node 1 connects to the main grid. The hourly electricity price of open market is provided in Table 2 [17]. The backward and forward sweep load flow algorithm is used in this paper [40,41], and at the end of each iteration, the iterative result is the cost of network loss. This algorithm has the following advantages: simple program and a fast convergent rate. It is also suitable for calculating the power flow of the IEEE 69-bus distribution test system.

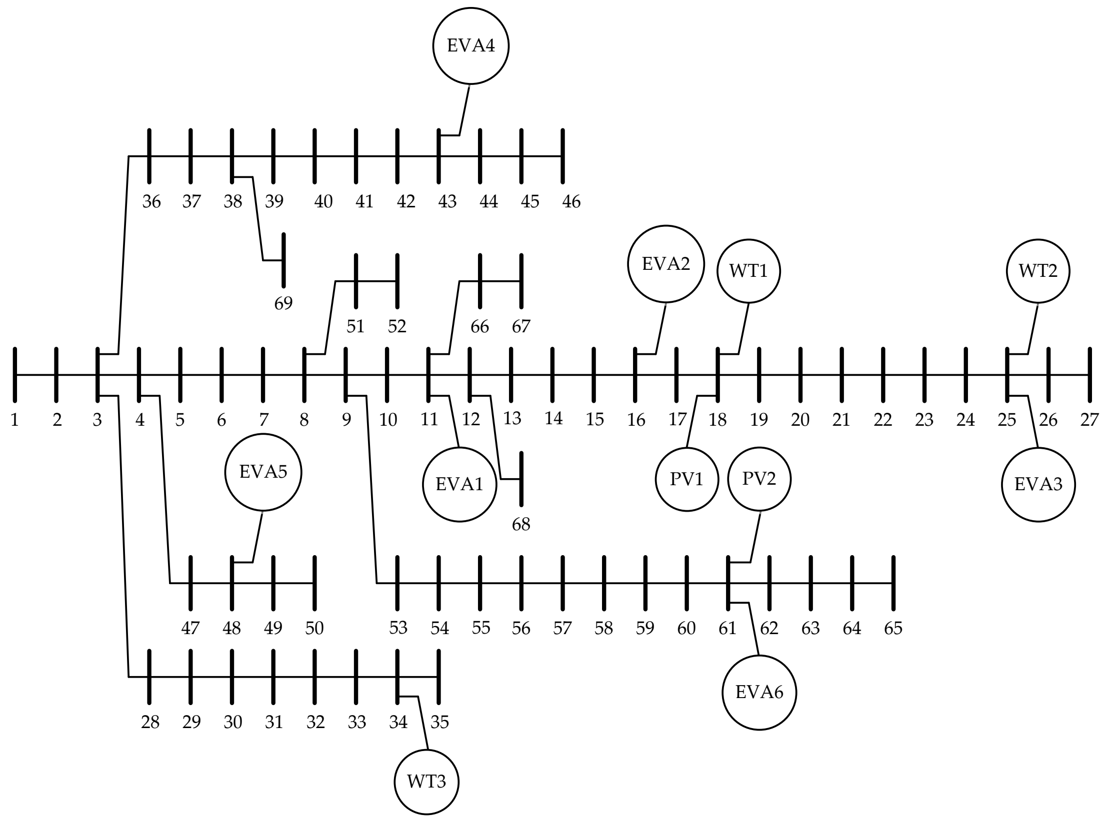

Figure 3. Modified IEEE 69-bus distribution test system.

