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A Consumer-Oriented Incentive Strategy for EVs Charging in Multi-Areas under Stochastic Risk-Constrained Scheduling Framework

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***Abstract*—The distribution of electric vehicles (EVs) charging areas is affected by customers' behaviors, which has strong temporal and spatial characteristics. Thus, some charging stations (CSs) are always busy practically, while others are not, which leads to lower charging efficiency and profit. To solve this, a consumer-oriented charging incentive strategy for EVs in multiple regions is proposed, which can guide the transfer, alleviate the congestion of CSs so as to improve the economy of scheduling. In this paper, by setting different charging prices in various regions, the price-based transfer model (PBTM) of EVs is constructed to describe price effects on EVs' transfer behaviors. Then, the PBTM is integrated into a stochastic scheduling scheme managed by the distribution system operator (DSO). Charging income and extra cost of line loss caused by charging are additionally considered to maximize the total profit of DSO when scheduling. Finally, the applicability and economic advantages of the proposed strategy are analyzed with different CSs' capacity as well as users' price sensitivity and EVs' regulation depth, and the influence of important parameters are investigated deeply.**

***Index Terms*—EVs, consumer-oriented, multiple regions, EV charging, incentive strategy, stochastic scheduling.**

NOMENCLATURE

Abbreviation	
CS	Charging station
PBTM	Price-based transfer model
SOC	State of charge
EV	Electric vehicles
DSO	Distribution system operator
RES	Renewable energy sources
DA	Day ahead
EP	Expected profit
DG	Distributed generator
PV	Photovoltaic
CVaR	Conditional value at risk
MCS	Monte Carlo simulation
PDFs	Probability distribution functions
OPF	Optimal power flow
CL	Common loads
Parameters and variables	
η	Charging efficiency
P_{EV}	The rated charging power of electric vehicles
E_{EV}	The rated battery capacity
i^*	CS *i* is selected by user *j*
$d_{i,j}$	The distance between area *i* and *j*
p_i^{ch}	The charging price of CS *i*
$p_{\max}^{ch,EV}$	The maximum charging price
k_i	The impact of capacity of CS *i*
n_i	The number of available electric plugs
α	The significance of the distance for CS selection
M	The number of areas
$u_{n\|k}(t)$	The transfer of user *n* from area *i* to station *k* in area *j* at the time *t*
$U_{ij}(t)$	The set of users that transfer from area *i* to area *j* at the time *t*
$\rho_{ij}(t)$ / $\hat{\rho}_{ij}(t)$	The (modified) EVs transfer possibility from area *i* to area *j* at the time *t*
$N_i^{arv}(t)$ / $\hat{N}_i^{arv}(t)$	The (modified) predictive number of arriving EVs of area *i* at time *t*
$\Delta p_{ij}^{ch,t}$	The price difference value between area *i* and *j* at time *t*
Δp_{ept}^{ch}	Users' expected price difference
$N_i^{ext}(t)$	The number of existing EVs of area *i* at time *t* considering price impact
$N_i^{org}(t)$	The number of original EVs of area *i* at time *t*,
$N_i^{lv}(t)$	The number of leaving EVs of area *i* at time *t*
$P_i^{ch}(t)$ / $P_{i,s}^{ch}(t)$ ($P_{i,t,s}^{ch}$)	The charging power of EVs in area *i* at time *t* /for scenario *s*
$P_{\max}^{S_k}$	The maximum charging power supplied by station *k*
P_i^{avg}	The average charging power of EVs in area *i*
Income_{CL} / Income_{EV}	The income from selling electricity to common loads / EVs
Cost_M	The total cost of trade with market

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Cost_{GEN}	The total cost of power generation
Cost_{R}	The cost of EVs regulation
Cost_{LLS}	The cost of extra power loss when EVs charging
$c_{t,s}^{MDA,sell}$	The whole selling price of DA market at time t for scenario s
$c_{t,s}^{MDA,buy}$	The whole buying price of DA market at time t for scenario s
$P_{t,s}^{DA,sell}$ / $P_{t,s}^{DA,buy}$	The selling /buying power from market at time t for scenario s
$C_i(P_{i,t,s}^{DG})$	The cost function of the ith DG unit
$C_{i,t,s}^{SU}$ / $C_{i,t,s}^{SD}$	The start-up / shut-down costs of the ith DG unit at time t for scenario s
$R_{i,up}$ / $R_{i,down}$	The ramping-up /-down rate of the ith DG
$c_{i,t}^{WT}$ / $c_{i,t}^{PV}$	The operating costs of WTs/PVs at time t
$c_{m,t}^{UPreg,DA}$ / $c_{m,t}^{DNreg,DA}$	The up-/down-regulation price of area m in DA market at time t
$P_{k,t,s}^{UPreg,EV}$ / $P_{k,t,s}^{DNreg,EV}$	The DA arranged up-/down-regulation power of station k at time t for scenario s
$c_{S_k}^{loss}$	The cost of the line loss of power when charging in station k
χ	The confidence level in CVaR
ξ	the greatest value of the profit in CVaR
η_s	The difference between EP in scenario s and ξ in CVaR
$P_{t,s}^{m}$ / $Q_{t,s}^{m}$	The active / reactive power from connected main grid at time t for scenario s
$P_{nr,t,s}$ / $Q_{nr,t,s}$	The active /reactive power flows from bus n to bus r at time t for scenario s
$V_{n,t,s}$	The voltage amplitude at bus n at time t for scenario s
$\theta_{n,t,s}$	The voltage angle at bus n at time t for scenario s
$y_{i,t,s}$ / $z_{i,t,s}$	Binary variables denoting start-up/shutdown of DG unit i at time t and scenario s.
$u_{i,t,s}$	Binary variable denoting commitment status of DG unit i at time t and scenario s.
φ	The regulation proportion of total charging power
δ	The percentage of maximum charging price

I. Introduction

CARBON neutralization has raised extensive focus toward utilization of renewable energy sources (RESs) such as wind and solar power. However, strong volatility and intermittency of RESs will inevitably increase system operation risks [1].

Stochastic scheduling can comprehensively consider uncertainties, evaluate system risks and make a tradeoff while scheduling. For example, in [2], a stochastic chance-constrained method has been used to reduce the destructive impact on power system from RES-based energy systems and microgrids. Similarly, a stochastic scheduling method has been proposed in [3] to reduce the expected operating cost and the impact of the worst-case scenario. As a necessary component of smart grid, flexible load sources (FLSs) can increase the economy and security of system operation, which have been applied to stochastic scheduling actions proposed in [4]-[5]. In [6], by modeling the randomness of residential loads, FLS has been taken as an important and relatively stable source to participate in stochastic scheduling. Similarly, by taking RESs, distributed generators (DGs) and uncertain demand response (DR) together as a virtual power plant (VPP), a two-stage risk-constrained stochastic scheduling has been proposed in [7]. Moreover, in [8] and [9], FLS has been used for stochastic dynamic optimization of an integrated energy system.

Electric vehicle (EV) is a special kind of FLS. To integrate EVs dispatching into an optimal scheduling problem, many research works have been carried out considering different objectives such as minimizing the total operation cost [10] or maximizing the whole profit of systems [11]. In [12], a hybrid decentralized robust-stochastic programming method has been proposed for coordinating EVs and energy hubs to acquire the highest profit, considering the uncertainty of EVs and the worst-case scenario. Similarly, aiming at the maximum benefits, an optimal scheduling strategy for EV aggregators (EVAs) has been proposed by considering the triple benefits of EV users, EVAs and the distribution system operator (DSO) [13]. Aiming at the minimum costs, a distribution enterprise operating mode for EVAs has been proposed by eliminating the penalties caused by uncertainties [10]. Nevertheless, to realize the active participation of EVs, incentive mechanism for charging is needed to support the decision-making plan or scheduling in the system level. Commonly, Time-of-Use (TOU) price [14] and Real-Time price (RTP) [15] are used to change users' choices on charging demand and periods. In later researches, these methods have gradually evolved into a charging menu based on RTP or TOU, and the purpose is the optimal charging cost [16]-[17]. There are also customers participating in the ancillary services [18], where the flexible charging and discharging ability of EVs is used to balance the real-time power supply and demand, so as to obtain market revenue. The above two parts including EVs dispatching and charging mechanism form a relatively complete framework of using EVs for system scheduling.

