[1]Jialun Zuo

Stackelberg Game-based Coordinative Dispatch of EV Charging Stations and Urban Distribution Systems Considering Temporal-spatial Dynamic Traffic Flow

JES

Journal of Electrical Systems

Abstract: This paper proposes a Stackelberg Game-based coordinative dispatch model of electric vehicle charging stations (EVCSs) and urban distribution systems (UDS) considering temporal-spatial dynamic traffic flow. The model is formulated hierarchically and consists of an upper-level problem and two lower-level problems. Firstly, a detailed EVCS dispatching model considering both electricity prices and charging service prices is developed in the upper-level. Then the electricity pricing model of UDS and travel decision model of EV users are proposed in the lower model. Particularly, a temporal-spatial dynamic model is developed to capture the traffic flow evolution in urban transport network preciously. EVCS, UDS operator (DSO) and EV users can make decisions independently as different stakeholders. Finally, a multi-layer iterative framework is designed to capture the tripartite benefit equilibrium of distribution grid, EV charging stations, and EV users, and to realize the effective solution of the model. Numerical studies based on a modified IEEE 33-bus system demonstrate the effectiveness and accuracy of our proposed approach.

Keywords: Stackelberg Game; multi-layer; benefit equilibrium;

1. Introduction

Electric vehicles (EVs) and their charging stations (EVCS) play an ever more important role in present-day modern urban transportation. With increased environmental awareness and technological advances, EVs have become a key factor in reducing urban pollution and achieving sustainable transportation. According to a report from the International Energy Agency, the number of EVs worldwide is expected to exceed 145 million by 2023, reflecting the rapid growth of electric vehicles. At the same time, the popularity and development of electric vehicle charging stations is placing new demands on urban infrastructure development. Charging stations not only need to be tightly integrated with the city's power grid, but also need to consider the coordination of their layout with traffic flow. The coupled interactions between EVCS and the distribution grid are becoming increasingly tight, which is particularly evident in the planning and management of urban power grids. As the number of electric vehicles increases, the charging demand grows accordingly, which challenges the stability and efficiency of the grid.

In the current revolution in energy and transportation, the popularity of electric vehicles (EVs) has brought about a significant impact on the power grid. On the one hand, the connection of numerous EVs to the grid has led to a dramatic increase in grid load, which poses a major challenge to the stable and safe running of the power grid. On the other hand, if appropriate incentive mechanisms are adopted, the EV fleet under EVCS is expected to provide significant flexibility resources to the distribution network, which provides new solutions to alleviate network congestion, promote renewable energy consumption/integration, and improve power supply reliability (which

[1] School of Electrical Engineering, Chongqing University, Chongqing, 400000, China

*Corresponding author's e-mail: zjl3108792657@163.com

provides new solutions to reduce network congestion, promote renewable energy consumption/integration, and improve power supply reliability). (The group is expected to provide new solutions to alleviate network congestion, promote renewable energy consumption (accommodation/consumption/integration) and improve power supply reliability. Therefore, the EVCS and distribution system can be used to provide new solutions to. Therefore, the problem of co-scheduling between EVCS and distribution networks has attracted much attention from the academic community. In [1], researchers explored the optimal configuration of EVCSs and evaluated the coordination strategies of EVCSs with charging programs, control management and EV traffic in the distribution network. In [2], a scheme to optimize the integration of the EVCS with the radial distribution system (RDS) through the utilization of static reactive power compensator (STATCOM) and distributed generation (DG) is explored. [3] proposes a V2G (Vehicle to grid) control strategy oriented towards the flexibility enhancement of aggregated EVs participating in the distribution system. In response to this, an optimal flexible dispatch method is introduced to enhance the power system's adaptability via the collaborative integration of adjustable voltage regulators, manageable distributed generation, collective electric vehicles, and energy storage systems. [4] Furthermore, a mixed-integer programming framework is proposed for the cooperative scheduling of RC in distribution networks. [5]

A blockchain-based trusted scheduling method is proposed for distribution grids in high renewable energy penetration power systems. [6] A model based on analytic polyhedral approximation has been crafted to effectively represent the dispatchable area for large-scale electric vehicles (EVs) under uncertainty. Additionally, a dual-layer cooperative optimization technique is suggested to facilitate the involvement of EV aggregators in the day-ahead optimal scheduling within distribution grids. [7] Moreover, a strategy for coordinated scheduling of EVs and thermostatically controlled loads (TCLs), enhanced by an advanced generative adversarial network (GAN), is introduced.