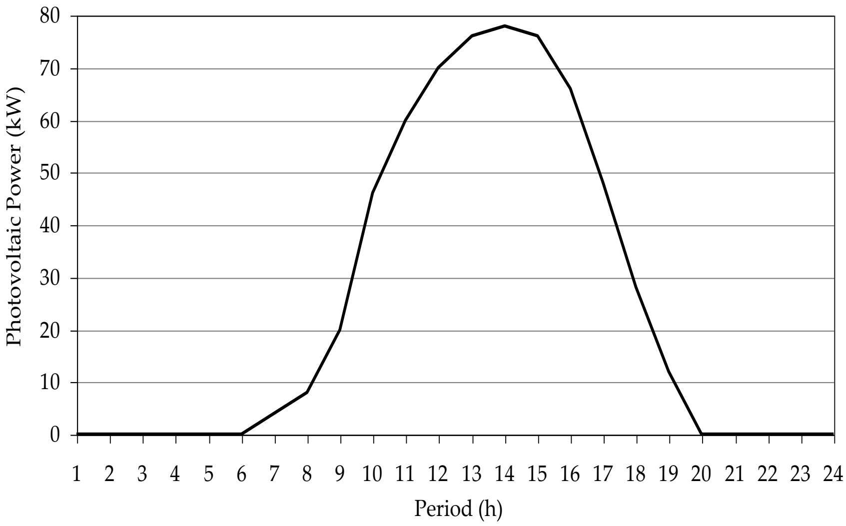

Figure 4. Photovoltaic power.

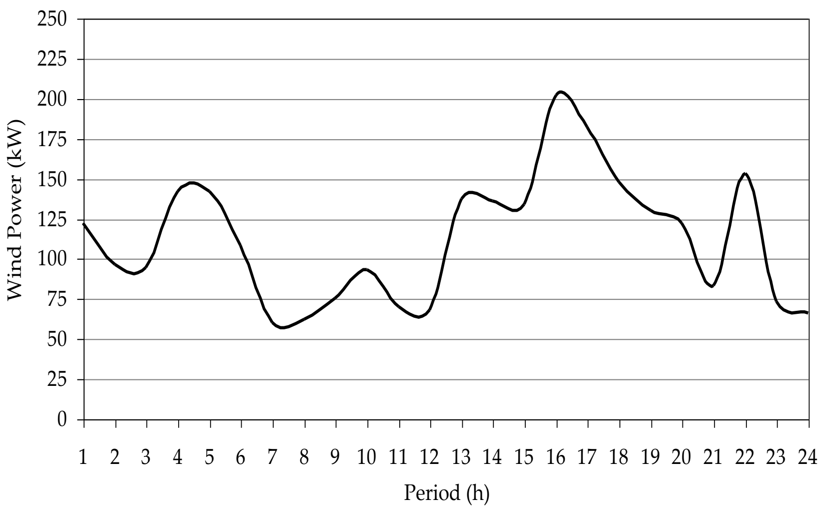

Figure 5. Wind power.

Table 1. The share of each bus from hourly demand.

Bus	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
%	1.5	1.4	3.85	0.9	1.5	1.2	0.8	0.6	1.7	1.3	2.9	1.4	1.7	1.6	1.8	1.3	1
Bus	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
%	2.5	0.9	0.4	2.1	1.7	1.4	1.2	1.5	1.1	0.9	1.4	1.2	0.9	0.7	0.05	1.5	1.6
Bus	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52
%	2.2	0.9	1.8	1.1	1.4	2.1	1.3	1.5	1.3	1.6	1.7	1.2	1.3	0.5	1.6	1.4	1.2
Bus	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69
%	1.4	1.6	1.8	0.8	3.4	1.3	1.1	0.8	2.4	3.7	1.3	1.2	1.5	2.1	1.4	1.3	1.3

Table 2. Energy prices during different hours.

Hour	1	2	3	4	5	6	7	8
λ($/kWh)	0.033	0.027	0.020	0.017	0.017	0.029	0.033	0.054
Hour	9	10	11	12	13	14	15	16
λ($/kWh)	0.215	0.572	0.572	0.572	0.215	0.572	0.286	0.279
Hour	17	18	19	20	21	22	23	24
λ($/kWh)	0.086	0.059	0.050	0.061	0.181	0.077	0.043	0.037

Six different cases were simulated and compared to analyze the proposed methodology, as described below. All the case studies were carried out using the C++ programming language on a 3.3 GHz personal computer (Lenovo, Wuhan, China).

Case 1: The modified IEEE 69-bus distribution test system includes 1100 PEVs, and 0% PEVs can be dispatched.

Case 2: The modified IEEE 69-bus distribution test system includes 1100 PEVs, and 30% PEVs can be dispatched.

Case 3: The modified IEEE 69-bus distribution test system includes 1100 PEVs, and 60% PEVs can be dispatched.