However, the above researches focus on the flexibility in charging time. Definitely, proper time management contributes to economical operation when EVs dispatching and charging mechanism are coordinated well, but two more challenges need to be addressed. One is the spatial characteristic, which will cause different incremental line losses when charging. Different charging locations will cause economic differences in system scheduling because the cost of line loss and charging congestion both in time and in the same place will have strong impacts. The other one is users' willingness. To guide EVs to charge at different locations, charging discounts in different areas must be sent to users. In most of the above-mentioned researches on charging mechanisms, price menus and charging packages have been bound in the hardware facilities of charging piles and stations. These methods cannot dominate users' driving behaviors, because the charging discount information of the piles /stations in different regions is not directly shared.

We can assume that if the charging prices of all piles or stations are sent to users, their driving behaviors will change when comparing the prices in different regions. Actually, many researchers noticed this and designed various competitive pricing strategies [19]-[24]. For example, from investors' perspective, a PEV fast charging station (CS) planning framework has been proposed in [19], which aims to maximize the total profit including both the capital cost and the operation profit. From the perspective of CS operators [20], a multileader–multifollower stackelberg game model has been improved under a 1-D system with two competing CSs and Poisson arriving EVs. If the price information is not completely shared, a Bayesian game framework has been proposed to solve EV pricing problem in [21]. All the above literatures show that the users' selections mainly depend on CS sizing, siting, and pricing. Users' selection models have been established in [19],[20] and [21],but only used for the CS operators including both existing private operators and new competitive investors. Different from [19],[20] and [21], researchers in [22] have completed a work from a central operator's perspective. A joint planning algorithm from a central planner's perspective has been proposed to allocate smart EV CSs and DGs in microgrids in [22].

Among the above mentioned research, pricing strategies are used for either CSs planning which is conducted by investors and planners, or optimal operation of CS operators. There is little research in that EVs pricing strategies are utilized for economic scheduling. From the perspective of the whole distribution system, it is also economically advantageous to combine EVs charging with scheduling of power grid. So, in our previous study [23], an incentive strategy for EVs charging was proposed to increase the scheduling profit of DSO. The idea of [23] shows that DSO can gain more profits when scheduling because the strategy can guide more EVs to charge in leisure CSs so as to increase DSO's benefit from selling more power. However, the applicability of [23] is limited because DSO hardly makes a deterministic schedule due to the day ahead (DA) prediction error from uncertain load and RES.

Therefore, to make that idea more practical in real-life settings under different uncertainties, an extension of the work is presented here by taking a stochastic risk-constrained scheduling framework into account. Several improvements are completed from modeling, strategy-designing and applicability analyzing, including 1) an advanced users' selection model with price sensitivity; 2) a more practical risk-constrained stochastic scheduling strategy combining scenarios, EVs guidance and regulation, charging power loss and risk estimation; 3) a comprehensive set of constraints and performance analysis on different conditions. The main contributions can be summarized as follows:

1) A stochastic scheduling framework embedded with an incentive charging strategy for EVs is proposed, in which DSO combines the scheduling of power grid and EVs charging by flexible price approaches to contribute to system operation.

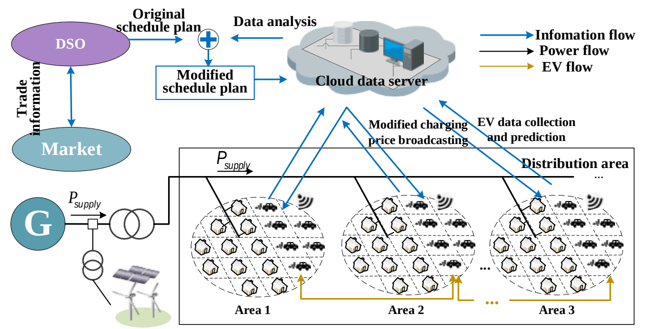


Fig.1 Concept for incentive EV charging strategy integrated in DSO's scheduling plan.

2) Users' selection model for CSs is modified and a price-based transfer model (PBTM) is proposed to describe the correlation between charging price and EVs transfer, and the flow model of EV population in multi-areas is constructed.

3) The PBTM is integrated into stochastic scheduling, and an advanced scheduling strategy is proposed. Apart from common scheduling approaches like DGs and RES cost, market trade, and CVaR risk, EVs charging income, incremental line loss cost caused by geographical charging, and flexible regulation cost provided by EVs are considered, which implicitly shows the spatial and temporal characteristics of EVs charging behaviors.

4) The applicability and economic advantages of the proposed strategy and the influence of important parameters from different aspects, such as charging station capacity, users' price sensitivity and EV regulation depth are discussed.

The remaining part of the article is organized as follows. Section II presents the description of the proposed incentive strategy. Section III describes price-based transfer model of EVs. Section IV presents the modeling approach and solution methodology. Section V presents simulation and numerical results. Finally, conclusions are drawn in Section VI.

II. Description Of The Proposed Incentive Strategy

With the help of advanced communication and digital technology such as cloud and edge computing, geographically distributed FLS can be managed by centralized methods. Fig.1 shows the overall structure of the proposed incentive charging strategy, which is integrated in the stochastic scheduling.

The DSO has a key role in this management process where the aim is to maximize the profit while meeting technical constraints. When EVs' charging request is intensified in certain areas at relatively short time periods, charging congestion could happen since EVs would be queued for long waiting time in those stations while other stations would be unoccupied with no or little profits. Thus, it is important for DSO to guide EVs among different areas for proper load sharing, efficient power regulation during peak periods, and keeping user's satisfaction as high as possible.

Generally, the DSO will make DA scheduling according to the prediction of loads, output of renewable energy and market price in the next day. By collecting historical data about the EVs' arrival times, DSO could analyze EVs' characteristic in each area via cloud servers. Then, DSO can induce drivers' charging activities by providing charging discount or financial incentive for each station. Moreover, with the help of cloud computing in modeling and analysis, a modified scheduling plan with a higher economical profit can be formed. Finally, the guidance is customer-oriented. The DSO need to broadcast the modified charging price in each station to EV drivers.

III. Price-Based Transfer Model of EVs

A. Modeling of SOC of an Individual EV

EVs can be served as distributed energy storage units to provide balance service e.g. economic scheduling and operation. For a grid-connected EV, the state of charge (SOC) plays an important role when an EV is used for balance service. SOC has a strong relationship on power capacity and duration time provided by an EV.

Generally, EVs' charging pattern can refer to the charging characteristics of lithium batteries. The SOC evolution model of one EV can be described as follows:

$$SOC(t+1) = SOC(t) + \frac{\eta P_{\mathrm{EV}}}{E_{\mathrm{EV}}} \Delta t \tag{1}$$

$$SOC_{\min} \le SOC \le SOC_{\max} \tag{2}$$

where $SOC(t+1)$ and $SOC(t)$ are the charged state of the electric vehicle in period k+1 and period k respectively. η is charging efficiency, P_{EV} is the rated charging power of electric vehicles, E_{EV} is the rated battery capacity.

B. Modeling of Fixed EV Transfer Process

Users also play an important role as they decide EVs' transfer process. Then, the time of connecting to grid is determined. So apart from a SOC model to know its charging process, a transfer model is necessary to know EVs' arriving time and numbers.