Unlike these existing studies, this paper examines the distribution network and EVCS as two separate entities and explores the game interaction between them in greater depth. This approach is more in line with the fact that the two belong to different subjects of interest and can more effectively reveal and solve the interactive game problems that exist.

And in fact, the EVCS and the distribution grid (DS) belong to different subjects. the DS can guide the charging behavior of the EVCS through reasonable tariff setting; at the same time, the different charging behaviors of large-scale EVs can significantly affect the DS tariff. Existing studies on DS and EVCS pricing have sufficient preliminary work. Literature [8] constructed a three-level location model considering dynamic pricing, including user decision, EVCS pricing, and EVCS location decision, and trained the optimal pricing strategy for EVCS using a soft actor-critic (SAC) reinforcement learning algorithm. Literature [9] uses multiplicative weighted Voronoi diagrams to model and analyze the electricity demand of EVCS. The price competition among EVCS is studied using Stackelberg game and the electricity price is determined. Literature [10] establishes a three-tier pricing framework where EVCs set charging prices at the upper tier, EVCs develop routes and charging options at the middle tier, and clear distribution grid tariffs at the lower tier. Literature [11] proposes a two-step approach to mathematically express the responsiveness of demand to the charging price considering the competitive effects established based on TN. Literature [12] proposes a privacy-preserving distributed deep reinforcement learning (DRL) framework that realizes a dynamic pricing strategy with the photovoltaic (PV) and energy storage systems integrated with multiple smart EVCSs for profit maximization under a dynamic pricing strategy.

However, although existing studies have considered the game relationship between EVCS and DS, they have only portrayed EV load as a fixed parameter or uncertain variable, and have not accurately portrayed EV charging demand based on the dynamic traffic flow, and the obtained results may lead to sub-optimal solutions.

Existing research on traffic flow has been applied to EV charging and discharging tariff setting and charging station planning. Literature [13] proposes a multi-period integrated pricing model that can characterize changes in electricity and travel demand. Literature [14] investigated the prediction of hourly traffic flow and renewable energy generation as well as the calculation of shortest paths to different charging stations (CS) using the proposed pricing methodology. Literature [15] derives theoretical congestion pricing estimates for a class of speed-flow relationships called generalized Drake models. Subsequently, an iterative method is suggested to identify the ideal congestion charge, utilizing the speed-flow dynamic and generalized cost metrics without relying on a demand function. The literature [16] describes the creation of two dynamic congestion pricing models, rooted in marginal cost pricing theory. These models facilitate calculating time-variable congestion fees through a convex control solution to the

optimal flow distribution challenge in dynamic systems. Literature [17] developed a mesoscopic and macroscopic model for describing automated traffic flow dynamics in a single freeway lane.

However, the existing literature only analyzes the traffic flow on the same time section, which is unable to portray the time-space traffic flow evolution due to the travel demand of EV users between different moments. Therefore, it is necessary to improve the existing traffic flow model to provide the traffic flow on each roadway at different moments to accommodate the time-space charge/discharge pricing of EVCS.

To fill the above research gaps, this paper introduces a coordinated scheduling framework utilizing Stackelberg game theory, tailored for electric vehicle charging stations and urban distribution networks.. The model aims to solve the game relationship between different stakeholders, while taking into account the complexity of spatio-temporal dynamic traffic flow. First, we build a detailed EVCS scheduling model in the upper-level problem, which integrates the effects of electricity price and charging service price. Second, in the lower layer model, we propose a UDS model for electricity price and a travel decision model for EV users. In particular, we build a spatio-temporal dynamic model to capture the evolution of traffic flows in urban transportation networks. As different stakeholders, EVCS, UDS operators (DSOs) and EV users can make decisions independently. Finally, We propose a solution method based on multi-layer iteration to capture the balance of interest of multiple subjects and to solve the above planning model effectively, so as to effectively solve the above multi-level problems. Through numerical studies, we verify the effectiveness and accuracy of the method. The results of the study based on the modified IEEE-33 node system show that the model can achieve effective coordination between EVCS and UDS, improve transportation efficiency, reduce energy consumption, and provide decision-making support for relevant stakeholders.