Case 4: The modified IEEE 69-bus distribution test system includes 1100 PEVs, and 100% PEVs can be dispatched.

Case 5: The modified IEEE 69-bus distribution test system includes 2000 PEVs, and 0% PEVs can be dispatched.

Case 6: The modified IEEE 69-bus distribution test system includes 2000 PEVs, and 100% PEVs can be dispatched.

6.2. Optimization Results

To demonstrate the performance of the proposed model, comparisons are made between six different dispatching modes of PEVs (described in Section 6.1). To demonstrate the validity and correctness of the proposed model, six cases with the different percentages of coordinated charging PEVs and different numbers of PEVs plugging into the network were simulated. The major difference of whether or not to obey the dispatching law between the PEVs can be described as follows. Under the dispatching law circumstances, PEVs' charging should be subordinated to the optimization results. However, under the uncoordinated charging circumstances, when the PEVs plug into the network, it is assumed that they will charge at once and remain charging until the charge is sufficient to meet the requirement. Figure 6 shows the typical load curves for 1100 PEVs under coordinated and uncoordinated dispatching law circumstances. Likewise, Figure 7 shows the typical load curves for 2000 PEVs under the coordinated and uncoordinated dispatching law circumstances. In both scenarios, peak load increases greatly and the load curve changes with the number of PEVs under uncoordinated charging circumstances. In addition, when more PEVs are plugging into the smart distribution network, the load curve changes even more and the peak load is higher. Compared with these cases, the results show that the proposed model for coordinating the PEVs' charging with the network load and electricity price on the open market can restrain the fluctuation of the load curve, particularly when more PEVs plug into the network. The effect of this restraint depends on the PEVs' charging coordination with the load of the distribution network dispatching.

The total costs of the six simulated charging strategies are compared in Figure 8, and the total distribution network losses of the six cases are shown in Figure 9. The results of cases 1–4 in Figures 8 and 9 showed that as the number of PEVs obeying the coordination dispatching strategy increase, the network losses and total operation cost decrease. When the network contains 2000 PEVs, the results of cases 5 and 6 show that the uncoordinated charging of the PEVs causes higher network losses and higher total operation cost, because the PEVs' charging in these cases mostly occurs when electricity prices are high and during the peak load period. On the other hand, shifting the PEVs' charging load to period of light load and employing the coordinated charging model in cheaper energy price periods offers many advantages such as reducing total operation cost and network loss. The implementation of a coordination charging strategy for PEVs in the distribution network and inclusion of more PEVs that obey the coordination dispatching rules reduced total operation cost somewhat and reduced network losses significantly. Thus, the coordinated charging strategy played a major role in reducing total operation cost and network losses.

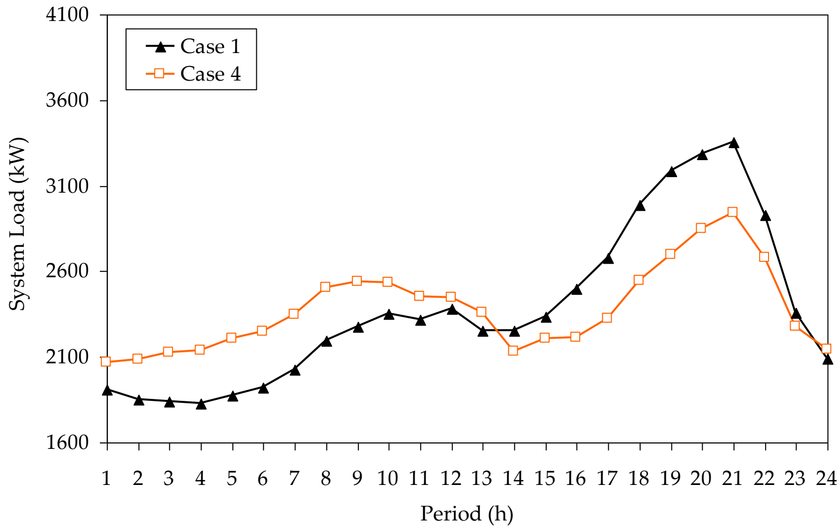

Figure 6. Load curve comparison of cases 1 and 4.