Normally, we assume that an EV user selects a particular CS based on 1) the electricity price offered by the CS, 2) its distance from the CS, and 3) the number of available electric plugs i.e. charging capacity the CS is equipped with. One's selection will take the minimum combined utility of the above three items as the target. Thus, according to literature [24], we can define a utility term that describe the selection of CS i by one EV user j, as follows:

$$Ut_j: \quad i^* = \arg\min d_{i,j}^{2\alpha} p_i^{ch} k_i \tag{3}$$

where i^* represents that CS i is selected by user j, $d_{i,j}^{2\alpha}$ is the distance between area i and j , and the nonnegative parameter α reflects the significance of the distance for CS selection, i.e., EVs are more reluctant to visit CSs which are far away when the value of α is large. p_i^{ch} is the charging price of CS i, and $k_i = (n_i)^{-2}$ represents the impact of capacity of CS i , which is the function of the number of available electric plugs.

Generally, without shared prices to users, we can assume one's selection will depend on the distance and CS capacity, which can be described as $i^* = \arg\min d_{i,j}^{2\alpha} k_i$. However, for a scheduling task conducted by DSO, the CSs are existed with fixed and pre-setting parameters. So, for an EV user, his/her selection will be relatively fixed according to his/her location at that time. Then for EVs population, the transfer process will also be fixed, which can be defined as follows: A number of M areas, which can be depicted as a set $AREA = \{Area_1, Area_2, ..., Area_{\mathrm{M}}\}$ and a total of K CSs $STN = \{S_1, S_2, ..., S_K\}$ is defined to form a multi-regions problem. Users are distributed among different locations in each area, so we also define a set of users by $U(t) = \{u_1(t), u_2(t), ..., u_N(t)\}$ to depict users' distribution at time t. According to (3), when user n transfers from area i to area j, a choice must be made by comparing the distance from the expected destination and the capacity of the destination as follows:

$$\underset{u_n \in Area\ i,\, S_k \in Area\ j}{u_{n|k}(t)} \quad : S_k^*(t) = \arg\min d_{u_n(t)S_k}^{2\alpha} k_{S_k} \tag{4}$$

where $u_{n|k}(t)$ represents the transfer of user n from area i to station k in area j at the time t. Generally, the locations of CSs are fixed, and the capacities of CSs are relatively fixed as well. If users couldn't receive the shared discount information, they will take the above two as main factors for decision-making. So there is a fixed transfer process between areas, the possibility of which can be formed by (5)-(6).

$$U_{ij}(t) = \left\{ u_{n|k}(t) \middle| \begin{array}{l} n = 1,2,3,\ ...,\ N, \\ u_n \in Area\ i, S_k \in Area\ j \end{array} \right\} \tag{5}$$

$$\rho_{ij}(t) = \frac{N_i^{arv}(t) - \left|U_{ij}(t)\right|}{N_i^{arv}(t)} \tag{6}$$

where $U_{ij}(t)$ represents the set of users that transfer from area i to area j at the time t, $\rho_{ij}(t)$ is the EVs transfer possibility from area i to area j at the time t, $N_i^{arv}(t)$ is the predictive number of arriving EVs of area i at time t, and $|\cdot|$ represents the number of elements of a set.

C. Modeling of EVs flow with price impact

Considering the price impact on charging choices, a PBTM can be established according to the two rules: 1) if the charging prices of different areas or stations are the same, the transfer probability of EVs will keep the same as (6). 2) if the charging price of one station can reach someone's expectation, the modified transfer probability of the user will reach up to 1.

According to consumer psychology model [25], the price impact can be modeled as linear function, denoted as (7)-(8).

$$f(\Delta p_{ij}^{ch,t}) = \left(\frac{1}{\rho_{ij}(t)} - 1 \right) \frac{\left(p_{i,t}^{ch} - p_{j,t}^{ch} \right)}{\Delta p_{ept}^{ch}} + 1 \tag{7}$$

$$\Delta p_{ij}^{ch,t} = p_{i,t}^{ch} - p_{j,t}^{ch} \tag{8}$$

where $\Delta p_{ij}^{ch,t}$ is the price difference value between area i and j at time t, $p_{i,t}^{ch}$ is the charging price of area i at time t, and Δp_{ept}^{ch} denotes users' expected price difference. Then, the modified transfer probability between different areas will be the product of original transfer probability and the price impact function, denoted by (9).

$$\hat{\rho}_{ij}(t) = \rho_{ij}(t) f(\Delta p_{ij}^{ch,t}) \tag{9}$$

Therefore, the total amount of EVs and the flow can be denoted as below:

$$\hat{N}_i^{arv}(t) = \left[\sum_{j=1, j\neq i}^{M} N_j^{arv}(t) \hat{\rho}_{ji}(t) - \left(N_i^{arv}(t)(1 - \sum_{j=1, j\neq i}^{M} \hat{\rho}_{ij}(t)) \right) \right] \tag{10}$$

$$N_i^{ext}(t) = N_i^{org}(t) + \hat{N}_i^{arv}(t) - N_i^{lv}(t) \tag{11}$$

Equation (10) describes the relationship of EVs' flow in and out between different areas. For each area, the modified number of arriving EVs consists of the number of EVs' flowing out to other areas and the number of EVs' flowing in from other areas. Once the number of arriving EVs is calculated, the total amount can be calculated according to (11), which depends on the number of original EVs, arriving EVs, and leaving EVs.

In (9)-(11), $\hat{\rho}_{ij}(t)$ is the modified EVs transfer possibility from area *i* to area *j* at the time *t*, $\hat{N}_i^{arv}(t)$ is the modified predictive number of arriving EVs of area *i* at time *t*, respectively, and $N_i^{ext}(t)$ is the number of existing EVs of area *i* at time *t* considering price impact. $N_i^{org}(t)$ is the number of original EVs of area *i* at time *t*, $N_i^{lv}(t)$ is the number of leaving EVs of area *i* at time *t*. $N_i^{org}(t)$ and $N_i^{lv}(t)$ can be predicted from history distribution. Finally, the total charging power can be calculated by (12):

$$P_i^{ch}(t) = P_i^{avg} N_i^{ext}(t) x_i^{on}(t) \tag{12}$$

where $P_i^{ch}(t)$ denotes the charging power of EVs in area *i*. P_i^{avg} is the average charging power of EVs in area *i*, and $x_i^{on}(t)$ represents the distribution of on-state EVs, both of which can be calculated by historical statistics.

IV. Modeling Approach And Solution Methodology

A. Problem formulation

In this section, an optimization problem of stochastic scheduling integrated with the incentive charging strategy is formulated to maximize the expected profit of DSO. The aim of the strategy is to determine the optimal energy dispatch, EV charging prices as well as charging power in different areas. Therefore, the decision variables include two parts, one of which is from incentive charging strategy and another is from stochastic scheduling.

In the first part, charging power of area *i* ($P_i^{ch}(t)$) is an important decision variable, which is a linear function of charging price ($p_{i,t}^{ch}$) according to (7)-(10). The charging power of area *i* ($P_i^{ch}(t)$) is the sum of charging power of stations located in this area ($P_{k,t,s}^{ch}$), which can be obtained once we calculate $P_i^{ch}(t)$ according to fixed transfer process, i.e. equation (3). In the second part, decision variables include commitment states of DG units ($u_{i,t,s}$), their scheduled active power ($P_{i,t,s}^{DG}$), start-up and shut-down costs of DGs ($C_{i,t,s}^{SU}$ and $C_{i,t,s}^{SD}$), power scheduled to be bought from and sold to the main grid ($P_{t,s}^{DA,buy}$ and $P_{t,s}^{DA,sell}$) and the scheduled up- and down- regulation power provided by EVs ($P_{k,t,s}^{UPreg,EV}$ and $P_{k,t,s}^{DNreg,EV}$)for all scenarios and 24h. The proposed strategy is given with more details in the following subsections.

