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Published in:
International Journal of Electrical Power & Energy Systems

DOI (link to publication from Publisher):
10.1016/j.ijepes.2023.109444

Publication date:
2023

Document Version
Publisher's PDF, also known as Version of record

Electrical Power and Energy Systems 154 (2023) 109444

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

A multi-time scale coordinated control and scheduling strategy of EVs considering guidance impacts in multi-areas with uncertain RESs

Zekun Li [a], Yi Sun [a], Hongyue Yang [a], Shiwei Wang [a], Yaqi Shen [a,*], Xianchun Wang [b], Kai Zhang [b], Amjad Anvari-Moghaddam [c]

[a] School of Electrical and Electronic Engineering, North China Electric Power University, Beijing 102206, China
[b] State Grid Hebei Electric Power Co., Ltd., Shijiazhuang 050022, China
[c] Department of Energy (AAU Energy), Aalborg University, 9220 Aalborg, Denmark

A R T I C L E I N F O

Keywords:
EVs
Multi-areas
Multi-time scale
Coupling effects
Economic scheduling
Coordinated control

A B S T R A C T

With the increased electrification of transportation sector, the electric vehicles (EVs) are deemed to be key players in energy scheduling act to realize more economical operation of distribution networks. EVs have the function of energy space–time transfer, and energy-space coupling effects need to be considered in scheduling. In this paper, EVs' spatial characteristics from multi-areas and characteristics of transferable charging power are both taken into account, then a multi-time scale coordinated control and scheduling strategy is proposed to achieve optimal schedules in both day-ahead (DA) and real-time (RT) periods. First, in DA periods, EVs are modeled as shiftable and location-flexible loads to participate in multi-areas' scheduling task managed by a unified distribution system operator (DSO). To attract more spatially distributed EVs to different charging stations and avoid charging congestion, a price-based transfer model (PBTM) is established to realize EVs charging guidance in different areas while integrated into the DA stochastic scheduling. Next, in RT periods, EVs are modeled as controllable loads to compensate RT power errors caused by uncertain renewable energy sources (RESs) and inaccuracies associated with DA prediction. Both DA and RT scheduling are coordinated with a RT control strategy for EVs, in which a state space model (SSM) is constructed to calculate charging power and then form 1-min control signals to realize the tracking of multi-time scale schedule. Simulation results demonstrate that the proposed coordinated control and scheduling strategy can guide more EVs to be grid-connected, promote multi-time scale economic scheduling, and benefit the EV users meanwhile.

1. Introduction

Renewable energy sources (RESs) have been focused by many researchers worldwide. However, a high penetration of RESs will bring huge challenges to power system operation and control due to their uncertain behaviours [1,2]. Therefore, the power system should be equipped with more adjustable resources to deal with various uncertainties. Demand response (DR) is an important and cost-effective solution for improving system operation through offering various services including frequency regulation [3,4], voltage control [5] and peak load shaving [6], among others.

As a typical DR resource, electric vehicles (EVs) can change power consumption flexibly and quickly. Some researchers apply EVs to solve the imbalance problem of power supply and demand, especially in distribution systems with distributed RESs. For example, in [7], an optimal charging and frequency reserve scheduling strategy of EVs is proposed for service provision in day-ahead (DA), which aims at seeking a benefit balance between the aggregator and EV users. In [8], in order to manage the imbalanced power caused by distributed photovoltaic (PV) generation, a novel control scheme for EVs is proposed to obtain a fast balance response from demand side and to considerably curtail the operation risk.

To utilize the EVs' regulation ability for power system operation, two levels of researches are explored, i.e. the system level and equipment level. On the system level, the main focus is on the operation benefit brought by EVs' regulation. For example, considering both charging and discharging characteristics of EVs, an estimation method for EVs' regulation capacity is designed to establish a contract for frequency

* Corresponding author.
E-mail addresses: jimmy_94@126.com (Z. Li), sy@ncepu.edu.cn (Y. Sun), yang_hong_yue@163.com (H. Yang), wsw157157@163.com (S. Wang), jsntsyq1994@163.com (Y. Shen), wang_xianchun2022@163.com (X. Wang), zk2212@126.com (K. Zhang), aam@energy.aau.dk (A. Anvari-Moghaddam).

https://doi.org/10.1016/j.ijepes.2023.109444
Received 5 January 2023; Received in revised form 18 June 2023; Accepted 12 August 2023

regulation caused by power imbalance in [9]. Also in [10], EVs are modelled as a flexible charging/ discharging resource to minimize the daily charging cost when considering uncertain RES. However, it is unreasonable and not viable to obtain balance services by EVs' discharging frequently [11]. So some researchers aim to provide balance service through EVs' charging management. In [12], an electric energy management strategy considering EVs, battery storages, and PV generation is proposed to minimize the cost of electricity whilst taking a full account of user' energy demand and travel patterns. In [13], a real-time (RT) charging management method for EVs is proposed to achieve the maximum consumption of RES in local microgrid-like system.

The above-mentioned researches are single time-scale, in most of which only DA or RT system operation benefits are considered. However, single-time scale scheduling cannot fully utilize EV regulation potential. There are also multi time-scale researches like [14–16]. In [14], a two-stage economic operating strategy of a photovoltaic (PV)-based microgrid is proposed by considering the solar uncertainty in DA stage and parking uncertainty in RT stage. In [15], a robust multi-time scale energy management strategy based on EVs' flexibilities is proposed to optimize power schedule in DA periods and power tracking method in RT periods. Also, in [16], a two-stage optimized framework for EV charging based on transactive control is addressed for the aggregator to minimize its total operating cost. No matter in single-time scale or multi-time scale, most researchers pay great attention to scheduling from the system level, but don't consider the coordination of EVs control from the equipment level. Under this circumstance, the actual control effect may be deviated from the scheduling, because the operator cannot consider all status of distributed EVs and the status affect the control actions.

On the equipment level, the main aim is to control EVs directly or by designing charging menus, incentive mechanisms in order to change EVs' charging behaviors indirectly. Such researches can create benefits for charging stations (CSs), and provide various balance service for RES-penetrated power grid, meanwhile. For example, in [17], a novel charging price strategy for CS is developed to determine the pricing rules for voltage security provided by EVs in the distribution system. In [18], a price-based service menu for EV charging is designed to let users pick their preferable charging options online. Similarly, in [19], a menu-based pricing mechanism is proposed for a CS to maximize the profit and social welfare. Further, to handle the negative impact from uncertain RT price and randomness of user's behaviors, an extended model-free approach based on deep reinforcement learning is put forward to form the optimal charging scheduling in [20]. Whereas, these researches only focus on single area, the application of which will be limited to a single CS or charging pile. Thus, these schemes can only be applied to a limited number of users, i.e. arrived users. Certainly, some researchers explore user-oriented strategies to conduct competition of CSs and realize the optimal benefit of multiple CSs. For example, from the perspective of CS operators [21], a multi-leader–multi-follower Stackelberg game model has been proposed with two competing CSs to obtain price equilibrium. Also in [22], a price competition among different CSs with RESs in different areas is investigated to determine the optimal charging price for EV users. Different from [17–20], the price information in [21,22] must be shared to users and then EV users can be guided before their arrival. However, the above researches focus on pricing methods, which are conducted by distributed managers. As a complement to previous studies, authors of [23] propose a customer-oriented charging incentive strategy in a DA scheduling for EVs in multi regions which realizes more EVs plugging in and more charging revenue of the system operator. Moreover, to make above idea more applicable, this charging incentive strategy is integrated into a stochastic scheduling framework to reduce the influence of uncertainty in [24], where a price-based transfer model (PBTM) is proposed and the applicability is discussed. However, the coordination of multi-time scales scheduling and EVs control is not considered.

To realize this coordination, the centralized scheduling of system level need to be made in a way to be consistent with EVs regulation potential on equipment level to track multi-time scale schedule. In practice, it is easily found that some CSs are totally occupied in the whole day, while others are idle most of the time. This will limit EVs regulation potential because of partial utilization of CSs, which will affect the optimization on both levels. These are mainly including: 1) the controllability of EVs on the equipment level cannot track scheduling signal due to fewer EVs access; 2) only a local optimal schedule can be made because EVs regulation potential is underutilized and unable to cope with extreme peak shaving; 3) the overall charging revenue of the system level is reduced when multi charging areas is considered, because of charging congestion in some busy CSs.

To bridge these gaps, a multi-time scale coordinated control and scheduling method is proposed in this paper, in which more EVs are guided to be connected to the grid and then used for regulation in both DA and RT scheduling. The contributions can be summarized as follows:

1) A multi-levels and multi-time scale scheduling and control framework is proposed to match distributed control performance of EVs more accurately to the RT schedule from distribution system operator (DSO). The coordinated framework contributes to the effective workflow among DSO, users, EVs, CSs and charging piles based on information interaction and sharing.
2) The proposed framework realizes cross-regional aggregation of EVs, which is characterized by centralized guidance and distributed control. Considering the psychological relationship between charging price and users' transfer behaviours, a user-oriented charging guidance method is proposed and integrated into extended DA stochastic scheduling to provide larger regulation potential for the power system.
3) EV is modelled as both shiftable load and controllable load in DA and RT scheduling to release flexibilities of EV control for system regulation, which aim at maximum DA profits and minimum RT cost, respectively. Users' regulation gains and loss of charge are determined by establishing different rules for shiftable and controllable loads.
4) A response curve is modelled to describe EV users' regulation degree and loss of charge, and used for addressing the RT errors with low cost. Based on the response curve, users have more flexible decision on how much charge load should be controlled.
5) The application of PBTM in our previous work is extended. On one hand, rebound effects of EV charging are considered in the application of PBTM on scheduling. On the other hand, PBTM is applied to improve the state space model (SSM). The combination of PBTM and SSM can realize EV population state estimation when EV flow exists in different areas.