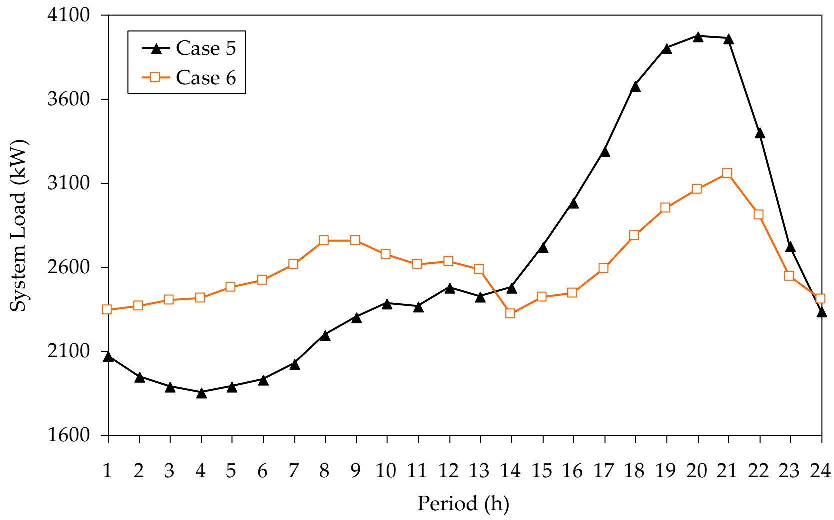

Figure 7. Load curve comparison of cases 5 and 6.

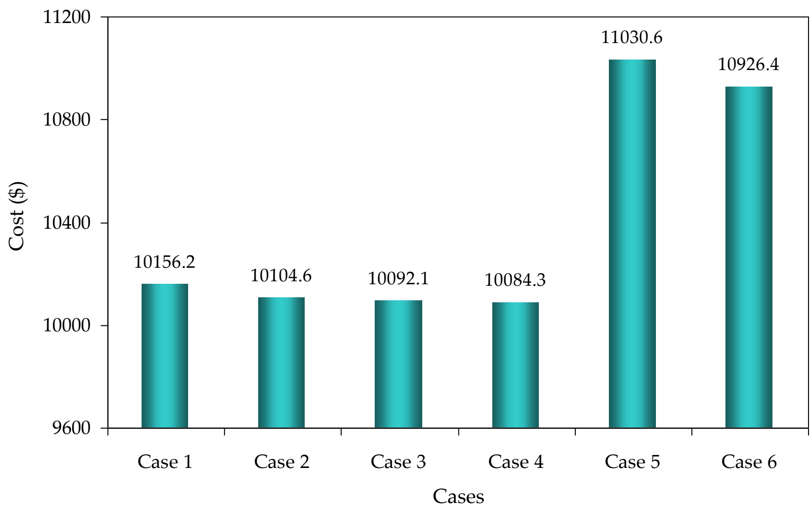

Figure 8. Total operation cost comparison of different cases.

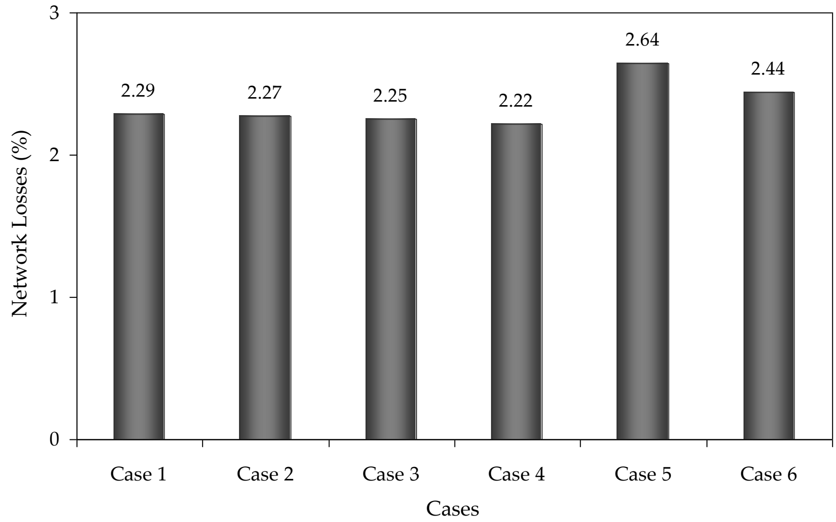

Figure 9. Network losses comparison of different cases.

