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Network security-aware charging of electric vehicles

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ABSTRACT

Large-scale integration of electric vehicles (EV) and wind power could have significantly negative impacts on power systems security. So, it is becoming an increasingly important issue to develop an effective network security-aware charging strategy of EVs. This paper proposes a multi-objective formulation for the optimal charging schedule of EVs while considering N − 1 security constraints. An EV aggregator representing a cluster of controllable EVs is modeled for determining the optimal charging schedule based on a trilevel hierarchy. On the top level, the grid control center determines the EV charging strategy from the proposed formulation, where bus voltage fluctuations, network power losses, and EV charging adjustments are considered as multi-objective functions. To reduce the computational burden, Lagrangian Relaxation (LR) is introduced to handle time coupled constraints and Benders Decomposition is introduced to handle contingencies. Case studies have been conducted on the New England 39-bus system, and the results verify the necessity of considering N − 1 security constraints and the effectiveness of the proposed formulation and solution approach.

1. Introduction

Electric vehicles (EVs) have been receiving considerable attentions worldwide as they are clean and green. However, the large-scale integration of EVs, without coordination, may bring negative impacts on power systems operation, such as lower voltage quality, larger power losses, and more harmonics [1]. Therefore, effective strategies should be developed to schedule the charging of EVs to mitigate the negative impacts and even benefit the grid [2].

In the literatures, studies about EV charging schedule are concentrated on distribution network. Up to now, only a few literatures discussed the charging issues of EVs from the transmission network viewpoint. Ref. [3] presented a bi-level model for coordinating the charging/discharging schedules of EVs. The upper-level model minimizes the system load variance to implement peak load shifting by dispatching each aggregator, and the lower one traces the dispatching scheme determined by the upper-level decision-maker by figuring out an appropriate charging/discharging schedules throughout a specific day. Ref. [4] proposed a multi-objective non-linear mixed integer optimization model for EV charging scheduling considering the uncertainties of photovoltaic and wind power in regional power grids. The fuzzy theory was used to change the multi-objective optimization model into a single-objective non-linear optimization problem.

EV charging schedule problems are mostly formulated as optimization issues aiming at improving voltage profile [5–7], flattening load profile [6–10], reducing power losses [7–11], offering ancillary services [12], minimizing the charging cost [13–15], or increasing user satisfaction level [16,17]. Ref. [5] presented a decentralized optimization methodology to coordinate EV charging to facilitate the voltage control on a residential distribution feeder. Ref. [10] presented a methodology to optimize power system demand due to EV charging load, and it was demonstrated that EV charging load has significant potential to flatten the national demand profile in the U.K. Ref. [11] proposed an optimization model considering EV charging demand and voltage constraints to minimize the power losses of distribution systems. Ref. [12] presented a stochastic method for optimal coordination of charging and frequency regulation for an EV aggregator using the Least Square Monte-Carlo technique while modeling electricity price uncertainty. Ref. [15] proposed an intelligent method to control EV charging loads in response to time-of-use price in a regulated market. Ref. [16] proposed a new metric to represent the EV user satisfaction fairness to achieve a tradeoff between the user satisfaction fairness and the total charging cost of electricity.

The existing EV charging scheduling methods did not take the $N-1$ security constraints into account. However, the secure operation of the system under $N-1$ contingency is an essential requirement [18]. This paper proposes a multi-objective optimization model for EV charging schedule considering $N-1$ security constraints. The main

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Nomenclature

Indices and sets

b	index for lines
i	index for EV aggregators
j,m	index for buses
k	index for generators
l	index for iterations
s	index for system operation scenarios: 0 denotes normal condition, and others represent contingencies
t	index for hours

Constants

T	scheduling duration (24 h in this paper)
n	number of EV aggregators
S	number of slave problems
N	number of buses
L	number of lines
Δt	time interval, 1 h in this paper
w_1,w_2,w_3	weighting factors of the three objectives
$d_{i,t}$	charging duration of EV aggregator i at time t
E_{ev}	total energy demands of EVs during one day
$P_b^{\max}$	upper limit of power flow through line b
$Pch_{i,t}^{\min}$	lower limit of charging power of EV aggregator i at time t
$Pch_{i,t}^{\max}$	upper limit of charging power of EV aggregator i at time t
$P_{\mathrm{Gk}}^{\min}$	lower limit of active power of generator k
$P_{\mathrm{Gk}}^{\max}$	upper limit of active power of generator k
$Q_{\mathrm{Gk}}^{\min}$	lower limit of reactive power of generator k
$Q_{\mathrm{Gk}}^{\max}$	upper limit of reactive power of generator k
$U_j^{\min}$	lower limit of voltage at bus j
$U_j^{\max}$	upper limit of voltage at bus j
U_j^d	desired voltage at bus j (per unit)
$\Delta U_j^{\max}$	maximum permissible voltage deviation at bus j
$Pch_{i,t}^{pre}$	predicted charging power of EV aggregator i at time t