B. Objective function of the proposed problem

The purpose of the DSO is to maximize the expected profit (EP) by guiding EVs from lower-capacity areas to larger-capacity areas to sell more electricity to users. The objective function is composed of the following parts:

$$\text{Max(EP)} = \begin{pmatrix} \text{Income}_{CL} + \text{Income}_{EV} - \text{Cost}_M \\ -\text{Cost}_{GEN} - \text{Cost}_{RG} - \text{Cost}_{LLS} \end{pmatrix} + \beta \text{CVaR} \tag{13}$$

where Income_{CL} is the income from selling electricity to common loads and Income_{EV} is the one made from EVs. Cost_M is the total cost of trade with market and Cost_{GEN} is the total cost of power generation, which includes the operation cost of DGs, PVs and WTs. Cost_R represents the cost of EVs regulation and Cost_{LLS} is the cost of extra power loss during EVs charging process. Different terms in (13) are formulated in the following.

$$\text{Income}_{CL} = \sum_{s=1}^{NS}\sum_{t=1}^{T} \pi_s c_{t,s}^{RDA,sell} P_{t,s}^{L} \Delta t \tag{14}$$

$$\text{Income}_{EV} = \sum_{s=1}^{NS}\sum_{t=1}^{T}\sum_{m=1}^{M} \pi_s p_{m,t,s}^{ch} \left(\sum_{S_k \in Area\ m} P_{k,t,s}^{ch} \right) \Delta t \tag{15}$$

In (14) and (15), π_s is the probability of occurrence of scenario *s*, Δt is the duration of time period *t* which can be one hour in DA schedule. $c_{t,s}^{RDA,sell}$ is the retail price of DA market at time *t* for scenario *s*, and $P_{t,s}^{L}$ represents the power of common loads at time *t* for scenario *s*. $p_{m,t,s}^{ch}$ is the charging price of area *m*, and $P_{k,t,s}^{ch}$ is the charging power of station *k*. Note that charging prices are set the same in different stations but in the same area to make the management of stations in the same area easier. Then, Cost_M includes both selling and buying transactions, which can be formulated as follows:

$$\text{Cost}_M = \sum_{s=1}^{NS}\sum_{t=1}^{T} \pi_s \left(c_{t,s}^{MDA,sell} P_{t,s}^{DA,sell} - c_{t,s}^{MDA,buy} P_{t,s}^{DA,buy} \right) \Delta t \tag{16}$$

where $c_{t,s}^{MDA,sell}$ and $c_{t,s}^{MDA,buy}$ are the whole selling price and buying price of DA market at time *t* for scenario *s*, $P_{t,s}^{DA,sell}$ and $P_{t,s}^{DA,buy}$ are the selling power and buying power , respectively. The term Cost_{GEN} stands for the cost of power production from various generation units. In this article, wind and photovoltaic (PV) units are considered as DSO-owned, generating together with DGs. Thus the Cost_{GEN} represents as follows:

$$\text{Cost}_{GEN} = \text{Cost}_{DGs} + \text{Cost}_{RES} \tag{17}$$

$$\text{Cost}_{DGs} = \sum_{s=1}^{NS}\sum_{t=1}^{T} \pi_s \begin{pmatrix} \sum_{i=1}^{N_G} C_i(P_{i,t,s}^{DG}) \\ +C_{i,t,s}^{SU} + C_{i,t,s}^{SD} \end{pmatrix} \Delta t \tag{18}$$

$$\text{Cost}_{RES} = \sum_{s=1}^{NS}\sum_{t=1}^{T} \pi_s \left(\sum_{i=1}^{N_{WT}} c_{i,t}^{WT} P_{i,t,s}^{WT} + \sum_{i=1}^{N_{PV}} c_{i,t}^{PV} P_{i,t,s}^{PV} \right) \Delta t \tag{19}$$

In (17)-(19), $C_i(P_{i,t,s}^{DG})$ is the cost function of the *i*th generator unit, usually taken as a quadratic function. $C_{i,t,s}^{SU}$ and $C_{i,t,s}^{SD}$ are the start-up and shut-down costs of the *i*th generator unit at time *t* for scenario *s*. $P_{i,t,s}^{DG}$, $P_{i,t,s}^{WT}$ and $P_{i,t,s}^{PV}$ are the *i*th outputs of different units, and $c_{i,t}^{WT}$, $c_{i,t}^{PV}$ are the operating costs of WTs and PVs at time *t*. Then Cost_{RG} can be calculated as below:

$$\text{Cost}_{RG} = \sum_{s=1}^{NS}\sum_{t=1}^{T} \pi_s \sum_{m=1}^{M} \begin{pmatrix} c_{m,t}^{UPreg,DA} \sum_{S_k \in Area\ m} P_{k,t,s}^{UPreg,EV} + \\ c_{m,t}^{DNreg,DA} \sum_{S_k \in Area\ m} P_{k,t,s}^{DNreg,EV} \end{pmatrix} \Delta t \tag{20}$$

where $c_{m,t}^{UPreg,DA}$ and $c_{m,t}^{DNreg,DA}$ is the up- and down- regulation price of area m in DA market, and $P_{k,t,s}^{UPreg,EV}$ and $P_{k,t,s}^{DNreg,EV}$ are the DA arranged up- and down- regulation power of station *k* at time *t* for scenario *s*, respectively.

Finally, it is important and economically advantageous to consider the extra power loss caused by EVs charging. EV is a special load that has spatial transfer characteristics of energy. Actually, there is different power loss in different locations of the power grid, i.e. the closer load is to power supply units, the less power loss is. When the charging demand is large, the location of this charging load will certainly affect economics of system operation. Therefore, it is significant for DSO to take the cost of this extra power loss into consideration when making economical scheduling. The cost of this power loss can be formulated as (21).

$$\text{Cost}_{LLS}=\sum_{s=1}^{NS}\sum_{t=1}^{T}\pi_s\sum_{m=1}^{M}\left(\sum_{S_k\in Area\ m}c_{S_k}^{loss}P_{k,t,s}^{ch}\right)\Delta t \tag{21}$$

where $c_{S_k}^{loss}$ is the cost of the line loss of power when charging in station *k*. The last term of the objective function is conditional value at risk (CVaR) that is multiplied by a risk factor. CVaR is a typical method to tradeoff profit and risk under various uncertain scenarios, which is denoted as follows [7],[29]:

$$\text{CVaR}=\left[\xi-(1-\chi)^{-1}\sum_{s=1}^{NS}\pi_s\eta_s\right] \tag{22}$$

where χ is the confidence level within a range of 0.90-0.99 normally. The auxiliary variable ξ is the greatest value of the profit and η_s is the difference between EP in scenario *s* and ξ.

C. Constraints of the proposed problem

The above objective function needs to satisfy the following constraints, including operating security, dispatchable capacity from DGs and EVs, EVs charging price limits, market trade limits, as well as CVaR constraints.

1) Linearized Power Flow Equations: To ensure the security of system operation, an AC power flow of distribution network for each scenario and at each time interval must be met. Equations (23) and (24) represent the active and reactive power balance between supply and demand sides at node *n* as follows.