The optimization dispatching model of PEVs' charging coordination with load and electricity price of the open market also can improve the smart distribution network's voltage. Cases 1, 4, 5 and 6 in period 21 illustrate this benefit. Cases 1 and 4 contain 1100 PEVs in the network, and the voltage magnitude at each node is shown in Figure 10. Cases 5 and 6 contain 2000 PEVs in the network, and the voltage magnitude at each node is shown in Figure 11. Among the four cases, PEVs cannot be dispatched in cases 1 and 5. According to data in Figures 10 and 11, the voltage deviation of cases 4 and 6 decrease in almost all hours compared to voltages when PEV charging was uncoordinated. In addition, the voltage deviation with the optimal dispatching strategy decreased much more when the number of PEVs plugging in the network increased to 2000 from 1100 (Figures 10 and 11).

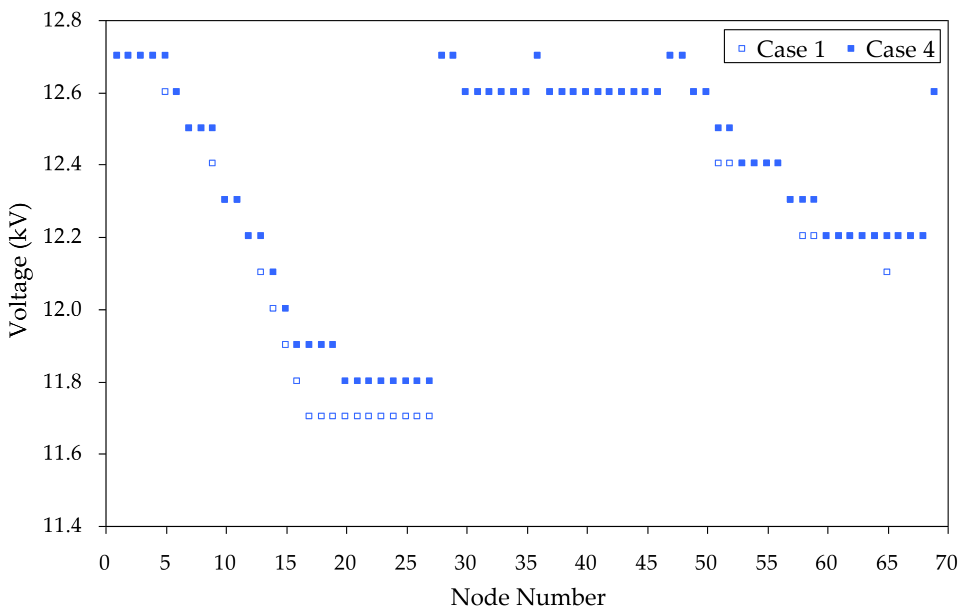

Figure 10. Voltage magnitude at each nodes of cases 1 and 4.