Variables

f_1,f_2,f_3	three objective functions
$P_{\mathrm{loss},t}$	power loss at time t
$R_{b,t}$	line resistance of line b at time t
$I_{b,t}^f + jI_{b,t}^e$	current thought line b at time t
$P_{ll,t}$	total load at time t
Pch_i	total charging power of EV aggregator i
$Pch_{i,t}$	optimal charging power of EV aggregator i at time t
$P_{j,t}^s$	active power injection at bus j at time t
$P_{\mathrm{Gk},t}^s$	active power of generator k at time t
$Q_{\mathrm{Gk},t}^s$	reactive power of generator k at time t
$Q_{j,t}^s$	reactive power injection at bus j at time t
$U_{j,t}^s$	voltage at bus j at time t (per unit)
$G_{jm,t}^s$	the element in j^{th} row and m^{th} column of the conductance matrix at time t
$B_{jm,t}^s$	The element in j^{th} row and m^{th} column of the susceptance matrix at time t
$\theta_{jm,t}^s$	voltage angle difference between buses j and m at time t
λ	Lagrangian multiplier for the time coupled constraint
$Pch_{i,t}^*$	trial charging strategy of EV aggregator i at time t
$I_{b,t}^s$	Current through line b at time t
x	state vector (bus voltage in this paper)
u	control vector (charging power of EV aggregators)
u_0	EV charging strategy vector in normal condition
u_0^*	trial EV charging strategy vector
u_s	EV charging strategy vector in contingency s
δ_b,δ_c	vectors of slack variables for $u_s = u_0^*$
Λ	dual variable vector for $u_s + \delta_c - \delta_b = u_0^*$

contributions of this paper include: (1) the day-ahead optimal EVs charging model, aiming at improving voltage profile, reducing network power loss, and improving user satisfaction, from the transmission network viewpoint is proposed; (2) the $N-1$ contingencies are taken into consideration to guarantees the secure operation of the system under $N-1$ contingencies, which is important for transmission systems. For better implementation, we introduce Lagrangian Relaxation (LR) [19] and Benders Decomposition (BD) methods to solve the proposed formulation. The former is to handle the time coupled constraint and the latter is to handle contingencies in the optimal EV charging scheduling model.

The rest of the paper is organized as follows. Section 2 presents the problem formulation. Section 3 proposes the solution methodology based on LR and BD. The proposed model and solution approach is tested with the IEEE 39-bus systems in Section 4. Conclusions and future work are discussed finally.

2. Problem formulation

2.1. Conceptual framework

Since the capacity of a single EV is too small to have a measurable influence on a transmission grid, an equivalent model (EV aggregator) that represents a cluster of controllable EVs is introduced here to describe their aggregated effects. Using these EV aggregators, a conceptual framework for optimal EV charging schedule based on a trilevel hierarchy is developed and shown in Fig. 1.

At the top level, the optimal dispatch is determined by the control center, and the objective is to determine the charging power of individual EV aggregators based on the predicted wind, solar, and load power. At the middle level, each EV aggregator receives the optimal schedule from the control center and decomposes them into charging strategies for individual EVs. At the bottom level, individual EV communicates with the aggregator, and follows the schedule it receives [20].

This paper focuses on the top transmission level to obtain a day-ahead schedule of EV aggregators for improving the system voltage profile, reducing the power loss, and improving user satisfaction. The main assumptions are as follows:

- The base case is formulated with unit commitment calculated in advance according to daily load curve, daily wind power curve, and predicted EV charging demand/ profile curves.
- The power outputs of conventional generators are adjusted according to the total load change during the optimization.

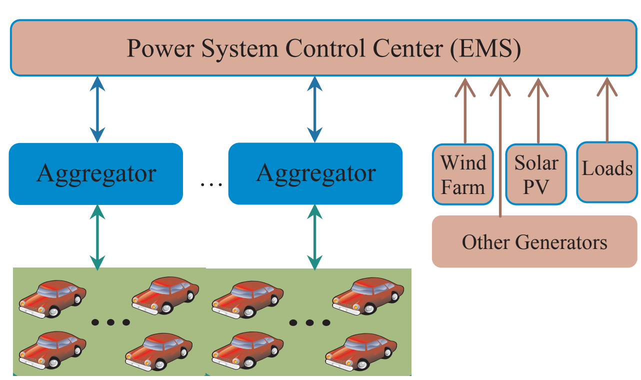

Fig. 1. Trilevel hierarchy for EV charging schedule.

- The minimum and maximum charging power of the stations are given according to Ref. [20].
- When the SOC of an EV is less than 0.4, it needs to be charged. When the SOC of an EV is higher than 0.8, the charging is stopped.

2.2. Objective function

In practical power systems, the voltage profile is the most fundamental concern. Second, minimizing the power loss is to serve economic purposes. Third, the satisfaction of the users is becoming an increasingly important factor to be considered. The former two objectives are beneficial to the power system, but they could lead to EVs charging load shifting and influence the users' satisfaction. However, EVs and their aggregators could get economic benefits from the incentives such as peak and valley prices and various services such as spinning reserve markets. In this paper, we focus on the charging scheduling from power system viewpoint, thus the above three factors are taken as the objective functions in the studies.