The structure of the article is as follows. Section 2 depicts the framework of multi-time scale coordinated control and scheduling. Section 3 describes the PBTM and SSM of EVs in multi-time scale. Section 4 presents the coordination of multi-time scheduling and control strategies in the stochastic scheduling framework. Finally, simulation results and conclusion are developed in Section 5 and Section 6, respectively.

2. Coordinated framework

In the past few years, communication and information technology developed fast and changed power systems. Geographically distributed DR resource can be aggregated by centralized or decentralized methods. Centralized control can be directly object-oriented, efficient and accurate, but it will face huge communication pressure. Decentralized control is executed locally, so it has little communication pressure, but the control accuracy and efficiency are relatively poor. Due to the large number of EVs, centralized control is difficult to implement, while the coordinated control is expected to have good performance.

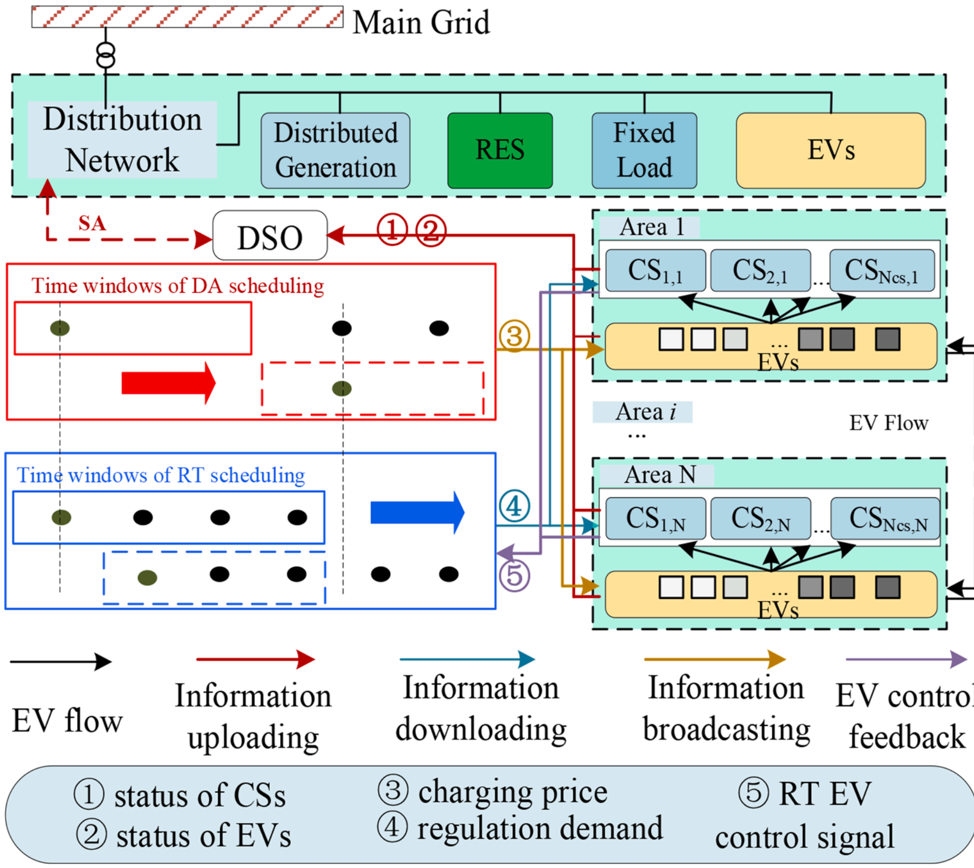

Fig. 1. Framework of the proposed multi-time scale scheduling and control strategy of EVs.

Fig. 1 shows the framework of the proposed coordinated strategy, which combines the advantages of centralized and decentralized methods. DSO sets different prices in different CSs, and broadcasts charging prices information to users. Then, users' charging behaviours will change according to the information and, as feedback, an updated central schedule considering users' behaviours will be formulated by DSO. The distributed control will be implemented by edge CSs and piles, that will collect EVs information and control them according to status of EVs, so as to track multi-time scale schedules. Considering the implementation of scheduling and control, power fiber is mainly used between DSO and CSs, while fiber, power broadband and wireless mobile communication coexist between CSs and piles. When DSO broadcasts price signals to users, wireless broadcast communication is mainly used. This coordinated framework realizes a trade-off between lots of power fiber investment and multi-level control accuracy.

The workflow mainly includes the following parts: 1) DSO estimates the state of the network by situation awareness (SA) technology and makes DA scheduling plans based on the collected historical data of CSs and EVs. 2) DSO can guide users' charging behaviours by providing charging discount or financial incentive in different CSs, then form a modified DA scheduling and broadcast the optimized charging prices to EV users. 3) According to the results of DA scheduling, DSO makes further RT schedule at a time scale of 15-minutes by considering EVs regulation. 4) Taking the RT schedule as a target, EVs are controlled at 1-minute time scale to track the target, which coordinated the schedule in system-level and control in equipment-level. 5) Charging management units in CSs (consisted of information collecting, edge computing and control modules) are responsible for estimation of the status of EV population and selection of appropriate EVs for control, so as to meet the multi-time scale schedule. 6) The selected EVs are controlled by their connected piles. In the proposed framework, RES, DGs, CSs are considered DSO-owned.

To ensure the coordination of DSO, users, EVs, and CSs, apart from the above-mentioned effective communication mechanism, mutual-benefits and risk management are also considered. For mutual-benefits, both DSO and users can obtain profits by DA and RT regulation in this framework. For risk management, stochastic scheduling, effective EVs regulation, and periodical correction for EVs status are adopted to reduce DSO's scheduling risks caused by uncertainties from WT, load, and market price.

3. PBTM and SSM of aggregated EVs in multi-time scale

3.1. Basic SOC model of an individual EV

The state of charge (SOC) of an EV is a necessary index when charging. It is important to meet the required SOC level at the end of charging process before user's departure. In practice, SOC of an EV can be approximated by [25]:

$$\begin{cases} SOC_{t+1} = SOC_t + \eta^{ch} P_t^{ch} \Delta t / E \\ P_t^{ch} \geqslant 0, SOC_{\min} \leqslant SOC_t \leqslant SOC_{\max} \end{cases} \tag{1}$$

where SOC is the state of charge of an EV, η^{ch},P^{ch} and E represent the charging efficiency, charging power and battery capacity of an EV. Note that EVs can also be discharged in certain scenarios like frequency regulation or provision of ancillary services as in [3,4,9]. Here, we only consider EVs as charging loads, i.e. $P_t^{ch} \geqslant 0$.

3.2. PBTM of EVs in multi-areas in hour-time scale

In system-level, DSO needs to make schedules from the perspective of profits. In our previous work [24], the PBTM is proposed for DSO to guide EVs in different CSs, and the applicability analysis shows that DSO

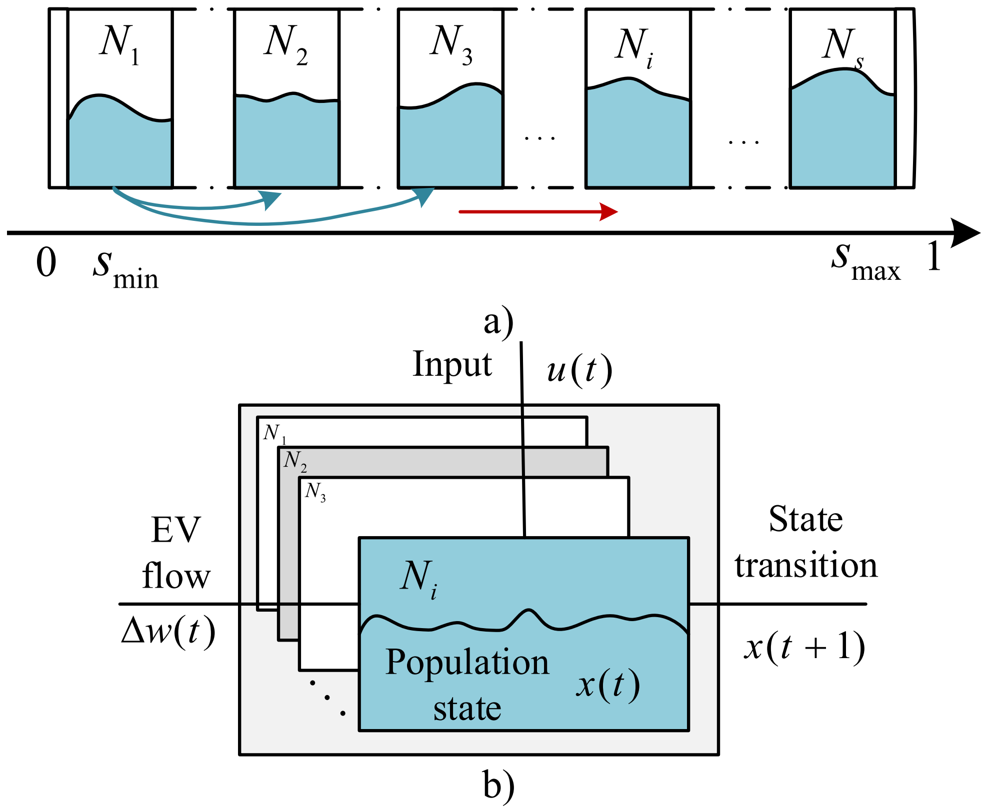

Fig. 2. State bins of EV population. (a) State bins transition (ON-STATE), (b) Time-varying factors in each bin.