$$\sum_{i=1}^{N_G^n}P_{i,t,s}^{DG,n}+\sum_{i=1}^{N_{RES}^n}P_{i,t,s}^{RES,n}-\hat{P}_{t,s}^{L,n}=\sum_{r=1}^{N_B}P_{nr,t,s} \tag{23}$$

$$\sum_{i=1}^{N_G^n}Q_{i,t,s}^{DG,n}+\sum_{i=1}^{N_{RES}^n}Q_{i,t,s}^{RES,n}-\hat{Q}_{t,s}^{L,n}=\sum_{r=1}^{N_B}Q_{nr,t,s} \tag{24}$$

$$P_{i,t,s}^{RES,n}=P_{i,t,s}^{WT,n}+P_{i,t,s}^{PV,n} \tag{25}$$

$$Q_{i,t,s}^{RES,n}=Q_{i,t,s}^{WT,n}+Q_{i,t,s}^{PV,n} \tag{26}$$

$$\hat{P}_{t,s}^{L,n}=P_{t,s}^{L,n}+\sum_{S_k\in bus\ n}P_{k,t,s}^{ch,n}+\sum_{S_k\in bus\ n}P_{k,t,s}^{UPreg,EV}-\sum_{S_k\in bus\ n}P_{k,t,s}^{DNreg,EV} \tag{27}$$

$$\hat{Q}_{t,s}^{L,n}=Q_{t,s}^{L,n}+\sum_{S_k\in bus\ n}Q_{t,s}^{ch,n}+\sum_{S_k\in bus\ n}Q_{k,t,s}^{UPreg,EV}-\sum_{S_k\in bus\ n}Q_{k,t,s}^{DNreg,EV} \tag{28}$$

$$P_{nr,t,s}=G_{nn}^l(2V_{n,t,s}-1)+\sum_{r=1,r\neq n}^{N_B}G_{nr}^l(V_{n,t,s}+V_{r,t,s}-1)+B_{nr}^l(\theta_{n,t,s}-\theta_{r,t,s}) \tag{29}$$

$$Q_{nr,t,s}=-B_{nn}^l(2V_{n,t,s}-1)-\sum_{r=1,r\neq n}^{N_B}B_{nr}^l(V_{n,t,s}+V_{r,t,s}-1)+G_{nr}^l(\theta_{n,t,s}-\theta_{r,t,s}) \tag{30}$$

When it comes to bus 1, which connects to the main grid, $P_{t,s}^m$ and $Q_{t,s}^m$ must be add into the left of (23) and (24), respectively [26]. From (23) to (30), $P_{nr,t,s}$ and $Q_{nr,t,s}$ represent the active and reactive power flows from bus *n* to bus *r*, which can be calculated by a general linearized form in [7], [26]and[27].

Other operating constraints for network security includes voltage limit (31)-(32) and line flow limits (33)-(34) [28].

$$V_n^{\min}\le V_{n,t,s}\le V_n^{\max} \tag{31}$$

$$\theta_n^{\min}\le\theta_{n,t,s}\le\theta_n^{\max} \tag{32}$$

$$P_{nr}^{\min}\le P_{nr,t,s}\le P_{nr}^{\max} \tag{33}$$

$$Q_{nr}^{\min}\le Q_{nr,t,s}\le Q_{nr}^{\max} \tag{34}$$

2) Dispatchable Distributed Generators Constraints: The output of DGs need to meet the minimum and maximum limits (35) as well as the power capacity limits (36).

$$P_{\min}^{DG}\le P_{i,t,s}^{DG}\le P_{\max}^{DG} \tag{35}$$

$$P_{\min}^{DG}u_{i,t,s}\le P_{i,t,s}^{DG}\le P_{\max}^{DG}u_{i,t,s} \tag{36}$$

Considering the feasible operational region, the minimum up/down time limits (37)-(38), and ramping rate limits (39)-(40) are set to ensure a reasonable operation.

$$\sum_{h=t}^{t+UT_i-1}u_{i,h,s}\ge UT_i y_{i,t,s} \tag{37}$$

$$\sum_{h=t}^{t+DT_i-1}(1-u_{i,h,s})\ge DT_i z_{i,t,s} \tag{38}$$

$$\left(P_{i,t,s}^{DG}-P_{i,t-1,s}^{DG}\right)z_{i,t,s}\le\min\left\{P_{i,t,s}^{DG}-P_{i,\min}^{DG},\Delta t\times R_{i,down}\right\} \tag{39}$$

$$\left(P_{i,t,s}^{DG}-P_{i,t-1,s}^{DG}\right)y_{i,t,s}\le\min\left\{P_{i,\max}^{DG}-P_{i,t,s}^{DG},\Delta t\times R_{i,up}\right\} \tag{40}$$

Where UT_i and DT_i are the minimum up and down time of DG unit i. Meanwhile, the binary variables of DGs should meet the following relationship when starting-up and shutting-down[29].

$$y_{i,t,s}-z_{i,t,s}=u_{i,t,s}-u_{i,t-1,s} \tag{41}$$

$$y_{i,t,s}+z_{i,t,s}\le 1 \tag{42}$$

3) EVs Charging and Regulation Constraints: The charging power of EVs in one area is the sum of charging power in several CSs, which can be denoted by (43). For a CS, the charging power cannot exceed the station's capacity (44). For an area, the total charging power depends on the number of on-state, so it should be limited by total number of EVs in this area (45).

$$P_{m,t,s}^{ch}=\sum_{S_k\in Area\ m}P_{k,t,s}^{ch},\forall Area\ m \tag{43}$$

$$0\le P_{k,t,s}^{ch}\le P_{\max}^{S_k},\forall S_k \tag{44}$$

$$0\le P_{m,s}^{ch}(t)\le P_m^{avg}N_m^{ext}(t),\forall Area\ m \tag{45}$$

EV is a flexible load, power of which can be easily regulated to provide balance service for power grid when needed. So, the up- and down- regulation capacity of EVs are considered into constraints (46) -(49). The regulation capacity is limited by both station's capacity and amount of EVs, which can be formulated as below:

$$0\le P_{m,t,s}^{ch}+\sum_{S_k\in Area\ m}P_{k,t,s}^{UPreg,EV}\le P_m^{avg}N_m^{ext}(t) \tag{46}$$

$$0\le P_{m,t,s}^{ch}+\sum_{S_k\in Area\ m}P_{k,t,s}^{UPreg,EV}\le\sum_{S_k\in Area\ m}P_{\max}^{S_k} \tag{47}$$

$$0\le P_{m,t,s}^{ch}-\sum_{S_k\in Area\ m}P_{k,t,s}^{DNreg,EV}\le P_m^{avg}N_m^{ext}(t) \tag{48}$$

$$0\le P_{m,t,s}^{ch}-\sum_{S_k\in Area\ m}P_{k,t,s}^{DNreg,EV}\le\sum_{S_k\in Area\ m}P_{\max}^{S_k} \tag{49}$$

In this article, users' satisfaction levels are also taken into consideration when users are participating in regulation services. The amount of power regulation has direct influence on user's dissatisfaction. Thus, to avoid excessive dissatisfaction, regulation limits should be met, which is denoted by (50):

$$\sum_{t=1}^{T}\left(\sum_{S_k\in Area\ m}\left(P_{k,t,s}^{UPreg,EV}+P_{k,t,s}^{DNreg,EV}\right)\right)\le\varphi\sum_{t=1}^{T}P_{m,s}^{ch}(t),\forall area\ m \tag{50}$$

Equation (50) ensures that the charging power deviation caused by regulation will not exceed a certain proportion of total charging demand. In (50), φ is the regulation proportion of total charging power, which shows elasticity of EVs and depends on different user groups' characteristics.

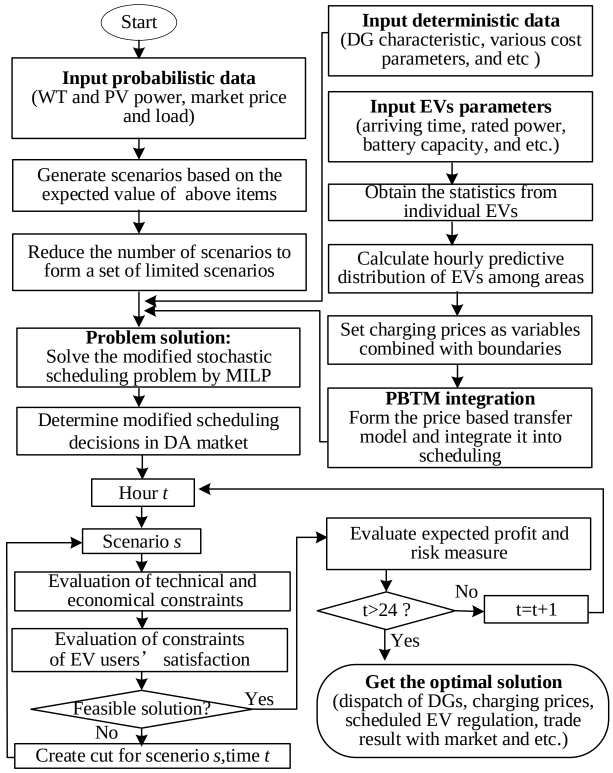


Fig.2. Flowchart of the proposed optimization procedure

4) EVs Charging price and transfer Constraints: In the proposed incentive charging strategy, DSO needs to design an attractive price for EVs. The optimized charging price cannot exceed the original price because if the optimized price is higher, that will be less attractive. So, a constraint for charging price is defined by (51).