The objective of the optimal charging schedule model in (1) is to obtain the daily charging curve for each EV aggregator to improve the system voltage profile (f_1), to reduce the power loss (f_2), and to meet user satisfaction (f_3).

$$\min\ w_1\times f_1+w_2\times f_2+w_3\times f_3 \tag{1}$$

$$f_1=\sum_{t=1}^{T}\sum_{j=1}^{N}(U_{j,t}-U_j^d)^2 \tag{2}$$

$$f_2=\sum_{t=1}^{T}\frac{\sum_{b=1}^{L}R_{b,t}I_{b,t}^2}{P_{tl,t}} \tag{3}$$

$$f_3=\sum_{t=1}^{T}\sum_{i=1}^{n}\left(\frac{Pch_{i,t}-Pch_{i,t}^{pre}}{Pch_{i,t}^{pre}}\right)^2 \tag{4}$$

where w_1, w_2 and w_3 are weighting factors of the three objective functions. $Pch_{i,t}$ represents the optimal charging power of EV aggregator i at time t, which is the main decision variable. In order to coordinate the system voltage profile, the power loss, and the user satisfaction, a combinatorial strategy with the portfolio optimization of the three objectives is employed.

The multi-objective optimization problem is organized into simple portfolio optimization which is shown as (1). The voltage profile objective in (2) is formulated as the sum of squared deviations of voltage [21]. The power loss objective in (3) is formulated as the ratio of the total power loss $P_{loss,t}$ to the total load $P_{tl,t}$. The user satisfaction objective in (4) is formulated as the sum of squared deviations of EV charging power. Note that the three weights can be adjusted according to specific requirements of a given system.

2.3. Constraints

Constraints about EVs and power networks are considered. Note that the constraints are for both base case and N − 1 contingencies. In the constraints shown in (5)–(10), s represents index for system operation scenarios: $s = 0$ corresponds to the operational constraints at normal conditions, and others represent the security constraints at contingencies.

(1) EV charging demands

The total EV charging demand must be covered throughout the daily charging process [6] as shown in (5).

$$\sum_{t=1}^{T}\sum_{i=1}^{n}Pch_{i,t}^s\times d_{i,t}=E_{ev}\ ,\quad \forall\ s \tag{5}$$

where $Pch_{i,t}^s$ is the charging power of EV aggregator i at time t under scenario s ($s = 0$ for base case, others for contingencies). $d_{i,t}$ is the charging duration of EV aggregator i at time t. E_{ev} is the total energy demand of all EVs during one day. The sum of all aggregated EV charging power during one day should be equal to the total energy demand.

(2) EV charging constraints

Due to the diverse driving habits of the EV owners, the number of grid-connected EVs is time-varying. So, the capacity limits of EV charging power vary with time correspondingly.

$$Pch_{i,t}^{\min}\leqslant Pch_{i,t}^s\leqslant Pch_{i,t}^{\max}\ ,\quad \forall\ i,t,s \tag{6}$$

where $Pch_{i,t}^{\min}$ and $Pch_{i,t}^{\max}$ depend on the capacity, the initial state of charge, charging time, type, and travel characteristics of EVs. In this paper, the charging constraints are set in (6) according to Ref. [20].

(3) Power output limits of generators

The power output limits of a generator are shown in (7).

$$\begin{cases}P_{Gk}^{\min}\leqslant P_{Gk,t}^s\leqslant P_{Gk}^{\max}\\ Q_{Gk}^{\min}\leqslant Q_{Gk,t}^s\leqslant Q_{Gk}^{\max}\end{cases},\quad \forall\ k,t,s \tag{7}$$

(4) Power flow equations

The power flow equations for every bus are shown in (8).

$$\begin{cases}P_{j,t}^s-U_{j,t}^s\sum_{m=1}^{N}U_{m,t}^s(G_{jm,t}^s\cos\theta_{jm,t}^s+B_{jm,t}^s\sin\theta_{jm,t}^s)=0\\ Q_{j,t}^s-U_{j,t}^s\sum_{m=1}^{N}U_{m,t}^s(G_{jm,t}^s\sin\theta_{jm,t}^s-B_{jm,t}^s\cos\theta_{jm,t}^s)=0\end{cases},\quad \forall\ j,t,s \tag{8}$$

(5) Voltage limits of buses

The voltage of each bus needs to be within a permissible range, as shown in (9). In this paper, the voltage constraints are set to ± 10% ($U^{\min} = 0.9$ and $U^{\max} = 1.1$).

$$U_j^{\min}\leqslant U_{j,t}^s\leqslant U_j^{\max}\ ,\quad \forall\ j,t,s \tag{9}$$

(6) Line flow limits

The current through each line must be below its limit as shown in (10).

$$I_{b,t}^s\leqslant I_b^{\max}\ ,\quad \forall\ b,t,s \tag{10}$$

3. Solution approach

The optimal charging schedule model in Section 2 represents a security constrained charging scheduling (SCCS) problem. It is a large time-coupled nonlinear optimization problem with a large number of variables and constraints. P_{ch} is the decision variable whose dimension is 72. The number of the constraints is more than 230,782. For the time-coupled constraint shown in (5), LR, as an excellent tool, relaxes the constraints by introducing a Lagrangian multiplier. In addition, BD is used to decompose the SCCS problem into a master problem that solves the base-case charging schedule and a set of slave problems that check the feasibility of the obtained charging schedule against the security constraints under individual contingencies.