can earn more profit. In simple terms, the PBTM is formed via the following parts. Firstly, a users' selection model $u_{n|k}(t)$ is modelled considering distance and charging capacity of CSs, which shows the direct association between a user and a CS. Then, considering that EVs transfer process between different areas is an accumulated effect, the EVs set $U_{ij}(t)$ is modelled from the perspective of areas. Further, the fixed transfer model $\rho_{ij,t}$ for EVs population is established without considering price impacts. Finally, a modified transfer probability model $\widehat{\rho}_{ij,t}$ is proposed considering the guiding effects of price on users. So the PBTM is depicted briefly as follows:

$$\begin{cases} \underset{\substack{u_n\in Areai,\\ S_k\in Areaj}}{u_{n|k}(t)} \;:\; S_k^*(t) = \operatorname{argmin} d^{2\alpha}_{u_n(t),S_k} c_{S_k} \\ U_{ij}(t) = \left\{ u_{n|k}(t) \left| \begin{array}{c} n = 1,2,3,\dots,N, \\ u_n \in Areai, \\ S_k \in Areaj \end{array} \right. \right\} \\ \rho_{ij,t} = \left(N^s_{i,t} - |U_{ij}(t)|\right) / N^s_{i,t} \\ \widehat{\rho}_{ij,t} = \rho_{ij,t} f(\Delta pr^{ch}_{ij,t}) \\ f(\Delta pr^{ch}_{ij,t}) = \left(\dfrac{1}{\rho_{ij,t}} - 1\right) \dfrac{\left(\Delta pr^{ch}_{ij,t}\right)}{\Delta pr^{ch}_{ept}} + 1 \\ \Delta pr^{ch}_{ij,t} = pr^{ch}_{i,t} - pr^{ch}_{j,t} \end{cases} \tag{2}$$

where $\widehat{\rho}_{ij,t}$ and $\rho_{ij,t}$ are the modified and fixed possibility of EVs' travelling behaviors, respectively.$\Delta pr^{ch}_{ij,t}$ represents the price difference,$pr^{ch}_{i,t}$ is EVs' charging price, and Δpr^{ch}_{ept} denotes users' expected price difference.$U_{ij}(t)$ is the set of EV users who travel from area i to area j,$u_{n|k}(t)$ represents the travel behavior of user n whose destination is station k. $N^s_{i,t}$ refers to the predictive number of arriving EVs, and $|\cdot|$ refers to the element amounts of a set. $S_k^*(t)$ represents that S_k is selected by a user, d is the distance, α is the impact factor and c represents the charging service capacity of S_k. For the above variables, the subscript i and j is the index of areas, t denotes that of time intervals, and k describes that of CSs.

Consequently, according to PBTM, EVs flow in different areas will change and the number of EVs can be denoted as below:

$$\widehat{N}^s_{i,t} = \left[\sum_{j=1,j\neq i}^{M} N^s_{j,t}\widehat{\rho}_{ji,t} - \left(N^s_{i,t}\left(1 - \sum_{j=1,j\neq i}^{M} \widehat{\rho}_{ij,t}\right)\right)\right] \tag{3}$$

$$N^{ext}_{i,t} = N^{org}_{i,t} + \widehat{N}^s_{i,t} - N^f_{i,t} \tag{4}$$

In (3)–(4),$\widehat{N}^s_{i,t}$ is the modified value of $N^s_{i,t}$. The equation (3) shows the modified prediction number of arriving EVs in area i considering the influence of different charging prices. M is the number of areas, $N^{ext}_{i,t}$ is the number of existing EVs of area i at time t considering price impact. $N^{org}_{i,t}$ is the number of original EVs of area i at time t, $N^f_{i,t}$ is the number of leaving EVs of area i at time t. $N^{org}_{i,t}$ and $N^f_{i,t}$ can be predicted from history distribution.

3.3. SSM of EVs of each area in minute-time scale

In equipment level, charging management needs to know EVs' status and control them flexibly to track multi-time schedules. It will be difficult to collect every EV's state information and handle it, especially in a short time period. Thus, to reduce the communication and data processing burden, a SSM is established to calculate EVs' regulation potential and control signals in RT periods.

In the SSM, the transition process is shown in Fig. 2 a). The state of population can be divided into Ns bins and the transition between each bin is depicted as a Markov process. It is supposed that there are Ns on-state bins in each time period. When EV population is fixed and charging without interruption, the state space of EV population changes with fixed regularity, which can be described as follows:

$$\boldsymbol{x}(t+1) = \boldsymbol{A}\boldsymbol{x}(t) \tag{5}$$

where $\boldsymbol{x}$ is the state vector which describes the state distribution of EVs. $\boldsymbol{A}$ is the fixed Markov transition matrix that covers EV population transition rules between different bins. $\boldsymbol{A}$-matrix can be calculated by the analytical method in [26], as follows:

$$A_{mn} = \int_{S_m}^{S_{m+1}} \int_{S_n - S_x}^{S_{n=1} - S_x} p(\Delta S) \cdot \mathrm{d}\Delta S \cdot \mathrm{d}S_x \tag{6}$$

where $m,n \in \{1,2,...,N_s\}$, A_{mn} is the element of A that represents the transition probability from bin N_m to bin N_n. ΔS is the variable that indicates the SOC variations of EVs during one time interval. S_X indicates an arbitrary value of SOC in bin Nm.

Actually, for each state bin N_i, the state changes with dependence on two external factors, i.e. control signal and EV flow, shown in Fig. 2 b). Thus, when the external factors are considered, the SSM can be described as follows:

$$\begin{cases} \boldsymbol{x}(t+1) = \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t) + \Delta\boldsymbol{w}(t) \\ y(t) = \boldsymbol{D}\boldsymbol{x}(t) \end{cases} \tag{7}$$

where $\boldsymbol{u}$ is the control vector that can be calculated according to multi-time scale scheduling results. $\Delta\boldsymbol{w}$ is the input vector that represents external plugging-in and plugging-out caused by EV flow among different areas, which can be obtained from PBTM. y represents the total charging power. $\boldsymbol{B}$ and $\boldsymbol{D}$ are the constant matrices.

In our proposed strategy, multi-areas are taken into consideration. For each area i, EVs will have the transition process as show in equation (7). Thus, the corrected SSM is developed by:

$$\begin{cases} \boldsymbol{x}_i(t+1) = \boldsymbol{A}_i\boldsymbol{x}_i(t) + \boldsymbol{B}\boldsymbol{u}_i(t) + \Delta\boldsymbol{w}_i(t) \\ y_i(t) = \boldsymbol{D}_i\boldsymbol{x}_i(t) \end{cases}, \forall Area_i \tag{8}$$

Respectively, $\boldsymbol{B}$ and $\boldsymbol{D}_i$ can be depicted by (7). Based on the PBTM, EVs flow in different areas can be predicted, so $\Delta\boldsymbol{w}_i(t)$ can be calculated by (8).

$$\begin{cases} \boldsymbol{B} = [-\mathbf{I}_{N_s\times N_s}\mathbf{I}_{N_s\times N_s}\mathbf{0}_{1\times N_s}]^T \\ \boldsymbol{D}_i(t) = P_i^{ch,avg}N_{i,t}^{ext}[-\mathbf{1}_{1\times N_s}\mathbf{0}_{1\times N_s} - \mathbf{1}_{1\times N_s}] \end{cases}, \forall Area_i \tag{9}$$

$$\Delta\boldsymbol{w}_i(t) = \left(\frac{\widehat{N}_{i,t}^s}{N_{i,t}^{ext}}(\boldsymbol{x}_i^s - \boldsymbol{x}_i(t))\right) - \left(\frac{N_{i,t}^f}{N_{i,t}^{ext}}(\boldsymbol{x}_i^f - \boldsymbol{x}_i(t))\right) \tag{10}$$

where $\boldsymbol{x}_i^s$ and $\boldsymbol{x}_i^f$ are state vectors that reveals the EVs' state distribution when plugging in and out in area i.

The regional SSM consisted of formula (8)–(10) contains two aspects of incomplete information. One is from A-matrix, the other is from EV flow. In the proposed framework, it is the default that DSO can obtain necessary information through calculation or prediction because CSs are DSO-owned and EVs' charging data is stored synchronously. However, considering that the stochastic behavior of EVs cannot be accurately predicted in DA periods, SSM is corrected periodically to maintain the performance.

4. Multi-time scale stochastic scheduling and control method

4.1. Hour-time scale stochastic scheduling with EVs guidance and DA regulation

In DA periods, DSO makes schedules according to the expected profit (EP). Considering the advantages of EVs in scheduling, there are two additional ways in our framework that will increase the scheduling profits. One is to guide more EVs to different CSs so as to obtain more plug-in EVs, and sell more electricity to EVs. The other is to take EVs as shiftable loads that can be regulated to realize peak shaving in DA periods.