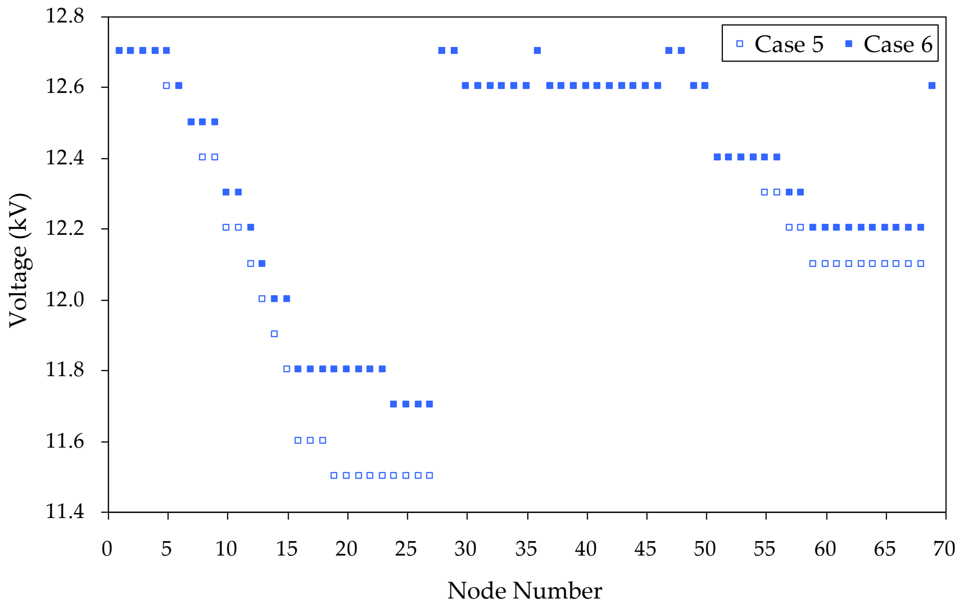

Figure 11. Voltage magnitude at each nodes of cases 5 and 6.

The foregoing results demonstrate that the proposed model of PEVs' charging coordination with load and electricity price of the open market has positive effects on smart distribution network security and voltage deviation. In all, the proposed strategy reduced some operation cost, and the other positive effects will lead to much improvement in crucial smart distribution network conditions. This will enhance the capacity of the network to accommodate more PEVs, thereby increasing the network profit.

7. Conclusions

In this paper, a bi-level programming dispatching model was developed for a smart distribution network. The target was to utilize the PEVs' charging coordination with the network load and electricity price on the open market through EVAs. Also, the proposed model can minimize the distribution network loss and the cost of energy obtained from the main grid and the DGs. An IPSO algorithm was developed and used to solve the proposed bi-level programming model. The proposed strategy was implemented and tested on a modified IEEE 69-bus distribution test system. The numerical results support the following conclusions.

(1) The bi-level programming dispatching model can decrease the peak and valley loads when there are different numbers of PEVs and different percentages of PEVs being dispatched, thereby increasing the security of the network.

(2) Moreover, the proposed model has many advantages such as reducing distribution network cost and losses, as well as voltage deviations at nodes.

(3) The proposed strategy is effective in a variety of simulated scenarios that are illustrative of real-world conditions.

(4) In all, the bi-level programming dispatching model including PEVs' coordination dispatching strategy will lead to much improvement in smart distribution network conditions.

In future work, we will analyze the model's performance in a real time environment (real-time market).

Acknowledgments: This work was support by the National Natural Science Foundation of China (51190104) and National Science and Technology Support Program of China (2013BAA02B02).