3.1. LR-based relaxation of time-coupled constraints

LR is a powerful relaxation technique. It can be used based on the observation that an optimization problem complicated by a lot of coupling constraints can be modeled as a relatively easy Lagrangian problem. As for the CS problem described by (1)–(10), constraint (5) is the only time-coupled coupling constraint. So we define the Lagrangian problem as (11).

$$\begin{aligned} \min \quad & w_1 \cdot f_1 + w_2 \cdot f_2 + w_3 \cdot f_3 + \lambda\left(\sum_{t=1}^{T} \sum_{i=1}^{n} Pch_{i,t} \cdot d_{i,t} - E_{\text{ev}}\right) \\ \text{s.t.} \quad & g(x,u) = 0 \\ & h(x,u) \leqslant 0 \end{aligned} \tag{11}$$

In (11), x is the state vector which represents bus voltage in this paper; u is the control vector which represents charging power of the EV aggregator; λ is the Lagrangian multiplier for the time-coupled constraint (5). $g(\cdot) = 0$ represents power flow equation constraints shown in (8). $h(\cdot) \leqslant 0$ represents inequality constraints, including (6), (7), (9) and (10).

It should be mentioned that, only the constraint for base case needs to be relaxed in (11). In vector form, we have

$$Pch = Pch^s, \quad \forall\, s \tag{12}$$

where u_0 and u_s represent the EV charging strategies in normal condition and contingency s, respectively. Eq. (12) represents the linking constraint between base case and contingency case.

3.2. BD-based handling of contingency constraints

(1) Fundamentals of Benders decomposition

The optimal charging model of EV aggregators considering N − 1 security constraints is a complex optimization problem that is difficult to solve directly [22]. There is slight coupling relationship between various operating scenarios, i.e., (12). So, BD could be introduced to decompose the original optimization problem into a master problem for base case and slave problems for individual contingencies. The iterative process between the master problem and slave problems continues until there is no violation on the security constraints [23]. Accordingly, the computational complexity can be reduced significantly and the computational efficiency can be improved.

(2) Master problem

The master problem is to find the trial charging strategy $Pch_{i,t}^{*}$, or u_0^{*} in vector form, which satisfies the base-case constraints. The master problem can be described as:

$$\begin{cases} \min\; w_1 \cdot f_1 + w_2 \cdot f_2 + w_3 \cdot f_3 + \lambda\left(\sum_{t=1}^{T} \sum_{i=1}^{n} Pch_{i,t} \cdot d_{i,t} - E_{\text{ev}}\right) \\ \text{s. t.} \\ \quad g(x_0,u_0) = 0 \\ \quad h(x_0,u_0) \leqslant 0 \\ \quad f_s^{*} + \Lambda^T (u_0 - u_0^{*}) \leqslant 0 \end{cases} \tag{13}$$

In (13), the objective function is the same as that of (11), which is for base case only, and the constraints include those for the base case ((6)–(10), $s = 0$) and the Benders cuts fed from the slave problems. $g(x_0,u_0) = 0$ and $h(x_0,u_0) \leqslant 0$ represent the equality and inequality constraints in the base case, respectively. $f_s^{*} + \Lambda^T(u_0 - u_0^{*}) \leqslant 0$ represents the Benders cut fed back from slave problem s which is discussed next.

In solving (13), once a solution is obtained, time-coupled coupling constraint (5) will be checked and λ will be updated. This process continues until (5) is satisfied.

(3) Slave problems

The slave problems check the feasibility of the obtained charging strategy $Pch_{i,t}^{*}$ (or u_0^{*} in vector form) against the security constraints. Benders cuts will be formed if there is any violation on the security constraints under contingencies. The slave problem formulation is shown in (14).

$$\begin{cases} \min\; f_s = \sum (\delta_c + \delta_b) \\ \text{s. t.} \\ \quad g(x_s,u_s) = 0 \\ \quad h(x_s,u_s) \leqslant 0 \\ \quad u_s + \delta_c - \delta_b = u_0^{*} \end{cases} \tag{14}$$

In (14), the constraints include those for the contingency case ((5)–(10)) and the linking constraints between the base case and the contingency case, i.e., (12). $g(x_s,u_s) = 0$ and $h(x_s,u_s) \leqslant 0$ represent the equality and inequality constraints in the contingency case, respectively. δ_c and δ_b are the slack variables of the linking constraints $u_s - u_0^{*} = 0$. The objective function in (14) is the summation of all slack variables.

If $\delta_c + \delta_b = 0$, no Benders cut is formed. Otherwise, a Benders cut in (15) is formed and fed back to the master problem.

$$f_s^{*} + \Lambda^T (u_0 - u_0^{*}) \leqslant 0 \tag{15}$$

where f_s^{*} is the value of the objective function in (14) and Λ is the dual variable vector for $u_s + \delta_c - \delta_b = u_0^{*}$. (15) indicates how the base case EV charging strategy (u_0) can be adjusted to eliminate potential security constraints violation in contingency case.

3.3. Flowchart

In our studies, the network security-aware charging issue of EVs is decomposed into one master problem, aiming at optimal charging of EVs, and a set of slave problems that check the feasibility of the obtained charging strategy from the master problem. The decision variables of the master problem are the EVs charging power of each aggregator 24 time dimensions. The objective of the master problem is LR relaxed portfolio optimization. The variables of the slave problem are the slack variables of the linking constraints $u_s - u_0^{*} = 0$. The solution procedures are as follows.