Thus, the objective function is based on the maximum EP, which will be composed of several parts:

$$\mathrm{Max(EP)} = \sum_{s\in\Psi}\pi_s \times profit_s \tag{11}$$

$$\begin{aligned} profit_s = \sum_{t=1}^{T}\Bigg\{ & c_{t,s}^{R,sl}P_{t,s}^{L} + \sum_{m=1}^{M} pr_{m,t,s}^{ch}\left(\sum_{S_k\in Area_m}\widehat{P}_{k,t,s}^{ch}\right) \\ & + \left(c_{t,s}^{MD,sl}P_{t,s}^{MD,sl} - c_{t,s}^{MD,by}P_{t,s}^{MD,by}\right) \\ & + \sum_{i=1}^{N_G}\begin{matrix} C_i(P_{i,t,s}^{DG}) \\ +C_{i,t,s}^{SU} + C_{i,t,s}^{SD}\end{matrix} + \sum_{i=1}^{N_{WT}} c_{i,t}^{WT}P_{i,t,s}^{WT} \\ & + \sum_{m=1}^{M}\left(c_{m,t}^{Ur}\sum_{S_k\in Area_m}P_{k,t,s}^{Ur} + c_{m,t}^{Dr}\sum_{S_k\in Area_m}P_{k,t,s}^{Dr}\right) \\ & + \sum_{m=1}^{M}\left(\sum_{S_k\in Area_m}c_{S_k}^{loss}\widehat{P}_{k,t,s}^{ch}\right)\Bigg\}\Delta t \end{aligned} \tag{12}$$

In (11)–(12), the first item includes the electricity sales revenue of conventional loads and EVs, the second item is the trade cost between DSO and the market, the third and the fourth items are the power generation cost of DGs and wind power, the fifth item is the regulation cost of EVs in DA periods, and the sixth item is the additional power loss cost caused by EVs charging. Also,π_s is the probabilities of scenarios in DA periods, Ψ represents the set of scenarios generated by stochastic behaviours from WT, market prices and loads in DA periods. $profit_s$ is the profit of DSO in scenario s, $c_{t,s}^{R,sl}$ is the price for conventional loads,$P_{t,s}^{L}$ is the power of conventional loads, $pr_{m,t,s}^{ch}$ is the charging price, $\widehat{P}_{k,t,s}^{ch}$ is the EV charging power after regulation,$c_{t,s}^{MD,sl}$ is the selling price to DA market,$P_{t,s}^{MD,sl}$ is the selling power,$c_{t,s}^{MD,by}$ is the buying price from DA market, $P_{t,s}^{MD,by}$ is the buying power, $P_{i,t,s}^{DG}$ is the output power of DGs, $C_{i,t,s}^{SU}$ and $C_{i,t,s}^{SD}$ are start-up and shut-down costs of DGs,$c_{i,t}^{WT}$ is the cost of wind turbines, $P_{i,t,s}^{WT}$ is the output power of wind turbine (WT), $c_{m,t}^{Ur}$ is the cost of up-regulation in DA periods,$P_{k,t,s}^{Ur}$ is the up-regulation power provided by EVs in DA periods, $c_{m,t}^{Dr}$ is the cost of down-regulation in DA periods, $P_{k,t,s}^{Dr}$ is the down-regulation power provided by EVs in DA periods, $c_{S_k}^{loss}$ is the cost of extra power loss caused by EV charging, and $P_{k,t,s}^{ch}$ is the original charging power of EVs before regulation. The costs for EVs regulation (i.e. $c_{m,t}^{Dr}$ and $c_{m,t}^{Ur}$) are considered as fixed values, because the total amount of regulation power is limited to a small threshold, which will not cause huge satisfaction from users. Note that, the subscript m, k, t, and s present the index of area, CS, time and scenario respectively. The charging prices are set the same in different CSs but in the same area to make the management of CSs in the same area easier.

In this stage, the scheduling goal is to meet the power demand in a relatively economic way. In this case, we don't change the power demand as much as possible, so EVs are taken as shiftable loads, which would have a rebound after regulation. Considering the power rebound effect, the actual charging power can be depicted as follows [32]:

$$\begin{aligned} \widehat{P}_{k,t,s}^{ch} = & P_{k,t,s}^{ch} - P_{k,t,s}^{Dr} + P_{k,t,s}^{Ur} + \beta_1\left(P_{k,t-1,s}^{Dr} - P_{k,t-1,s}^{Ur}\right) \\ & + \beta_2\left(P_{k,t-2,s}^{Dr} - P_{k,t-2,s}^{Ur}\right) + \ldots + \beta_h\left(P_{k,t-h,s}^{Dr} - P_{k,t-h,s}^{Ur}\right) \end{aligned} \tag{13}$$

where $\beta_1,\beta_2,...,\beta_h$ is the rebound coefficients at time t-1,t-2,and t-h. Correspondingly, h should meet $h < t$.Here, only the rebound power from last hour is considered because EVs in our strategy are equipped with fast-chargers.

4.2. Minute-time scale scheduling with coordinated RT control of EVs

In RT periods, DSO is required to provide compensation for scheduling errors resulting from inaccuracies in DA predictions and fluctuations in wind power generation. From the decision-making model (10), the number of EVs and their charging power are determined hourly. The start-up and shut-down plans for DG units are also determined in DA periods. Therefore, in order to balance the errors between RT and DA periods on a shorter time scale, possible power regulation methods include adjusting the charging power of EVs, adjusting the power output of DGs, and buying and selling electricity in RT market. If power balance cannot be achieved, load shedding needs to be considered. DSO incurs adjustment costs when making these adjustments, thus the objective is to minimize costs, which is shown as follows:

$$\mathrm{Min(EC)} = \sum_{\omega \in \prod} \pi_\omega \left(\sum_{t=\tau_0}^{\tau_0+\tau} Cost_{t,\omega} \right) \tag{14}$$

$$Cost_{t,\omega} = \left\{ \begin{array}{l} \sum_{i=1}^{N_G} C_i(\Delta P_{i,t,\omega}^{DG}) + c_{t,\omega}^{MR,sl} \Delta P_{t,\omega}^{M,sl} - c_{t,\omega}^{MR,by} \Delta P_{t,\omega}^{M,by} \\ +c^{VOLL} P_{t,\omega}^{LOL} + \sum_{m=1}^{M} c_{m,t}^{reg,RT} \sum_{S_k \in Area_m} \Delta P_{k,t,\omega}^{reg,EV} \end{array} \right\} \tau \tag{15}$$

In (15), the first item is DGs adjustment cost, the second and the third items are trade cost with the RT market, the fourth item is load shedding cost, and the fifth item is EVs' RT regulation cost. π_ω is the probabilities of scenarios in RT periods, $\prod$ represents the set of scenarios generated by stochastic behaviours from WT, market prices and loads in RT periods, $Cost_{t,\omega}$ is the total RT cost in time slot t of scenario ω, $\Delta P_{i,t,\omega}^{DG}$ is the adjusted output of DGs, $c_{t,\omega}^{MR,sl}$ is the selling price to RT market, and $\Delta P_{t,s}^{M,sl}$ is the adjusted selling power, correspondingly. $c_{t,s}^{MR,by}$ is the buying price from RT market, and $\Delta P_{t,s}^{M,by}$ is adjusted buying power, correspondingly. Also c^{VOLL} denotes the cost of load shedding, and $\Delta P_{t,s}^{LOL}$ is the load shedding power in RT periods.$c_{m,t}^{reg,RT}$ is the cost of EVs regulation in RT periods, and $\Delta P_{k,t,\omega}^{reg,EV}$ is EVs' regulation power.

In this stage, the scheduling goal is eliminating the power errors. In this case, it is reasonable to change both supply and demand to meet the balance in a short time scale. So EVs are taken as controllable loads, which can be up/down-regulated to eliminate scheduling errors. Correspondingly, DSO pays a flexible regulation fee according to the amount of power regulation provided by EVs, because the more power DSO wants to regulate, the more dissatisfaction users would have, and then DSO needs to pay more for this. According to [27], the amount of controlled power will have a piecewise linear relationship with RT regulation price. In our strategy, this relationship can be denoted as follows:

$$\phi_{m,t,\omega}^{reg,EV} = \left\{ \begin{array}{l} \phi^{reg,\max}, c_{m,t}^{reg,RT} \geqslant \phi^{reg,\max}/v \\ \phi^{reg,\min}, c_{m,t}^{reg,RT} \leqslant \phi^{reg,\min}/v \\ v c_{m,t}^{reg,RT}, others \end{array} \right. \tag{16}$$

$$\sum_{S_k \in Area_m} \Delta P_{k,t,\omega}^{reg,EV} = \phi_{m,t,\omega}^{reg,EV} P_{m,t,\omega}^{reg,\max} \tag{17}$$

where $\phi_{m,t,\omega}^{reg,EV}$ is the regulating proportion of EVs, and v is a coefficient that reflects users' sensitivity to price.

4.3. Constraints for multi-time scale scheduling

1) Constraints for DA scheduling: Some constraints for DA security operation, output capacity and trade limits should be met. Normally, linearized power flow equations are used to verify the security, which can be derived as follows:

$$\left\{ \begin{array}{l} \sum_{i=1}^{N_G^n} P_{i,t,s}^{DG,n} + \sum_{i=1}^{N_{WT}^n} P_{i,t,s}^{WT,n} - P_{t,s}^{L,n} - \sum_{S_k \in busn} \widehat{P}_{k,t,s}^{ch} = \sum_{r=1}^{N_B} P_{nr,t,s} \\ \sum_{i=1}^{N_G^n} Q_{i,t,s}^{DG,n} + \sum_{i=1}^{N_{WT}^n} Q_{i,t,s}^{WT,n} - Q_{t,s}^{L,n} - \sum_{S_k \in busn} \widehat{Q}_{k,t,s}^{ch} = \sum_{r=1}^{N_B} Q_{nr,t,s} \end{array} \right. \tag{18}$$

where $P_{nr,t,s}$ and $Q_{nr,t,s}$ refer to active and reactive power flows which can calculated according to literature [28]. Moreover, the constraints for voltage magnitude and angle limits, line flow limits, and power generation limits are also considered in this paper. More information about mathematical modelling of these constraints can be found in [29].