$$0 \le p_i^{ch}(t) \le p_{\max}^{ch,EV} \tag{51}$$

Equation (51) aims to avoid negative charging price caused by blind competition and contributes to a reasonable price interval. Apart from (51), users' expectation p_{ept}^{ch} on price should also be limited in this interval. Consequently, price differences between different areas will not exceed users' expectation as once the difference reached p_{ept}^{ch}, user's transfer behavior will certainly change according to the proposed PBTM in Section III. Therefore, a set of price constraints is formulated by (52)-(55).

$$p_{ept}^{ch} = \delta p_{\max}^{ch,EV} \tag{52}$$

$$0 \le \delta \le 1 \tag{53}$$

$$-p_{ept}^{ch} \le \Delta p_{ij}^{ch,t} \le p_{ept}^{ch} \tag{54}$$

$$\Delta p_{ij}^{ch,t} = -\Delta p_{ji}^{ch,t} \tag{55}$$

Where δ is the percentage of maximum charging price which shows users' price sensitivity, and $p_{\max}^{ch,EV}$ is the maximum charging price, which can be taken as normal charging price.

5) Market Transaction Constraints: The power trade with market should meet the certain limits, which depends on market requirements and tie-line capacities. So the constraints can be denoted by (56)-(59).

$$0 \le P_{t,s}^{DA,buy} \le P_{\max}^{buy} \tag{56}$$

$$0 \le P_{t,s}^{DA,sell} \le P_{\max}^{sell} \tag{57}$$

$$0 \le P_{t,s}^{DA,buy} \le P_{\max}^{line} \tag{58}$$

$$0 \le P_{t,s}^{DA,sell} \le P_{\max}^{line} \tag{59}$$

6) CVaR Calculation Constraints: The following constraints must be considered once CVaR is calculated according to [29].

$$\eta_s + \mathrm{Max(EP)}\big|_s \ge \xi \tag{60}$$

$$\eta_s \ge 0 \tag{61}$$

D. Problem Solution Methodology

Fig.2 illustrates the solution methodology of the proposed framework. Generally, the flow of solving stochastic scheduling problem includes: 1) data input, 2) scenarios generation and reduction, 3) solution for MILP with security and reliability constraints. In the first part, both deterministic parameters and probabilistic parameters are input. In the second part, uncertainties associated with WT, PV, load, and market price are modeled using the Monte Carlo simulation (MCS) method according to their probability distribution functions (PDFs). A tree with a total of 10^4 scenarios is generated and consequently 20 scenarios are clustered by the K-means algorithm. In the last part, all reduced scenarios are implemented to the stochastic optimization to maximize EP as well as system security verification by considering optimal power flow (OPF).

Differently, to integrate the incentive charging strategy into stochastic scheduling, an extra series of steps are added into Fig.2. Before solving the MILP problem, heterogeneous parameters of rated power, battery capacity and charging efficiency, as well as arriving and leaving time, are initialized and counted into statistics. Then the hourly distribution of EVs charging demand in each area can be obtained. Moreover, charging prices are taken as variables to form a PBTM and to modify the objective function in section IV. Also, a step of evaluation of users' satisfaction limits is needed after considering economical and security constraints. The modified model is also a MILP problem, and the final optimized results include scheduled deployment of DGs, regulation of EVs, the optimal charging price in each area, and etc.

V. Simulation And Numerical Results

A. Case study and simulation parameters

The strategy proposed in this paper is applied to a modified IEEE 30-bus distribution system coupled with a city route map. As can be seen in Fig.3, the whole map is divided into 3 areas, and each area is equipped with a fast CS. The whole distribution network is composed of 3 dispatchable DG units, 20 wind turbines and 15 PV units, which are distributed in different buses as shown in Fig.3. The parameters of DGs and renewable generation are as shown in TABLE I.

The expected average output of RESs, as well as load data are obtained from pieces of the historic statistics from a power plant, and the market price is from [28], which can be seen in Fig.4. In the composition of load, common fixed load and EVs are set according to different proportion. Totally, 1233 EVs from the whole optimized periods are generated by Monte Carlo method, all of which have a parameter distribution as shown in TABLE II. The other parameters for the proposed strategy are listed in TABLE III.

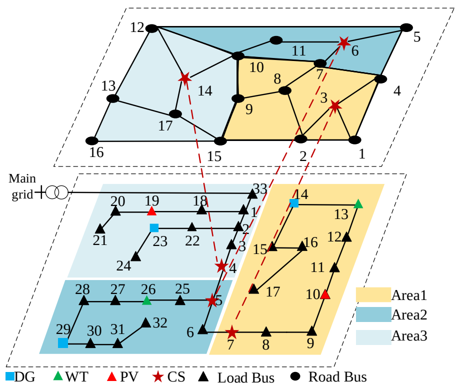


Fig.3. Traffic-grid coupling networks and CSs distribution

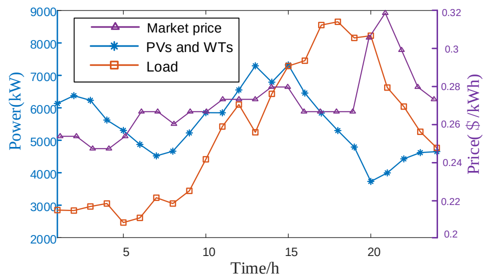


Fig.4. The hourly expected value of RES, load and price.

TABLE I
INFORMATION OF GENERATING UNITS

Unit	Min-Max Generation (kW)	Marginal Cost ($/kWh)	Start-up Cost($)	Shut-down Cost($)	Amount
DG	30-400	0.055	0.09	0.08	2
DG	30-600	0.045	0.09	0.08	1
WT	0-80	0.060	-	-	20
PV	0-75	0.040	-	-	15

TABLE II
PARAMETERS OF EVS AND INITIALIZATION

Parameters	Value	Initialization	Value
Rated charging power	20-40(kW)	Arriving time	Random
Rated battery capacity	40-90(kW/h)	Staying time	0.5-2 h
Charging efficiency	1	SOC	0.2-0.7

TABLE III
OTHER GLOBAL PARAMETERS

Parameters	Value ($/kWh)	Parameters		Value ($/kWh)
Max charging price	0.462	retailed price		0.385
Up-regulation price	0.023	Cost of loss	Area 1	0.8
Down-regulation price	0.277		Area 2	0.6
Selling price to market	0.060		Area 3	0.4

TABLE IV
CASES AND SCENES SETTINGS

settings	Capacity of CSs		
	Area1 (kW)	Area2 (kW)	Area3 (kW)
Case 1	1000	1000	5000
Case 2	1500	1000	4500
Case 3	1500	1500	4000
Case 4	2000	1500	3500

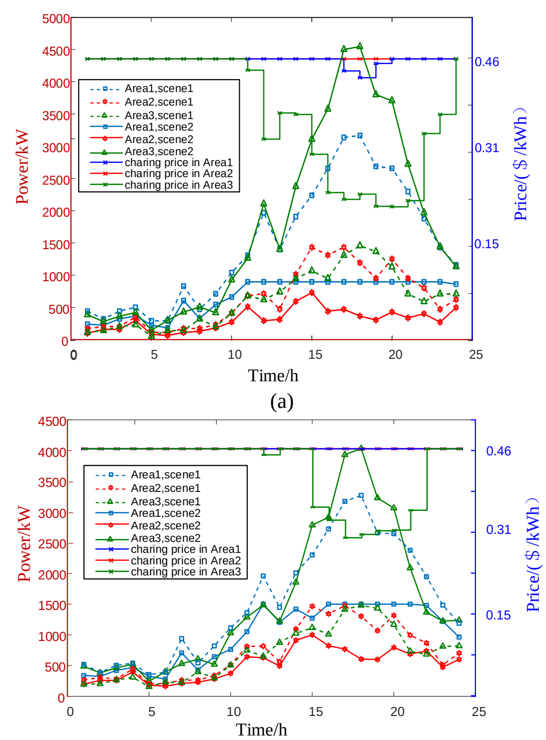
Scene index	Scene description
Scene 1	EVs transfer with a fixed price
Scene 2	EVs transfer with a modified price

In Table IV, four cases divided by different capacities of fast CSs and two scenes with different price settings are set to verify the applicability. The simulation is completed with a 24 h horizon under different cases by considering users' price sensitivity, EVs elasticity for power regulation, and risk levels. The simulation is completed by CPLEX based on MATLAB 2019b on a PC with 16GB RAM and AMD 4800U@4.2GHz processor.