Step 1: Read EV parameters, generator parameters, daily loads and other system parameters.
Step 2: Initialize all constraints and Benders cuts of slave problems.
Step 3: Solve the master problem that is the LR relaxed portfolio optimization. A trial charging strategy can be obtained.
Step 4: Screen all contingencies and form the candidate contingency set.
Step 5: Check the feasibility of the trial charging strategy under all contingencies one by one. If the trial charging strategy can maintain system security operation, $f_s = 0$, no benders cut turn back, or fed back $f_s^{*} + \Lambda^T(u_0 - u_0^{*}) \leqslant 0$ to master problem, turn to Step 3 until all slave problems meet security constraints.

The flowchart of the above solution process is shown in Fig. 2.

4. Case studies

4.1. Test system and parameters

The modified New England 39-bus test system is used for case studies in a computer with i7-6700 2.6 GHZ processor and 8 GB memory. Two wind farms are located at buses 30 and 35, and their daily power curves can be found in [24]. The detailed test system parameters can be found in [25]. Three EV aggregators are connected to the network at

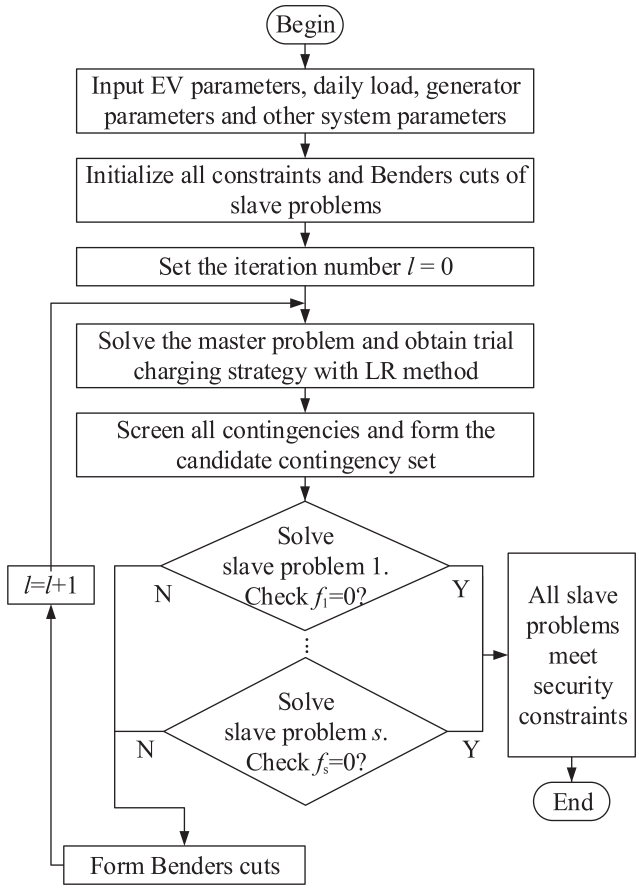

Fig. 2. Flowchart of the solution process.

buses 3, 10 and 23. The parameters of EVs are obtained by survey data [26]. The three weights of the objectives are set as $w_1 = 0.5$, $w_2 = 0.25$ and $w_3 = 0.25$ in case studies.

It is an important issue to predict the EVs charging demand. The decisive factors affecting the charging load of EVs in a region include the number and types of electric vehicles, travel characteristics, charging strategies, etc. In [27], the authors presented a statistical model to predict the EV charging load. In [28], the charging traffic flow was introduced as a discrete sequence to describe charging start events, and a set of equations are proposed to build a probabilistic EVs charging load model. In [29], the historical traffic data and weather data of South Korea were used to formulate the forecasting model. In [30], a novel methodology was developed to calculate the dynamic transition of the combined SOC distribution from one timeslot to the next for a large number of EV units, and a SOC-based charging strategy was then proposed to estimate the aggregated power demand. In our study, the Monte Carlo simulation method was used to simulate the starting SOC and the initial charging time of individual EVs, and further to obtain the predicted daily charging power curves of the EV aggregators [24]. Due to space limitations, the calculation process is not shown in this paper.

The charging power curves of EV aggregator 1 under predicted charging mode and scheduled mode are shown in Fig. 3. It can be seen that, under predicted charging mode, most of the EVs will be charged at noon and in the evening. In this case, the system voltage in some regions may decline sharply, because other loads are also relatively large during those times [24]. Therefore, it is of great significance of develop an optimal charging schedule to shift the charging power of EVs to other times and make the charging curves more smooth.

4.2. Necessity of considering N − 1 security constraints

The charging curves of EV aggregator 1 with and without the security constrains are also shown in Fig. 3. It can be seen from the comparison of the charging curves of EV aggregator 1 with and without the security constrains that, there are relatively large adjustments during times 6:00–8:00 and 15:00–18:00. It means that without security-aware, if $N - 1$ contingencies occur at these times, the system may go to abnormal conditions. Firstly, we discuss the lowest voltage when contingency occurs at each line, which shows the necessity of N − 1 security constraints. Then, we discuss the detailed daily voltage curves of buses when specific N − 1 contingency occurs.

If the charging schedules of EV aggregators are obtained without considering N − 1 security constraints, the lowest voltages of the system during a day when a contingency occurs are plotted as the black columns in Fig. 4. If the charging schedules are obtained using the proposed method, the results are plotted as the yellow columns in Fig. 4. It can be observed that the voltage profiles of the system can be greatly improved.