For EVs, some special constraints should be set according to our strategy. Firstly, the charging power after regulation should not exceed the maximum charging power of all EVs, as well as the capacity of CSs, which are depicted by (19). Secondly, DA regulation degree should be limited within a certain range (20), because that is related to users' satisfaction. Also, the optimized charging price should not exceed the original price and users' expectation on price should be limited in an interval, which are depicted by (21) So, the constraints can be formulated as below:

$$\left\{ \begin{array}{l} 0 \leqslant \sum_{S_k \in Area_i} \widehat{P}_{k,t,s}^{ch} \leqslant P_i^{ch,avg} N_{i,t}^{ext} \\ 0 \leqslant \sum_{S_k \in Area_i} \widehat{P}_{k,t,s}^{ch} \leqslant \sum_{S_k \in Area_i} P_{S_k}^{\max} \\ 0 \leqslant \widehat{P}_{k,t,s}^{ch} \leqslant P_{S_k}^{\max}, \forall S_k \end{array} \right. \tag{19}$$

$$\sum_{t=1}^{T} \left(\sum_{S_k \in Area_i} \left| P_{k,t,s}^{Ur} - P_{k,t,s}^{Dr} \right| \right) \leqslant \varphi \sum_{S_k \in Area_i} P_{k,t,s}^{ch}, \forall Area_i \tag{20}$$

$$\left\{ \begin{array}{l} 0 \leqslant \sum_{S_k \in Area_i} \widehat{P}_{k,t,s}^{ch} \leqslant P_i^{ch,avg} N_{i,t}^{ext} \\ 0 \leqslant \sum_{S_k \in Area_i} \widehat{P}_{k,t,s}^{ch} \leqslant \sum_{S_k \in Area_i} P_{S_k}^{\max} \\ 0 \leqslant \widehat{P}_{k,t,s}^{ch} \leqslant P_{S_k}^{\max}, \forall S_k \end{array} \right. \tag{21}$$

where $P_{S_k}^{\max}$ is the maximum charging power served by CS k, δ denotes a proportion of original charging price and is used to measure EV users' price sensitivity. φ means the regulation degree of EVs, which is a percentage of total charging power.

2) Constraints for RT scheduling: In RT stages, the linearized power flow equations can be derived as (22). Similarly, the voltage limits and line flow limits in [29] should be included in RT scheduling.

$$\left\{ \begin{array}{l} \sum_{i=1}^{N_G^n} P_{i,\tau,\omega}^{DG,n} + \sum_{i=1}^{N_{WT}^n} P_{i,\tau,\omega}^{WT,n} - P_{\tau,\omega}^{L,n} - \sum_{busn \in Area_i} \widetilde{P}_{i,\tau,\omega}^{ch,n} + P_{\tau,\omega}^{LOL,n} = \sum_{r=1}^{N_B} P_{nr,\tau,\omega} \\ \sum_{i=1}^{N_G^n} Q_{i,\tau,\omega}^{DG,n} + \sum_{i=1}^{N_{WT}^n} Q_{i,\tau,\omega}^{WT,n} - Q_{\tau,\omega}^{L,n} - \sum_{busn \in Area_i} \widehat{Q}_{i,\tau,\omega}^{ch,n} + Q_{\tau,\omega}^{LOL,n} = \sum_{r=1}^{N_B} Q_{nr,\tau,\omega} \end{array} \right. \tag{22}$$

For EVs, the RT charging power and RT regulation degree should be limited as below:

$$\left\{ \begin{array}{l} 0 \leqslant \widetilde{P}_{i,\tau,\omega}^{ch} \leqslant P_i^{ch,avg} N_{i,t}^{ext} \\ 0 \leqslant \widetilde{P}_{i,\tau,\omega}^{ch} \leqslant \sum_{S_k \in Area_i} P_{S_k}^{\max} \\ 0 \leqslant \widehat{P}_{k,t,s}^{ch} + \Delta P_{k,\tau,\omega}^{reg,EV} \leqslant P_{S_k}^{\max}, \forall \tau \in t, \forall S_k, s, \omega \\ (16)-(17) \end{array} \right. \tag{23}$$

3)Constraints for the market in both periods: In both DA and RT scheduling, DGs need to meet some constraints. These include power capacity, the minimum start-up/shutdown time and ramping rate limits in DA stages, and the power capacity and ramping rate limits in RT

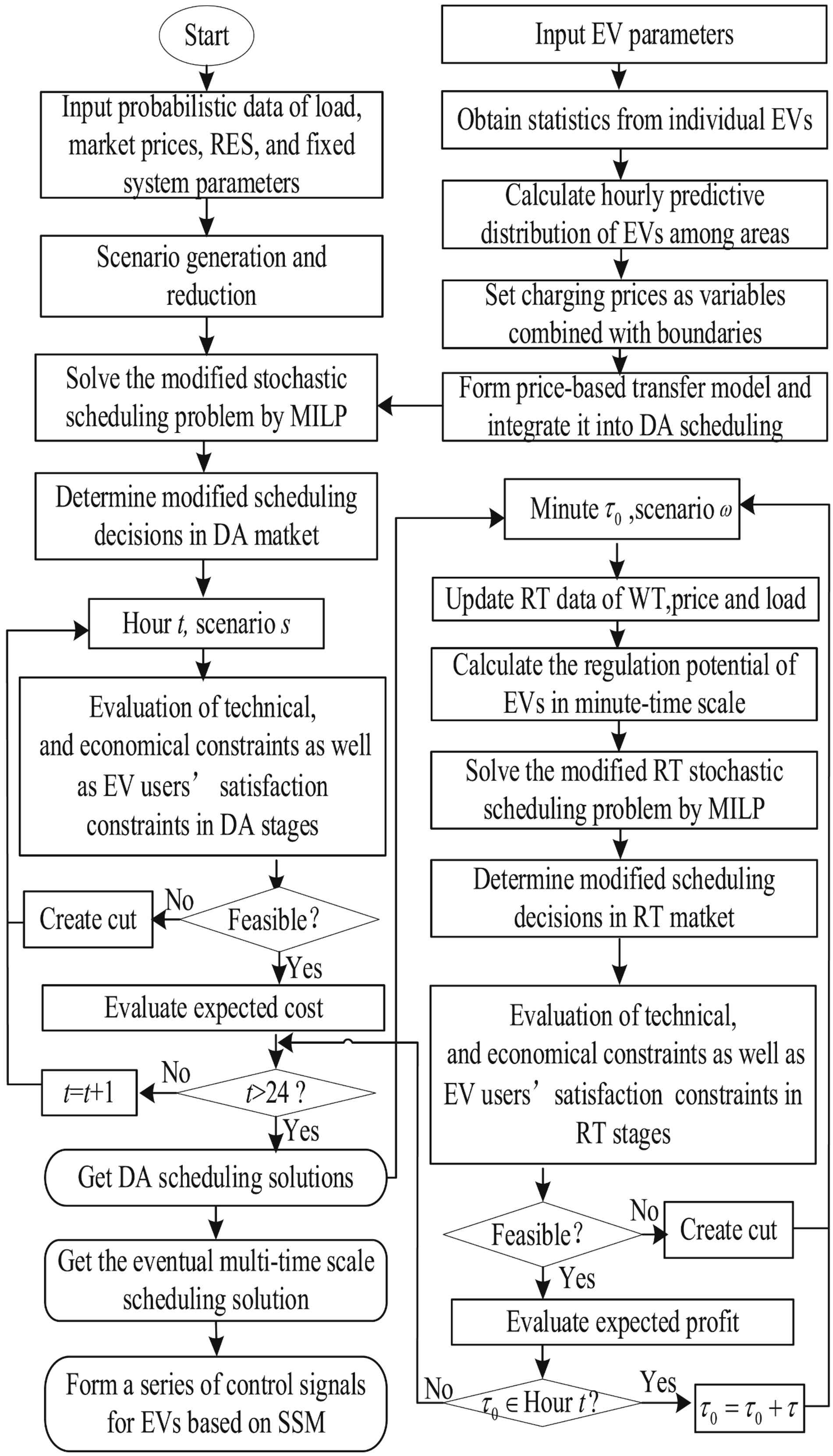

Fig. 3. Flowchart of the proposed optimization procedure.

stages. The description of such constraints will be similar to those reported in [30]. Meanwhile, the power transaction with market should be limited according to the tie-line capacities as follows:

$$\begin{cases} 0 \leqslant P^{MD/MR,sl/by}_{t/\tau,s/\omega} \leqslant P^{buy/sell}_{\max} \\ 0 \leqslant P^{MD/MR,sl/by}_{t/\tau,s/\omega} \leqslant P^{line}_{\max} \end{cases} \tag{24}$$

4.4. Signals calculation of EVs distributed control

Once the optimal schedule in RT periods is made, the regulation power of EVs can be obtained. Then, the coordinated control signals for EVs will be formed and sent to CSs by DSO. The EVs control signals are 1-min time scale, which can be calculated and coordinated with RT scheduling results by the below formulas.

$$\widetilde{P}^{ch}_{i,\tau,\omega} = \sum_{s \in \psi} \pi_s \sum_{S_k \in Area_i} \widehat{P}^{ch}_{k,t,s} + \sum_{\omega \in \prod} \pi_\omega \sum_{S_k \in Area_i} \Delta P^{reg,EV}_{k,\tau,\omega}, \forall t \in T, \tau \in t \tag{25}$$

$$\widetilde{x}_i(\kappa) = \frac{\widetilde{P}^{ch}_{i,\tau,\omega} - y_i(\kappa)}{N^{ext}_{i,\kappa} P^{ch,avg}_i}, \forall \kappa \in \tau \tag{26}$$

$$u_{i,j}(\kappa) = \begin{cases} -\max\left(\min\left(-\widetilde{x}_i(\kappa) - \sum\limits_{h=j+1}^{N_s} x_{i,h}(\kappa), x_{i,j}(\kappa)\right), 0\right), \widetilde{x}_i(\kappa) < 0 \\ \max\left(\min\left(\widetilde{x}_i(\kappa) - \sum\limits_{h=1}^{j-1} x_{i,h}(\kappa), x_{i,j}(\kappa)\right), 0\right), \widetilde{x}_i(\kappa) \geqslant 0 \end{cases} \tag{27}$$

where $\widetilde{P}^{ch}_{i,\tau,\omega}$ is the target charging power of EVs after DA and RT scheduling, which is 15-min time scale. $\widetilde{x}_i(\kappa)$ is the proportion of EVs that need to be controlled in CS i, $x_{i,j}(\kappa)$ and $u_{i,j}(\kappa)$ represents the EVs distribution and control signals of state bin j in CS i at time κ respectively. Finally, after multi-time scale scheduling and coordinated control, EVs' actual charging power can be estimated by SSM:

$$\begin{cases} \widetilde{\boldsymbol{x}}(\kappa+1) = \boldsymbol{A}\widetilde{\boldsymbol{x}}(\kappa) + \boldsymbol{B}\boldsymbol{u}(\kappa) + \boldsymbol{C}\boldsymbol{w}(\kappa) \\ \widetilde{y} = \boldsymbol{D}\widetilde{\boldsymbol{x}}(\kappa) \end{cases} \tag{28}$$