B. Performance of the incentive strategy

Four cases of CSs without enough charging capacities are compared in scenes of fixed and modified prices. In this part, to avoid the impacts from various parameters of the incentive strategy, which will be discussed later in the article, some parameters are set as follow: δ is set to 0.5, and φ is set to 0.01. Fig.5 shows a comparative study where, Scene 1 denotes the situation that EVs transfer with fixed price, representing the practical phenomenon that EV users are unaware of the charging price difference between areas. Scene 2 elaborates on the proposed incentive strategy that EVs transfer with modified prices. Analysis shows that the largest charging demand is in Area 1, followed by Area 2 and 3, and the peak demands in Area 2 and 3 are far less than that in Area 1. However, Area 1 is equipped with a low capacity CS, which could hardly meet the demand during peak periods. After optimization by the proposed incentive strategy, EVs' mobility pattern as well as the charging demand is changed in different areas. The adjusted result is that the largest demand is shifted to Area 3 which has larger charging capacity.

Moreover, by increasing the capacity of Area 1 as shown in Case 1 to Case 4, smaller number of EVs have to be guided to other areas for charging. Meanwhile, the necessary price reduction during the whole time period gets smaller, denoting that the larger charging demand is, the lower price will be needed to guide EVs in lower-capacity but highly-demanded stations to larger-capacity but less-demanding stations.



(a)

(b)

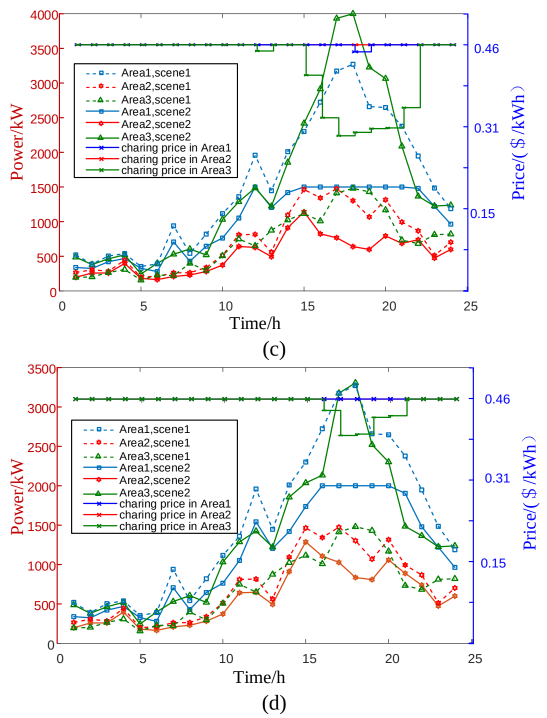


Fig.5 Charging demand and modified charging price in differ-rent areas under (a) case 1, (b) case 2, (c) case 3, (d) case 4.

C. Discussion about users' price sensitivity

Users' price sensitivity plays an important role in the performance of the proposed incentive strategy. To achieve a good guiding performance, it is necessary to discuss price sensitivity in order to adjust different incentive degrees to meet various expectations. Here, the total price reduction of all destinations that attract EVs to charge by setting lower prices is analyzed. As can be seen in Fig.6, different values of δ represent various sensitivities. The larger the value of δ is, the less sensitive the user is. With the increase of expected charging discount, users become insensitive and the CSs need to provide further price reductions to attract EVs, which in turn bring less profit to the CS as can be clearly observed in all cases. Therefore, at higher price-sensitivity of users, the DSO just needs to introduce minor incentives to guide EVs through different areas.

D. Discussion about EVs elasticity for power regulation

EVs elasticity for power regulation will be expanded with the proposed incentive strategy, which can provide more controllable power for balancing services. In Fig.7, a comparison between Case 1 and Case 4 in area 3 is made considering different scenes to see how elastic EVs would be toward power regulation. The upper and lower boundaries depict how much power EVs can provide for up/down regulation. As can be observed, in Case 1, the upper boundary and charging power in Scene 2 are larger than that in Scene 1. It means both up- and down- regulation ability from EVs are expanded. In Case 4, charging power in Scene 2 is larger, which also shows a stronger curtailment ability. Moreover, the proposed incentive strategy is with more improvement on elasticity in case 1 than case 4, denoting a higher suitability for solving charging congestion in small-capacity stations. To make this clearer, the peak period is selected to show one kind of elasticity, i.e. curtailment

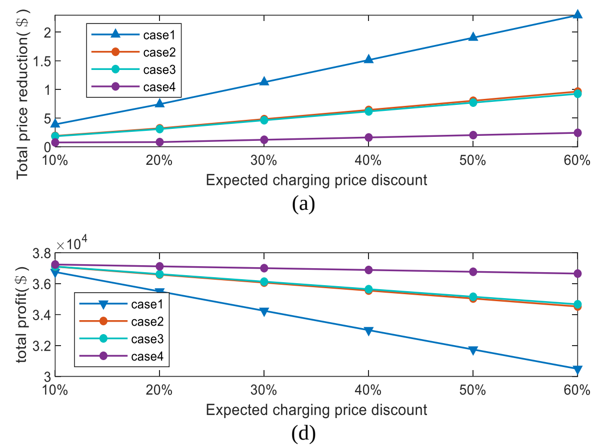


Fig.6. Total price reduction and total profits of all areas in different cases. (a) total price reduction. (b) total profits.

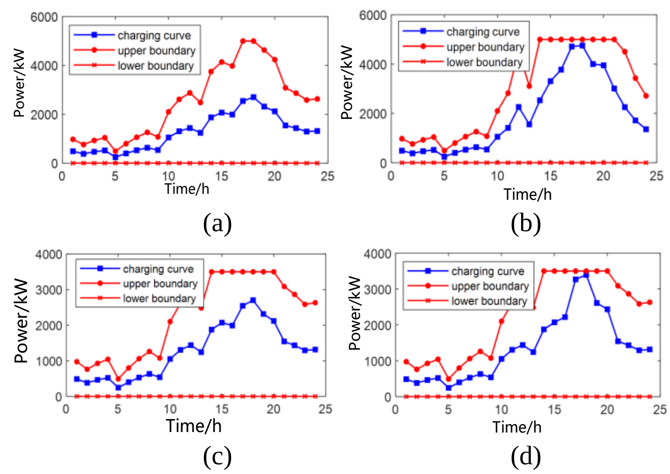


Fig.7. Charging curves and elasticity of EVs in Area 3 in different cases. (a) Case 1, Scene 1. (b) Case 1, Scene 2. (c) Case 4, Scene 1. (d) Case 4, Scene 2.