Take branch 23 for example. The daily voltage curves of bus 11 when branch 23 is disconnected are shown in Fig. 5. For the charging schedules of EV aggregators obtained without $N - 1$ security constraints, bus 11 will experience low voltage at time 15:00. So, it can be concluded that considering $N - 1$ security constraints is very important for determining the EV charging schedule. Without the consideration of $N - 1$ security constraints, the system is likely to experience voltage problem when a contingency occurs.

4.3. Effectiveness of the proposed method

Figs. 6–8 present the system voltage profiles, the cumulative power losses, and the net system load profiles, obtained by using the proposed charging mode and the predicted charging mode, respectively.

It can be seen from Fig. 6 that the centralized EV charging causes a voltage dip at 19:00 under predicted charging mode. The proposed method can obtain an effective charging schedule that shifts the EV charging loads to other periods when the system voltage problem is not prominent. The proposed charging schedule can achieve peak load shifting (Fig. 8), improve system voltage profile (Fig. 6), and greatly reduce power losses of the system (Fig. 7).

4.4. Effectiveness of the portfolio optimization

The three objective functions and their combination in (1) are selected to compare the charging schedules of EV aggregators. The

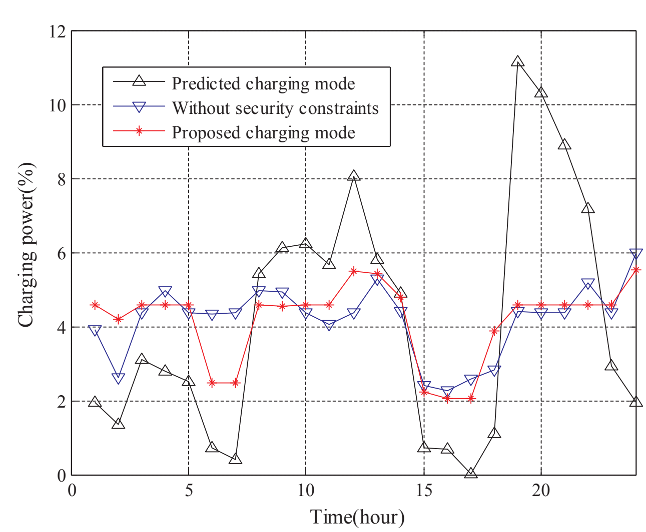

Fig. 3. Charging curves of EV aggregator 1.

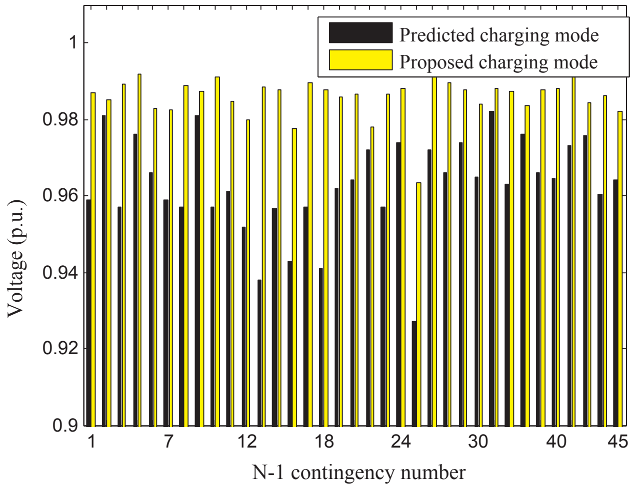

Fig. 4. The lowest voltages in the system under individual N − 1 contingencies.

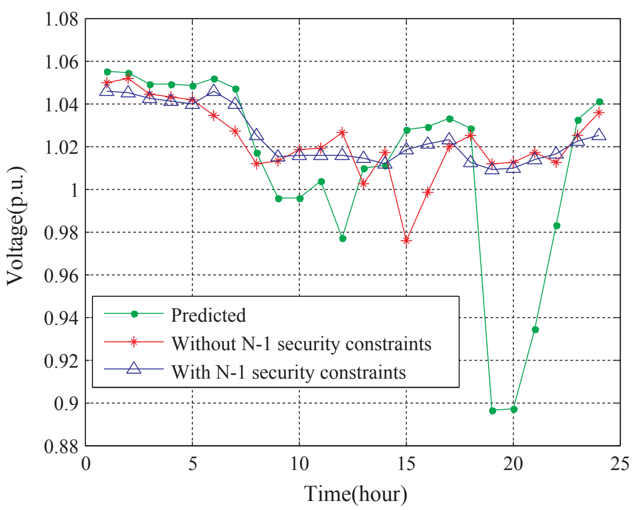

Fig. 5. Daily voltage curves of bus 11 when branch 23 is disconnected.

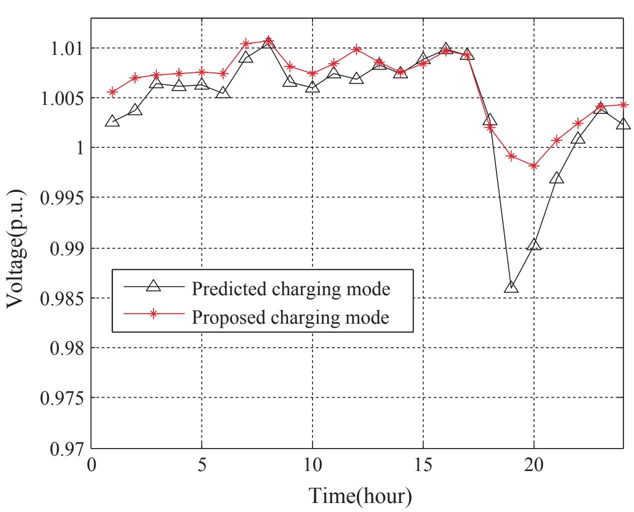

Fig. 6. Voltage magnitude curves of bus 21.