4.5. Methodology and flowchart of solution

The proposed coordinated framework is illustrated in Fig. 3. The process for scenarios generation and reduction are similar with literature [33], in which Monte Carlo is used for modelling uncertainties from WT, market prices and loads, and K-means algorithm is adopted. A tree with a total of 10^4 scenarios is generated and consequently 20 scenarios are clustered. In the DA stage, EVs charging incentive strategies are integrated into DA scheduling of DSO. Therefore, before solving the examined mixed integer linear programming (MILP) problem, heterogeneous parameters including rated charging power, efficiency, and battery, as well as travelling time of EVs, are initially generated. Then the hourly distribution of charging demand in different areas can be calculated. Then, EVs' charging prices are regarded as variables to establish the PBTM and to form a modified DA scheduling for DSO. Finally, the results of the DA scheduling are verified by DA constraints.

In the RT stage, the DA deployment of DGs and charging price are taken as known values, which are used to further optimize RT scheduling (i.e. DG output, EV regulation and market trade in RT periods). To utilize EVs controllability when charging, the predictive distribution of EVs is updated and EVs' regulation potential is calculated in 15-min time scale. Then a modified RT scheduling with the participation of EVs regulation can be made according to minimal operation cost. The function of EVs regulation cost in RT stage (i.e. formula (16)) is nonlinear, here it is solved piecewise. When the variable $c^{reg,RT}_{m,t}$ exceeds the boundary, the model is linear. When the variable $c^{reg,RT}_{m,t}$ is within a certain range, formula (14) is transformed into a convex quadratic function. Both can be solved by CPLEX.

When verifying the results, besides verifying the security and economic constraints, it is also necessary to verify the satisfaction constraints of EV users to ensure that there will not be too much dissatisfaction. The final RT scheduling results will form 1-min time scale control signals by SSM to match the target of multi-time scale scheduling.

Table 1
Information of generating units.

Unit	Min-Max Generation (kW)	Marginal Cost ($/kWh)	Start-up Cost ($)	Shut-down Cost ($)	Amount
DG	160–800	0.068	0.09	0.08	1
DG	200–1200	0.055	0.09	0.08	1
DG	80–600	0.120	0.09	0.08	2
WT	0–100	0.055	–	–	30

Table 2
Other global parameters.

Parameters	Value	Parameters	Value
Max charging price	0.385 ($/kWh)	Selling price to market	0.04 ($/kWh)
Up-regulation price in DA stage	0.015 ($/kWh)	Retailed price	0.246 ($/kWh)
Down-regulation price in DA stage	0.046 ($/kWh)	Coefficient ν	0.8 (kWh/$)

Table 3
Charging settings.

Maximum DA/RT regulation proportion			20 %
users' expected charging price difference			10 %
Maximum charging price discount percentage			50 %
Capacity of charging stations(kWh)	**Area1**	**Area2**	**Area3**
	2000	1500	5000
Cost of loss of charging stations($/kWh)	**Area1**	**Area2**	**Area3**
	0.24	0.18	0.12

5. Simulation and numerical results

5.1. Parameters setup

The proposed strategy is advantageous that the DA scheduling, RT scheduling and distributed control at the rate of 1-hour-time scale, 15-minutes-time scale and 1-minute time scale, respectively, are coordinated well. So the simulation will cover the three process.

To analyze the advantages of the proposed strategy, an advanced IEEE 30-bus distribution network is adopted. The network is coupled to a 3-areas city map and the deployment of CSs can be seen from [24]. There are 4 dispatchable DG units, and 30 small WTs distributed in different buses. The parameters of DGs and WT are listed in Table 1. The data of RES and loads is generated according to [28], and a maximum penetration rate of WT is set to 48 % in the distribution system, which is connected to the external main network to maintain the power balance between supply and demand. A total of 1233 EVs is generated by Monte Carlo method, the parameters of which are set the same as that in [24]. Other parameters for the proposed coordinated strategy are listed in Table 2 and Table 3.

5.2. DA scheduling results

1) Economic scheduling: In the DA stage, we integrate the guidance strategy for EVs charging into DA scheduling, and also regulate EVs

Table 4
Four cases in DA periods.

Case index	Details	
1-1	Fixed charging price	Without DA regulation of EVs
1-2	Fixed charging price	With DA regulation of EVs
1-3	Modified charging price	Without DA regulation of EVs
1-4	Modified charging price	With DA regulation of EVs

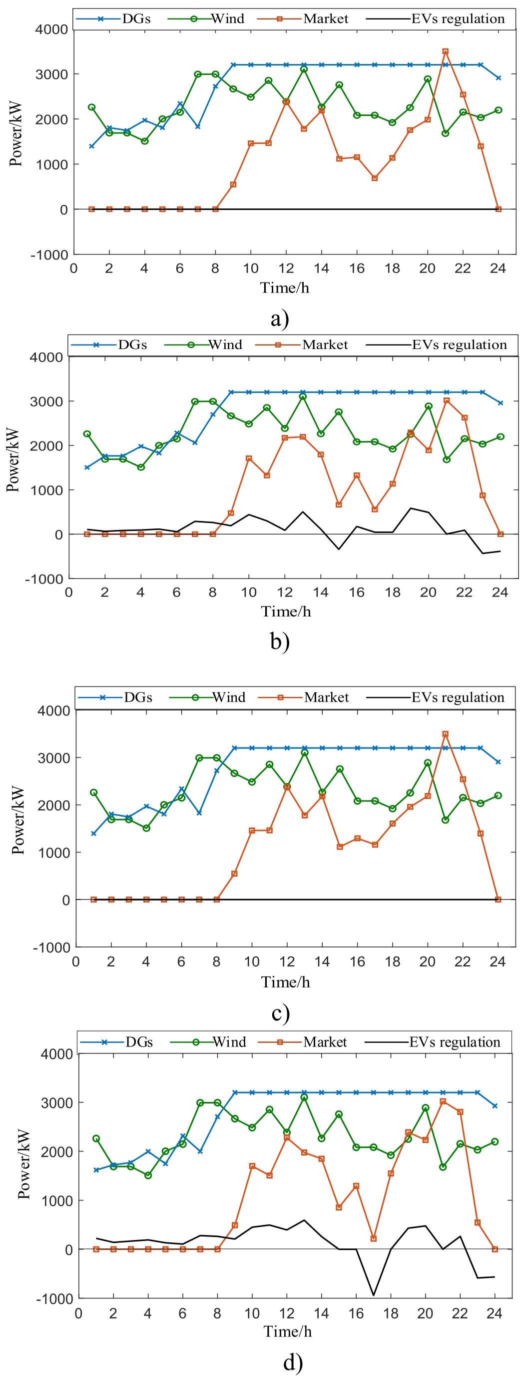

Fig. 4. Economic schedule results in different cases. (a) Case 1-1; (b) Case 1-2; (c) Case 1-3; (d) Case 1-4.

charging power in order to maximize DA operating profit of DSO. Therefore, in order to compare and highlight the superiority of the DA strategy in this paper, four cases (seen in Table 4) are set, among which

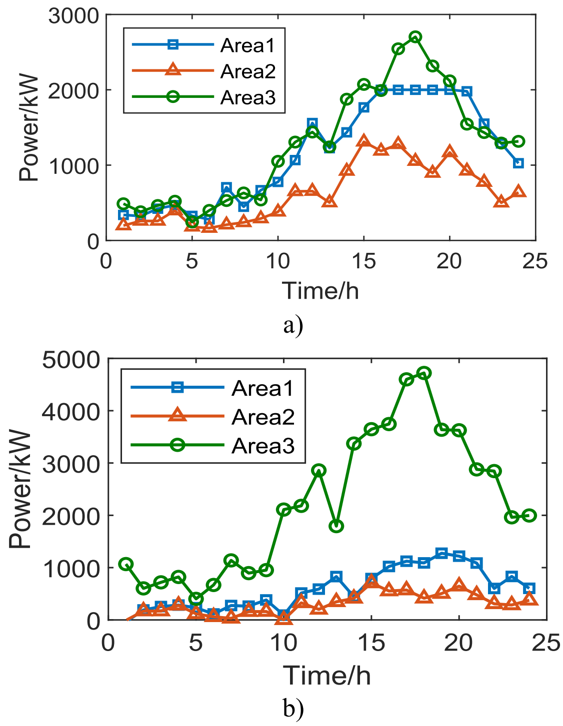

Fig. 5. The performance of guidance strategy based on PBTM. (a) Before guidance, (b) after guidance.

Case1-4 represents our proposed DA strategy.

The economic scheduling results of each case are shown in Fig. 4. Wind power output is relatively stable throughout the day, fluctuating between 1500 and 3000 kW, while the load has a peak in the afternoon and evening. When the load demand is not high (e.g., from 00:00 to 8:00), DGs can supply the demand. In other times, DSO needs to purchase power from the market. In Case1-1 and Case1-3, EVs are not regulated and DSO needs to purchase more than 3000 kW of electricity at the peak load at 21:00, while in the other cases, DSO purchases less electricity and realizes peak curtailment. By comparing Case1-2 and Case1-4, it is understood that Case1-4 has a larger commitment from EVs regulation than Case1-2, and the total purchased electricity is less, indicating that the guidance strategy in this paper can attract more EV plugging-in and provide more dispatchable capacity by EVs.