Author Contributions: Changhong Deng proposed the concrete ideas of the proposed optimization method. Ning Liang performed the simulations and wrote the manuscript. Jin Tan checked this paper's language, Gongchen Wang debugged part of programs. All of the authors revised the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Green, R.C.; Wang, L.; Alam, M. The impact of plug-in hybrid electric vehicles on distribution network: A review and outlook. *Renew. Sustain. Energy Rev.* **2011**, *15*, 544–553. [CrossRef]
2. Longo, M.; Yaïci, W.; Zaninelli, D. "Team play" between renewable energy sources and vehicle fleet to decrease air pollution. *Sustainability* **2016**, *8*, 1–17. [CrossRef]
3. Díaz, A.; Ramos-Real, F.; Marrero, G.; Perez, Y. Impact of electric vehicles as distributed energy storage in isolated systems: The case of tenerife. *Sustainability* **2015**, *7*, 15152–15178. [CrossRef]
4. Fernández, L.P.; Román, T.G.S.; Cossent, R.; Domingo, C.M.; Frías, P. Assessment of the impact of plug-in electric vehicles on distribution networks. *IEEE Trans. Power Syst.* **2011**, *26*, 206–213. [CrossRef]
5. Zhang, X.; Xie, J.; Rao, R.; Liang, Y. Policy incentives for the adoption of electric vehicles across countries. *Sustainability* **2014**, *6*, 8056–8078. [CrossRef]
6. Deilami, S.; Masoum, A.S.; Moses, P.S.; Masoum, M.A.S. Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile. *IEEE Trans. Smart Grid.* **2011**, *2*, 456–467. [CrossRef]
7. Lopes, J.A.P.; Soares, F.J.; Almeida, P.M.R. Integration of electric vehicles in the electric power system. *Proc. IEEE* **2011**, *99*, 168–183. [CrossRef]
8. Clement-Nyns, K.; Haesen, E.; Driesen, J. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *IEEE Trans. Power Syst.* **2010**, *25*, 371–380. [CrossRef]
9. Letendre, S.; Watts, R.A. Effects of plug-in hybrid electric vehicles on the Vermont electric transmission system. In Proceedings of the Transportation Research Board Annual Meeting, Washington, DC, USA, 11–15 January 2009.
10. Lund, H.; Kempton, W. Integration of renewable energy into the transport and electricity sectors through V2G. *Energy Policy* **2008**, *36*, 3578–3587. [CrossRef]
11. Sortomme, E.; El-Sharkawi, M.A. Optimal scheduling of vehicle-to-grid energy and ancillary services. *IEEE Trans. Smart Grid* **2012**, *3*, 351–359. [CrossRef]
12. Guille, C.; Gross, G. A conceptual framework for the vehicle-to-grid (V2G) implementation. *Energy Policy* **2009**, *37*, 4379–4390. [CrossRef]
13. Kempton, W.; Tomić, J. Vehicle-to-grid power fundamentals: Calculating capacity and net revenue. *J. Power Sources* **2005**, *144*, 268–279. [CrossRef]
14. Ota, Y.; Taniguchi, H.; Nakajima, T.; Liyanage, K.M.; Baba, J.; Yokoyama, A. Autonomous distributed V2G (vehicle-to-grid) satisfying scheduled charging. *IEEE Trans. Smart Grid* **2012**, *3*, 559–564. [CrossRef]
15. Liu, W.; Niu, S.; Xu, H.; Li, X. A new method to plan the capacity and location of battery swapping station for electric vehicle considering demand side management. *Sustainability* **2016**, *8*, 1–17. [CrossRef]
16. Carrión, M.; Zárate-Miñano, R. Operation of renewable-dominated power systems with a significant penetration of plug-in electric vehicles. *Energy* **2015**, *90*, 827–835. [CrossRef]
17. Zakariazadeh, A.; Jadid, S.; Siano, P. Multi-objective scheduling of electric vehicles in smart distribution system. *Energy Convers. Manag.* **2014**, *79*, 43–53. [CrossRef]
18. Bayram, I.S.; Michailidis, G.; Devetsikiotis, M. Electric power allocation in a network of fast charging stations. *IEEE J. Sel. Areas Commun.* **2013**, *31*, 1235–1246. [CrossRef]
19. Kavousi-Fard, A.; Abbasi, A.; Rostami, M.A.; Khosravi, A. Optimal distribution feeder reconfiguration for increasing the penetration of plug-in electric vehicles and minimizing network costs. *Energy* **2015**, *93*, 1693–1703. [CrossRef]
20. Papadopoulos, P.; Skarvelis-Kazakos, S.; Grau, I.; Cipcigan, L.M. Electric vehicles' impact on British distribution networks. *IET Electr. Syst. Transp.* **2012**, *2*, 91–102. [CrossRef]
21. Richardson, P.; Flynn, D.; Keane, A. Optimal charging of electric vehicles in low-voltage distribution systems. *IEEE Trans. Power Syst.* **2012**, *27*, 268–279. [CrossRef]