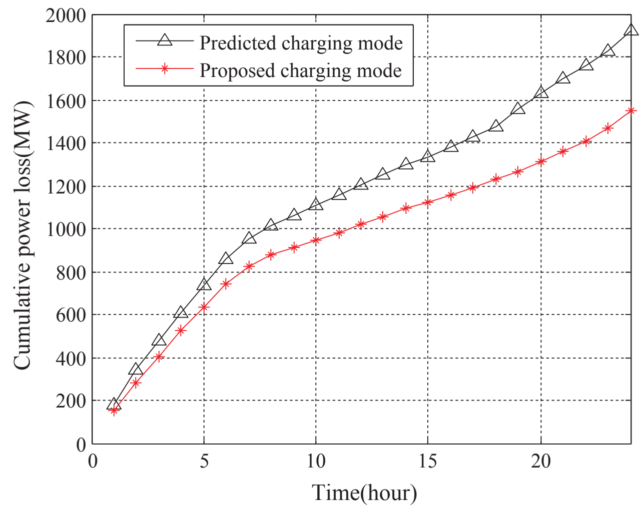

Fig. 7. Cumulative power loss curves of the system.

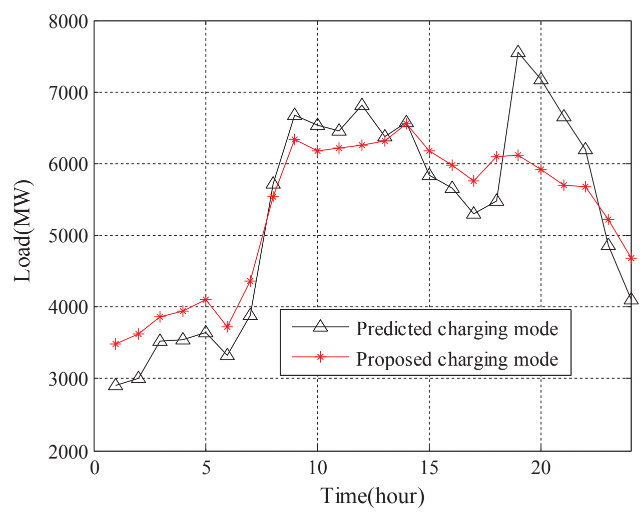

Fig. 8. Net load curves of the system.

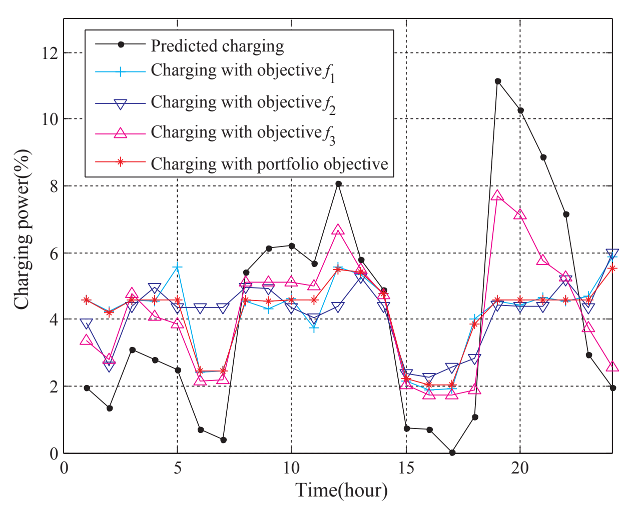

Fig. 9. Charging curves of EV aggregator 1 under different objectives.

charging curves of EV aggregator 1 under the objective f_1, f_2, f_3, and the portfolio of the three are shown as Fig. 9. The voltage profile is the most important factor. The charging curve is most similar with that under the portfolio objective. The charging curve can be flattening with objective f_1, f_2 and the portfolio objective. However, users' satisfaction needs fewer changes. Combinatorial optimization can reconcile the contradiction between the two aspects. The voltage deviations, the power losses, and the charging deviations are compared in Table 1.

Table 1
Objective values with different objective functions.

Objective	Voltage deviations	Power losses	EV charging deviations
f_1	0.00148	0.01616	0.04230
f_2	0.00153	0.01569	0.04344
f_3	0.00230	0.02222	0.02129
portfolio	0.00152	0.01657	0.03746

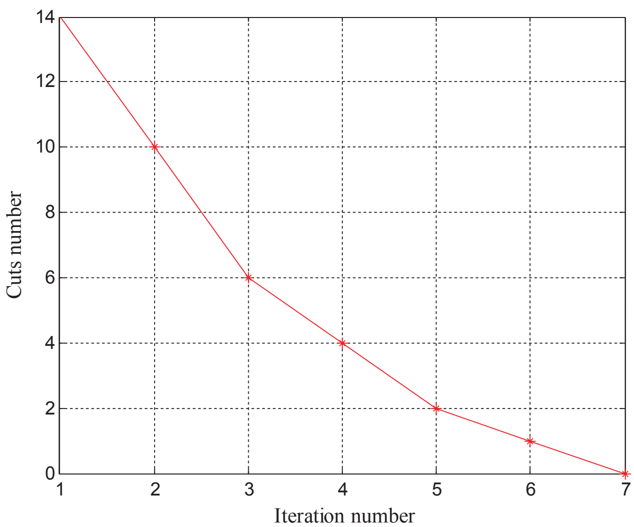

Fig. 10. Number of Benders cuts fed back during the iterations.