2) EV guidance analysis: The EV guidance strategy based on PBTM is deemed more suitable for solving problems, where there is a mismatch between charging capacity and charging demand in different regions [23]. In this regard, Fig. 5 shows the guidance results under different charging capacity settings listed in Table 3.

As shown in Fig. 5a, before guidance, the charging demand of Area 1

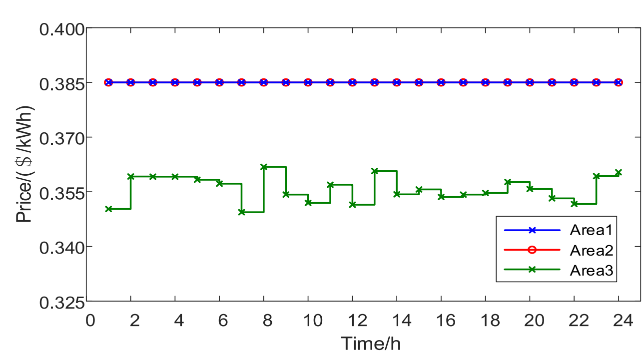

Fig. 6. Modified price for EV charging in different areas.

Table 5
Comparison of different cases in DA periods.

Case	1-1	1-2	1-3	1-4
DSO's DA profit ($)	17,902	19,272	18,529	19,855
Profit from EVs charging ($)	28,126	27,848	27,059	26,608
Charging Cost saving for users ($)	0	0	1628	1594
Total charge of EVs (kWh)	73,130	72,404	74,585	73,323
Regulation cost for users ($)	0	117	0	173

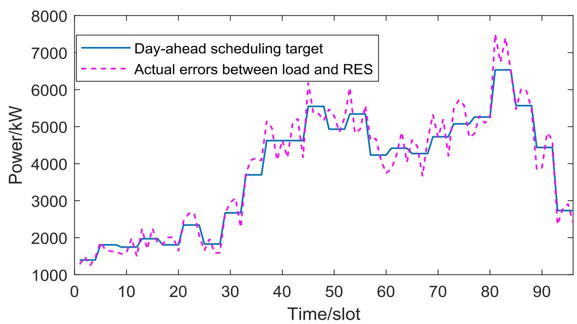

Fig. 7. Actual errors in RT periods.

and Area 3 is relatively high, but the charging capacity of Area 1 is limited, so the charging demand of Area 1 will reach the charging power limit in peak periods. In practice, some EVs cannot be charged, and CSs in Area 1 will be always busy. However, Area 3 has a large charging capacity that can meet a large charging demand. Therefore, the proposed strategy can guide more EVs from Area 1 that may be in charging congestion, to Area 3. The result after guidance is shown in Fig. 5 b. It can be seen that a large amount of EVs charging demand is transferred to Area 3 which has a larger service capacity.

To avoid heavy charging congestion in Area 1 and transfer EVs from Area 1 to Area 3, DSO needs to adjust the charging price of Area 3 and broadcast it to users. The adjusted charging price is shown in Fig. 6. The overall charging price in Area 3 is reduced, while the price in the other two areas remains unchanged. Consequently, EVs charging demand in Area 1 is transferred to Area 3. Meanwhile, after Area 3 price adjustment, there is price difference between Area 2 and Area 3, which will also lead to partial relocation of charging demand from Area 2 to Area 3. However, charging demand in the three regions does not reach the capacity limits and more EVs can be plugged in at the same time.

3) Profit analysis: According to the cases in Table 4, we compared the DSO's profit and charging fee saving of users as shown in TABLE.V. Through the comparison of 4 cases, it can be seen that the DSO's profit is the highest by using the proposed strategy (i.e. Case1-4). The electricity sales revenue of Case1-1 and Case1-2 is higher than that of Case1-3 and Case1-4. This is because the charging price in Area 3 has been reduced, which leads to a decrease in the electricity sales revenue. However, by our strategy more EVs can be accessed, resulting in more amount of regulation power from EVs, which can reduce market trade cost in peak periods and achieve a higher revenue on the whole.

It shows that in Table 5, after guidance, users can enjoy a discount charging price, that helps to save more charging fees. Also, if users provide regulation power to grid when needed, they can get more subsidies. So, in our strategy, users can actually save charging costs and obtain subsidies at the same time, and the total operating income of DSO is the maximum at this time, which promotes a double-win structure.

5.3. RT scheduling results

1) Economic scheduling: In the RT stage, actual errors between load and wind generation, and DA plan are given in Fig. 7. In order to eliminate the RT power deviation, DGs, EVs and market trade power can be adjusted. The aim of our strategy in RT periods is to promote power balance by EVs control. The scheduling results with or without EVs RT control are compared in Fig. 8. Normally, when the load demand is high (8:00–23:00), DSO need to buy power from the market, because load demand exceeds the total output of WTs and DGs, which can be seen in Fig. 8 a). However, in our proposed strategy, DSO can reduce the electricity purchase from RT market by cutting down EVs charging power, which can be seen in Fig. 8 b), and then promote economic operation.

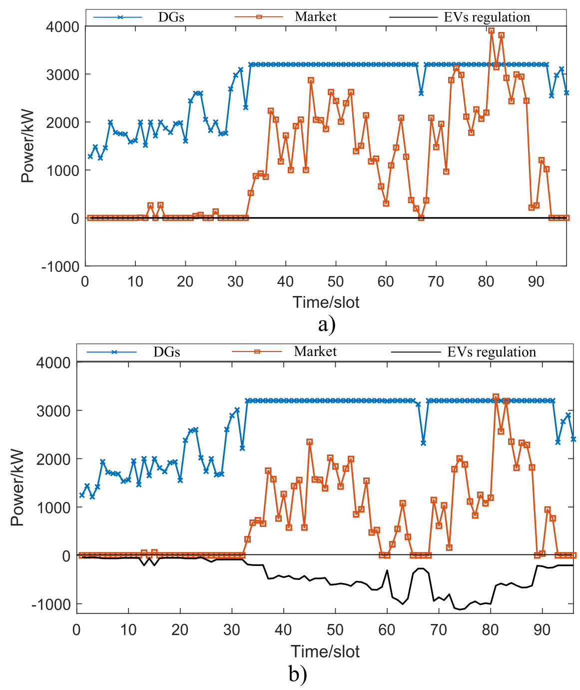

Fig. 8. Economic schedule results in different cases in RT periods. (a) Case 2-1; (b) Case 2-2.

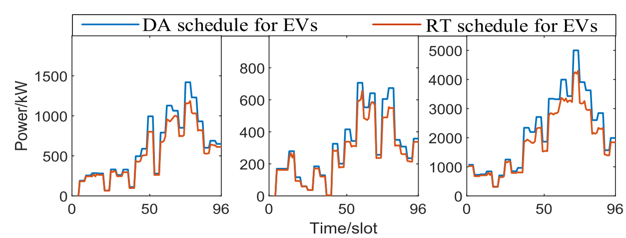

Fig. 9. RT scheduling results for EVs.

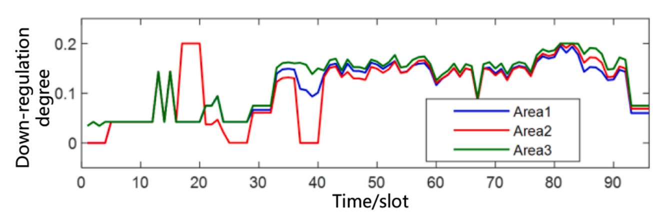

Fig. 10. EVs regulation degree in RT scheduling.

2) Scheduled charging demand in RT periods: According to the above RT scheduling results, Fig. 9 shows the reduced charging demand of EVs in different regions. When load demand is low (23:00–8:00), DGs has the up-regulation capacity and it is relatively cheap, so DGs can be used for regulation during such periods. However, when load demand is high (8:00–23:00), DGs have no more capacity to increase their outputs, so

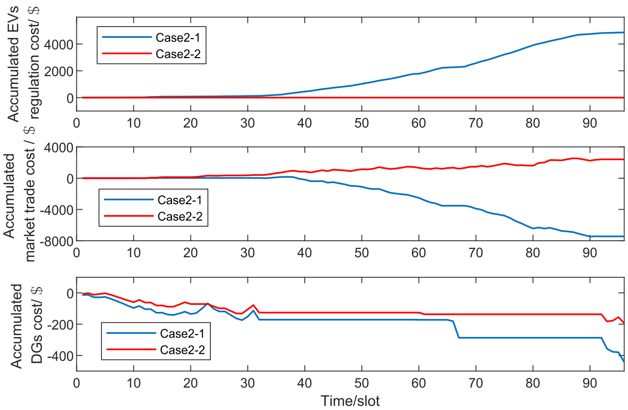

Fig. 11. Comparison of various scheduling costs in RT periods.

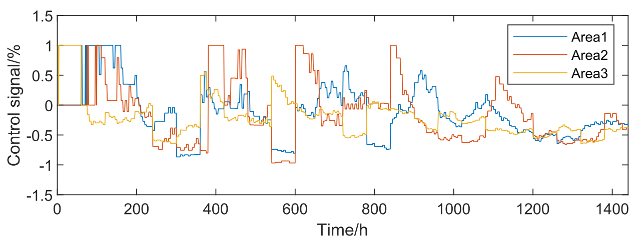

Fig. 12. Control signals for EVs based on SSM.

only EVs regulation and market transaction can be adopted. Therefore, the amount of EVs regulation power is relatively large when market price is high, whereas that is relatively small when market price is low.