TABLE V.
COMPARISONS OF PEAK CURTAILMENT CAPACITY OF TWO SCENES IN DIFFERENT CASES

	Scene 1(kW)			
Case Index	**Area 1**	**Area 2**	**Area 3**	**total**
1	1000	1000	2119.12	4119.12
2	1500	1000	2119.12	4619.12
3	1500	1168.261	2119.12	4787.381
4	2000	1168.261	2119.12	5287.381
	Scene 2(kW)			
Case Index	**Area 1**	**Area 2**	**Area 3**	**total**
1	1000	538.8942	3950.635	5489.529
2	1500	794.1621	3197.224	5491.386
3	1500	794.1621	3197.224	5491.386
4	2000	1058.85	2434.427	5493.277

capacity. A statistic comparison is made to see the improvement in different cases as shown in Table. V.

Consequently, as seen from the table, no matter which case, the proposed incentive strategy can take full advantage of elasticity from EVs in different areas to provide power regulation services.

Due to the regulation potential, the curtailment conducted by EVs can be seen from Fig. 8. Taking Fig. 4 as a reference, it is easy to find that in the peak period, buying energy from the market is expensive and as a result, EVs are willing to contribute to peak curtailment in three areas if appropriate incentives are provided by the DSO to do so.

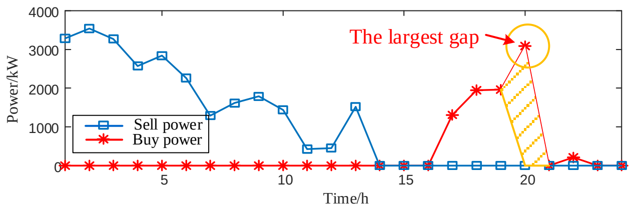


Fig.8. Peak curtailment conducted by EVs.

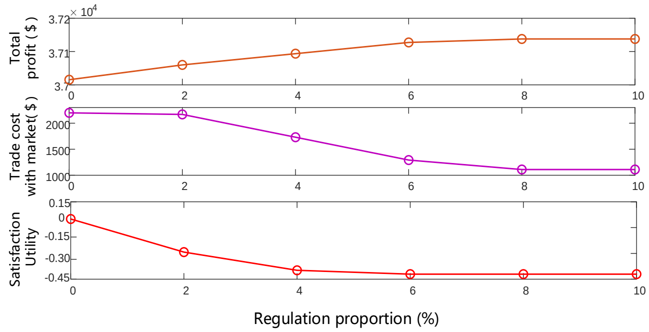


Fig.9. Trading cost with market and profits under different elasticity as well as satisfaction.

However, too much participation in regulation will certainly increase EV users' dissatisfaction. So a regulation proportion is significant for DSO to secure a curtailment plan when needed. Here, a quadratic utility function $U(x,\omega)$ is used for evaluating users' satisfaction [30]. According to convergence of users' satisfaction utility [31], a maximum 10% of φ is set to restrict the over-regulation and heavy dissatisfaction. As shown in Fig.9, with the increase of regulation proportion, the total profit of DSO will increase with a decrease of trading cost with electricity market. Meanwhile, it shows a decrease on EV users' satisfaction when more regulation proportion are allowable. The negative curve in Fig.9 represents the loss of satisfaction caused by down-regulation in peak periods.

E. Improvement and scalability verification

The proposed incentive strategy is integrated into a stochastic scheduling problem to evaluate its economic advantages in both risk-neutral case (i.e., $\beta=0$) and risk-averse case (i.e., $\beta=10$). In this subsection, we set $\delta=0.5$, $\varphi=0.08$. Fig.10 depicts the economic comparison of different cases and scenes. Here, as a general result, we can also see that the expected profit decreases as risk

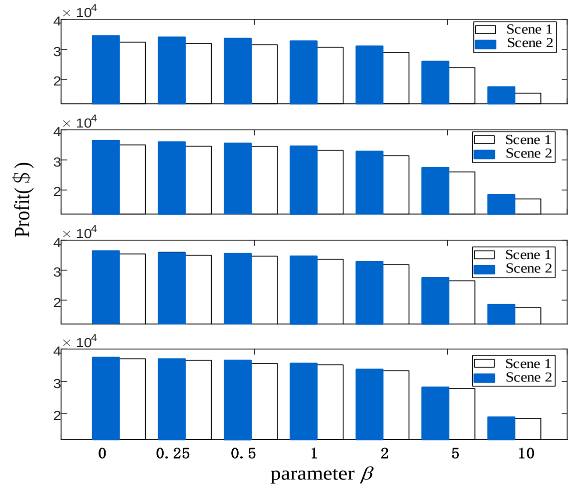


Fig.10. DSO's EP versus CVaR for different values of β

aversion increases. Additionally, comparing Scene 1 and Scene 2 in different cases, Scene 2 (the proposed strategy) can contribute to a higher profit at the same value of β no matter what the value is. Also, in Case 1(shown at the top), the economic advantage is more obvious because the proposed strategy is more suitable for solving the low-capacity but high-demand difficulties.

Apart from the application in IEEE 30-bus distribution system, similar cases are set in IEEE 118-bus distribution system (more information can be found in [32]) to see its scalability. The total computation times for the proposed strategy under different operating conditions are less than 5 min in all cases. Power flow based on the optimal results can be fast converged in IEEE 33_bus distribution system and a little longer converged in IEEE 118_bus distribution system, that denotes the applicability of our strategy. Meanwhile, based on Scene1, TABLE. VI shows DSO's profit improvement rates brought by our strategy (i.e. in Scene 2) at different CVaR parameters in the above two systems. According to the above analysis that our strategy is more suitable for solving the low-capacity but high-demand difficulties. The improvement rate ranges from 6.37% to 13.34% in the system with 33 buses and from 7.61% to 17.24% in that with 118 buses, respectively. In other cases, there are also profit improvements in both systems when our strategy is adopted, that illustrates a good scalability of the proposed strategy.

TABLE VI.
COMPARISONS OF THE IMPROVEMENT AND CONVERGENCE IN TWO DIFFERENT DISTRIBUTION SYSTEMS

Index	**Improvement rate in Scene 2 in IEEE 33-bus distribution system (%)**							Security verification	**Improvement rate in Scene 2 in IEEE 118-bus distribution system (%)**							Security verification
β	0	0.25	0.5	1	2	5	10		0	0.25	0.5	1	2	5	10	
Case1	6.37	6.46	6.54	6.72	7.12	8.63	13.34	√	7.61	7.72	7.83	8.06	8.57	10.56	17.24	√
Case2	4.05	4.10	4.16	4.27	4.51	5.44	8.31	√	4.31	4.37	4.43	4.56	4.84	5.91	9.41	√
Case3	2.86	2.89	2.93	3.01	3.18	3.83	5.79	√	3.22	3.26	3.31	3.40	3.60	4.39	6.93	√
Case4	1.09	1.11	1.12	1.15	1.22	1.46	2.18	√	1.39	1.41	1.43	1.47	1.55	1.89	2.94	√

VI. CONCLUSION

This article integrated an incentive strategy for EV charging into stochastic schedule framework. DSO's EP was maximized by a risk-constrained stochastic optimization as well as by considering the EVs transfer among areas. The proposed incentive strategy was applied to a modified traffic-grid coupling network and 4 cases combined with 2 scenes were presented. The results show that the proposed strategy could contribute to the total profit of DSO while being highly useful to EVs users and charging stations in terms of waiting time and energy costs/revenues. The main concluding remarks of this article can be highlighted as follows:

1) The proposed incentive charging strategy can increase the whole profit by giving charging price discount in different areas. Moreover, the strategy guides more EVs to change charging stations and avoid charging congestion, while gaining higher profits.

2) Both users' price sensitivity and EVs' elasticity for power regulation have an important influence on the proposed incentive charging strategy. The more price-sensitive the users are and the larger elasticity EVs have, the more profit DSO would earn.

3) The proposed strategy can be easily integrated in stochastic scheduling process in both risk-neutral and risk-averse cases. It will be feasible for DSO to make decision under different uncertainties and form a more economical dispatch plan.

Future work will base on this incentive charging strategy, mainly focusing on the EVs' real-time control after charging guidance to smooth the uncertainties caused by renewable energy.

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