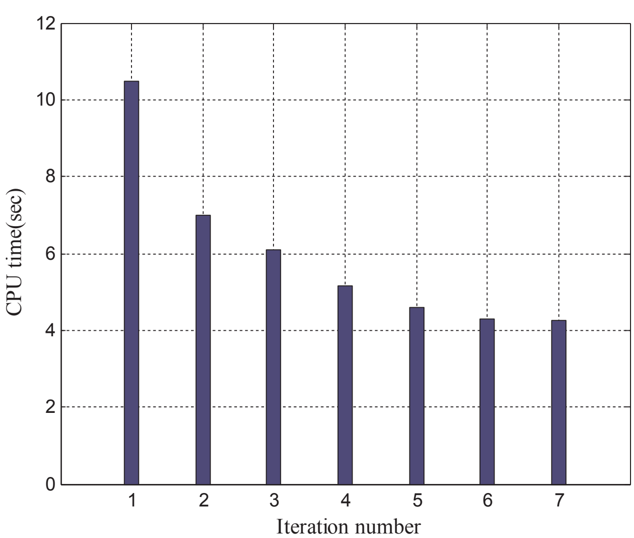

Fig. 11. The longest CPU time that one slave problem takes in each iteration.

When f_1 is selected as the objective function, the charging schedules can greatly improve the system voltage profile and reduce the power loss. However, as the EVs charging is guided and controlled, the charging power curve of EVs will change. As a result, the user satisfaction represented by EV charging deviation will be affected to a certain extent. When f_2 is selected as the objective function, the power losses of the system could be minimized, and the voltage profile could also be enhanced, but the charging power curve further deviates from the original one. When f_3 is selected, the charging power deviations would be less than those in other cases, as it aims at satisfying the preferred user requirements. However, the system voltage profile deteriorates heavily. Meanwhile, the power losses are also much larger.

It can be concluded from the above analysis that, in order to coordinate the system voltage profile, the power losses and the user satisfaction, it should employ a combinatorial strategy with the portfolio optimization of the three objectives. As shown in the case with portfolio objective, such a charging schedule can ensure the voltage profile and mitigate the voltage issue. Moreover, the portfolio optimization can preferentially select the optimal schedules which can reduce the power losses and improve the user satisfactions.

4.5. Computational efficiency

LR is introduced in this paper to handle the time-coupled EV charging energy demand constraints. The base charging scheduling problem without considering security constraints is solved in 4 iterations in 113 s. However, without LR, the charging scheduling problem is solved in 211 s by the same program.

BD builds the slave problems for checking transmission network security constraints and forming Benders cuts when needed. Assume that each N − 1 contingency occurs in one time interval. There are 35 contingencies considered in this case study. Without BD, the number of variables is about 5812. It is not easy to directly solve such a problem for practical power systems, because of the limited computing resources. In this paper, BD is applied to solve the optimization problem with N − 1 security constraints. The problem converges after 7 iterations. Fig. 10 shows the number of Benders cuts fed back at each iteration.

It can be seen that the optimization problem can converge quickly. There are 14 Benders cuts fed back at the first iteration, and there is no benders cut after 7 iterations. The longest CPU time that one slave problem takes in each iteration is shown as Fig. 11. It indicates that BD is effective in solving the proposed optimal EV charging problem considering network security constraints.

5. Conclusion

This paper proposes a multi-objective formulation for the optimal charging schedule of EVs with N − 1 security constraints. An EV aggregator representing a cluster of controllable EVs is modeled for determining the optimal charging schedule based on a trilevel hierarchy. On the top level, the grid control center determines the EV charging strategy from the proposed formulation, where bus voltage fluctuations, network power losses, and EV charging adjustments are considered as multi-objective functions. To reduce the computational burden, Lagrangian Relaxation (LR) is introduced to handle time- coupled constraints, and Benders Decomposition is introduced to decompose the EVs charging formulation into one master problem that solves the base-case charging schedule and a set of slave problems that check the feasibility of the obtained charging schedule against the security constraints under individual contingencies.

Case studies have been conducted to demonstrate the effectiveness of the proposed formulation and solution method. The results show that the proposed charging strategy can solve the potential security problems of the system, and the portfolio optimization can preferentially select the optimal schedule to improve the system voltage profile, reduce the system power losses, and improve the user satisfactions.

In this paper, unit commitment is set in advance. A better strategy could be obtained by the co-optimization of the EV charging with unit commitment. In addition, we only discuss the optimization strategy of the control center. Future works can be done to the optimization strategy of the EVs aggregator, which may provide more exact limits of charging power of EV aggregators to the control center.

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