Fig. 10 shows EVs regulation proportion. Since EVs' regulation cost is related to the regulating proportion, which means the higher the proportion is, the more cost DSO needs to pay to users. During peak load periods, the regulating proportion fluctuates between 10 % and 20 % but don't reach 20 %, because when the proportion reaches 20 %, the regulation cost is higher than buying power from the market in some periods.

3) RT operation cost analysis: In order to compare the advantages brought by EVs regulation in RT stage, two cases are set up. Case2-1 represents the proposed RT strategy that EVs are used for regulation, combined with market trade and DGs adjustment. However, Case2-2 represents the situation where EVs are not used for regulation. Fig. 11 compares various scheduling costs in the RT stage.

The cost of purchasing power from market is positive, because in Case2-2, the load demand from 8:00 to 23:00 is relatively high, and the output of DGs reaches the upper limit, and the imbalance needs to be met by purchasing power from the power market. However, in Case2-1, DSO pays users for EVs regulation, so the regulation cost of EVs is increased, but the power purchase cost is greatly reduced. In our strategy, the cost of purchasing power is negative, that indicates a cost saving trend.

Further, in order to eliminate the small power deviation, DGs' outputs are partially adjusted. In Case2-2, the total output of DGs was reduced, resulting in cost savings of approximately \$200. While in Case2-1, the cost of DGs is saved more, which is more than \$400.

Therefore, according to the above analysis of DA and RT scheduling, our proposed strategy can attract more EVs to be plugging-in, and also provide greater regulation capacity. Moreover, multi-time scale scheduling with EVs regulation can increase the income of DSO and promote the economic operation of the whole distribution network.

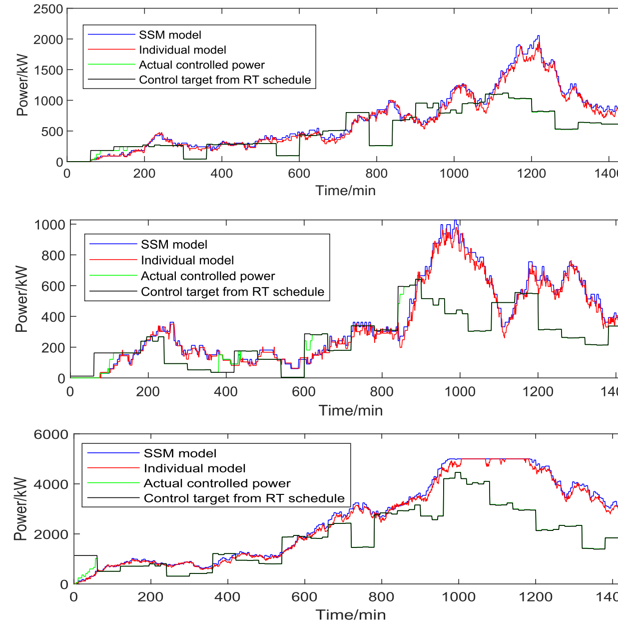

Fig. 13. The performance of EVs control in different areas.

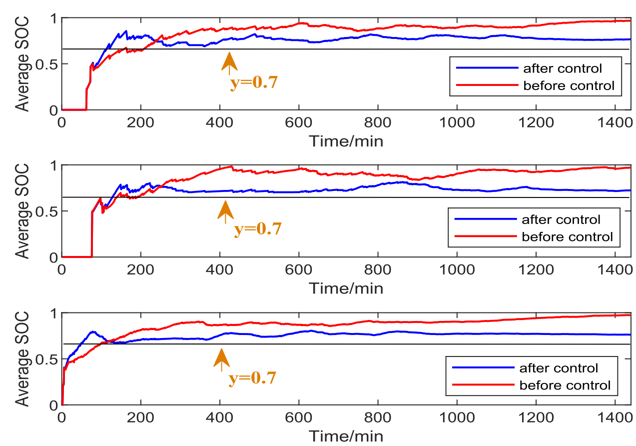

Fig. 14. Comparison of EVs' average SOC.

5.4. Coordinated EVs control results

Multi-time scale scheduling is performed by DSO and requires the support from CSs. According to the DA and RT scheduling results, EVs control signals shown in Fig. 12 can be obtained to track the scheduling results. If the control signal is positive, the EVs charging power is up-regulated. If the control signal is negative, the EVs charging power is down-regulated.

Since EVs can be regarded as shiftable loads in DA periods, the load rebound after load-shifting is taken into account, so the up-regulation and down-regulation in DA periods are relatively equal. However, EVs are used as controllable loads in RT periods, and used for peak curtailment mostly. Thus, in general, there are relatively more negative signals.

Fig. 13 describes the SSM performance and the coordinated control results of EVs. It can be seen that 1) SSM can better track the actual EVs charging curve and relieve the computational pressure caused by a large number of EVs modelling individually; 2) By controlling SSM output, the charging power of total EVs can track multi-time scale scheduling plans well. Therefore, our strategy realizes the coordination between EVs control of 1-min time scale and multi-time scale scheduling.

As the control signals are mostly negative in Fig. 12, down-regulation

Table 6
Comparison of single scheduling and coordinated EVs control and scheduling.

Scenarios	Case index*		DSO			Users	
			DA profit/($)	RT cost/($)	Total profit/($)	Users' earnings/($)	Average charging price/($/kWh)
S1	1-1	2-2	17901.54	1966.77	15934.77	0.00	0.38
S2	1-2	2-2	19272.31	1970.46	17301.85	117.24	0.38
S3	1-3	2-2	18529.23	2050.62	16478.62	1627.66	0.36
S4	1-4	2-2	19855.39	2135.54	17719.85	1767.33	0.36
S5	1-1	2-1	17901.54	−3058.31	20959.85	4919.07	0.31
S6	1-2	2-1	19272.31	−2902.15	22174.46	4736.03	0.31
S7	1-3	2-1	18529.23	−3354.92	21884.15	6902.87	0.28
S8	1-4	2-1	19855.39	−2986.46	22841.85	6683.43	0.28

*Annotation: "1-" represent the cases in DA periods, the details of which can be tracked to Table 4. "2-" represents the cases in RT periods, "2-1" and "2-2" represents the RT scheduling strategy with and without considering EVs control, which can also be tracked to Part C3 of Section 5.

of EVs is needed in most of periods, which will lead to the reduction of actual charging quantity. Therefore, Fig. 14 shows the average SOC of EVs in three areas. Before EVs control, the average SOC of EVs can reach 0.9–1, while after EVs control, the average SOC is stable above 0.7. According to the existing work [24,34], users' dissatisfaction and charging power can be described in terms of a quadratic utility function. The loss of SOC will definitely cause users' dissatisfaction because EVs cannot reach the desired SOC in our strategy. However, from a practical perspective, 98 % of users' daily driving mileage is less than 100 km, and 80 % of users' daily driving mileage is less than 50 km [31]. No matter it is a BYD E5 with small battery capacity, which has 40kWh and NEDC 305 km or Tesla Model S with large battery capacity, which has 90kWh and NEDC 500 km, our strategy can meet users' daily requirements with 70 % battery. So the proposed strategy can meet most users' daily requirements in practice.

5.5. Comparison of single scheduling and coordinated EVs control and scheduling

Eight scenarios are designed to analyse the advantages of multi-time scale scheduling and coordinated EVs control on economic operation of distribution network. Table 6 shows an overall comparison of different scenarios. From S1 to S8, the effects of EVs guidance, EVs regulation in DA periods and EVs control in RT periods are compared.

S1 represents the single scheduling, in which EVs guidance, DA and RT EVs regulation are not adopted. The scheduling profit of DSO is the lowest in all scenarios, and users cannot obtain savings or enjoy discounted charging price. From S2 to S8, different parts of our strategies were added, indicating that the DA incentive charging strategy and EVs regulation in both DA and RT periods can improve the overall scheduling profit. Users can also obtain certain subsidies from EVs regulation and control. S8 represents the proposed strategy, where DSO has the highest profit, while users can obtain high EVs regulation subsidies, and the average charging cost of EVs is the lowest. Therefore, this strategy is beneficial to both DSO and users.

6. Conclusion

In this article, a multi-time scale scheduling and coordinated control strategy for EVs was proposed. EVs distributed in multi regions were considered to maximize DSO's EP in DA stage and minimize operation cost in RT stage, which are coordinated with a 1-min scale control strategy in equipment level. The advantages of proposed strategy are analyzed in an advanced traffic-grid coupling distribution network and the profits in a total of 8 scenarios were compared. The results showed that the proposed strategy could promote the DSO's DA profit by attracting more EVs to be plugged in and reduce the cost of RT operation by EVs regulation. The main concluding remarks of this article can be highlighted as follows:

1) Based on PBTM, the proposed incentive charging strategy was integrated into DA scheduling, which increased the whole profit by attracting more EVs to plug in and regulate EVs' shiftable charging power. Moreover, it avoided charging congestion, while users could gain profits.
2) A RT stochastic scheduling strategy with a time scale of 15 min was put forward by taking EVs as controllable loads, which reduced the cost of RT scheduling and gave users benefit according to their regulation degree of EVs.
3) On the equipment level, a SSM with 1-min control signals was established to capture EVs' status and track multi-time scale scheduling target. It was advantageous in dealing with huge communication pressure and EVs control accuracy.

To utilize the flexibility of demand side, future work will focus on the coordination of EVs and other controllable loads to contribute to the economic operation of multi-energy systems.

CRediT authorship contribution statement

Zekun Li: Conceptualization, Writing – review & editing. **Yi Sun:** Supervision. **Hongyue Yang:** Methodology. **Shiwei Wang:** Methodology. **Yaqi Shen:** Writing – original draft. **Xianchun Wang:** Investigation. **Kai Zhang:** Validation. **Amjad Anvari-Moghaddam:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

Acknowledgements

This work was supported in part by the Science and Technology Projects from the State Grid Corporation under Grant SGHEXT00YJJS2200014.

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