22. Bayram, I.S.; Tajer, A.; Abdallah, M. Capacity planning frameworks for electric vehicle charging stations with multiclass customers. *IEEE Trans. Smart Grid* **2015**, *6*, 1934–1943. [CrossRef]
23. Hilshey, A.D.; Hines, P.D.; Rezaei, P.; Dowds, J.R. Estimating the impact of electric vehicle smart charging on distribution transformer aging. *IEEE Trans. Smart Grid* **2013**, *4*, 905–913. [CrossRef]
24. Shao, S.; Pipattanasomporn, M.; Rahman, S. Grid integration of electric vehicles and demand response with customer choice. *IEEE Trans. Smart Grid* **2012**, *3*, 543–550. [CrossRef]
25. Su, W.; Chow, M.Y. Performance evaluation of an eda-based large-scale plug-in hybrid electric vehicle charging algorithm. *IEEE Trans. Smart Grid* **2012**, *3*, 308–315. [CrossRef]
26. Bae, S.; Kwasinski, A. Spatial and temporal model of electric vehicle charging demand. *IEEE Trans. Smart Grid* **2012**, *3*, 394–403. [CrossRef]
27. Olivella-Rosell, P.; Villafafila-Robles, R.; Sumper, A.; Bergas-Jane, J. Probabilistic agent-based model of electric vehicle charging demand to analyse the impact on distribution networks. *Energy* **2015**, *8*, 4160–4187. [CrossRef]
28. Ma, Z.; Callaway, D.S.; Hiskens, I.A. Decentralized charging control of large populations of plug-in electric vehicles. *IEEE Trans. Control Syst. Technol.* **2013**, *21*, 67–78. [CrossRef]
29. Ortega-Vazquez, M.A.; Bouffard, F.; Silva, V. Electric vehicle aggregator/system operator coordination for charging scheduling and services procurement. *IEEE Trans. Power Syst.* **2013**, *28*, 1806–1815. [CrossRef]
30. Vagropoulos, S.I.; Kyriazidis, D.K.; Bakirtzis, A.G. Real-time charging management framework for electric vehicle aggregators in a market environment. *IEEE Trans. Smart Grid* **2015**, *7*, 948–957. [CrossRef]
31. He, Y.; Venkatesh, B.; Guan, L. Optimal scheduling for charging and discharging of electric vehicles. *IEEE Trans. Smart Grid* **2012**, *3*, 1095–1105. [CrossRef]
32. Wu, D.; Aliprantis, D.C.; Ying, L. Load scheduling and dispatch for aggregators of plug-in electric vehicles. *IEEE Trans. Smart Grid* **2012**, *3*, 368–376. [CrossRef]
33. Momber, I.; Wogrin, S.; Gomez, S.R.T. Retail pricing: A bilevel program for PEV aggregator decisions using indirect load control. *IEEE Trans. Power Syst.* **2016**, *31*, 464–473. [CrossRef]
34. Yao, W.; Zhao, J.; Wen, F.; Xue, Y.; Ledwich, G. A hierarchical decomposition approach for coordinated dispatch of plug-in electric vehicles. *IEEE Trans. Power Syst.* **2013**, *28*, 2768–2778. [CrossRef]
35. Santos, A.; Mcguckin, N.; Nakamoto, H.Y.; Gray, D.; Liss, S. *Summary of Travel Trends: 2009 National Household Travel Survey*; FHWA-PL-ll-022; US Department of Transportation Federal Highway Administration: Washington, DC, USA, 2011.
36. Bracken, J.; McGill, J.T. Mathematical programs with optimization problems in the constraints. *Oper. Res.* **1973**, *21*, 37–44. [CrossRef]
37. Kennedy, J.; Eberhart, R. Particle swarm optimization. *IEEE Int. Conf. Neural Netw.* **1995**, *4*, 1942–1948.
38. Zhao, J.; Wen, F.; Dong, Z.Y.; Xue, Y.; Wong, K.P. Optimal dispatch of electric vehicles and wind power using enhanced particle swarm optimization. *IEEE Trans. Ind. Inform.* **2012**, *8*, 889–899. [CrossRef]
39. Granville, S. Optimal reactive dispatch through interior point methods. *IEEE Trans. Power Syst.* **1994**, *9*, 136–146. [CrossRef]
40. Chang, G.W.; Chu, S.Y.; Wang, H.L. An improved backward/forward sweep load flow algorithm for radial distribution systems. *IEEE Trans. Power Syst.* **2007**, *22*, 882–884. [CrossRef]
41. Teng, J.H.; Chang, C.Y. Backward/forward sweep-based harmonic analysis method for distribution systems. *IEEE Trans. Power Deliv.* **2007**, *22*, 1665–1672. [CrossRef]