The main contributions of this paper are as three folds：

Contribution 1: A charging station-distribution network co-scheduling model based on the Stackelberg game;

Contribution 2: A semi-dynamic time-space dynamic traffic flow based on residual flow theory for EV user charging pricing model is developed

Contribution 3: A solution method based on multi-layer iteration is proposed to capture the balance of interests of multiple subjects and realize the effective solution of the above planning model.

The rest of this paper is structured in the following manner: Section II outlines the architecture and framework of the energy-transport system under examination. Sections III and IV introduce the pricing model and its corresponding solution algorithm. Numerical Studies and conclusions are respectively elaborated upon in Section V.

2. Problem Description

2.1 System Overview

The energy-traffic coupling system considered in this paper is shown in Figure 1. The energy network is a distribution-level power system. Its electricity comes from the distributed renewable energy (such as wind power, photovoltaic, etc.) in the system and the distribution transformers connected to the superior, which supply the power load to the city base load and the charging load of the charging stations through the distribution network. The distribution network and the transportation network are coupled through the EVCS. EVCS is usually located on the road nodes of the road network, purchasing electricity from the distribution network and providing paid charging services for electric vehicles.
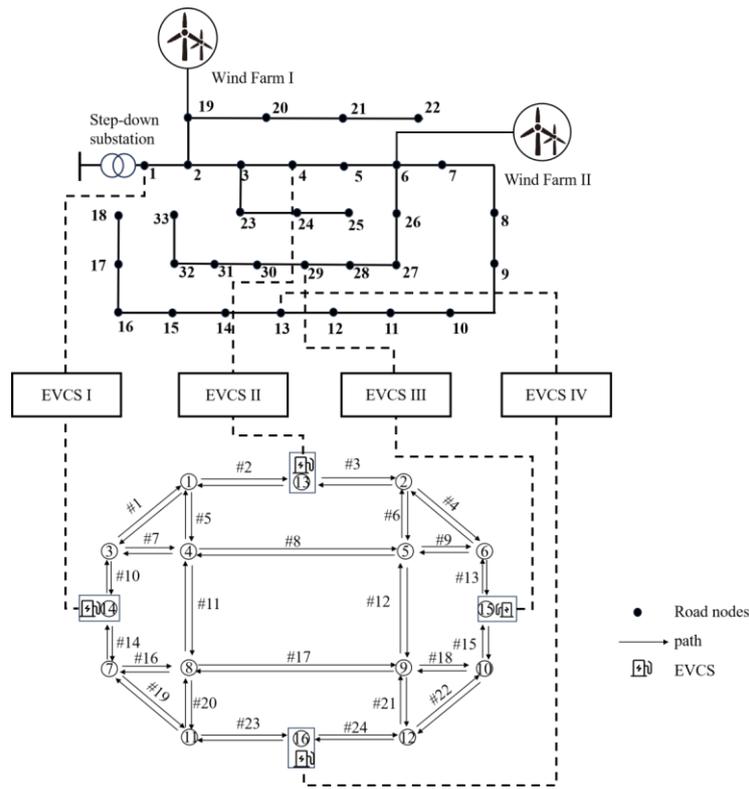
Figure 1

By formulating reasonable spatial-temporal electricity price, the distribution network can guide the spatial-temporal distribution of EV charging load, so as to realize various benefits such as peak load shifting and valley filling, renewable energy consumption and alleviating network congestion, and improve the operation economy of the distribution network. Based on the electricity price provided by the distribution network, EVCS releases the charging electricity price optimized based on the day ahead in advance for the reference of EV users to make decisions. EV users can check the charging cost of the charging station through the intelligent charging navigation system, and obtain relevant information when traveling. Based on this information, multiple travel route schemes can be planned, and the expected travel time and charging cost can be obtained, and the optimal scheme can be selected. Hence, the operational conditions of both road and distribution networks influence the determination of charging prices, which in turn impacts the charging and traveling patterns of electric vehicle users, subsequently affecting the operational status of the road and distribution networks.

2.2 Interactive relationship
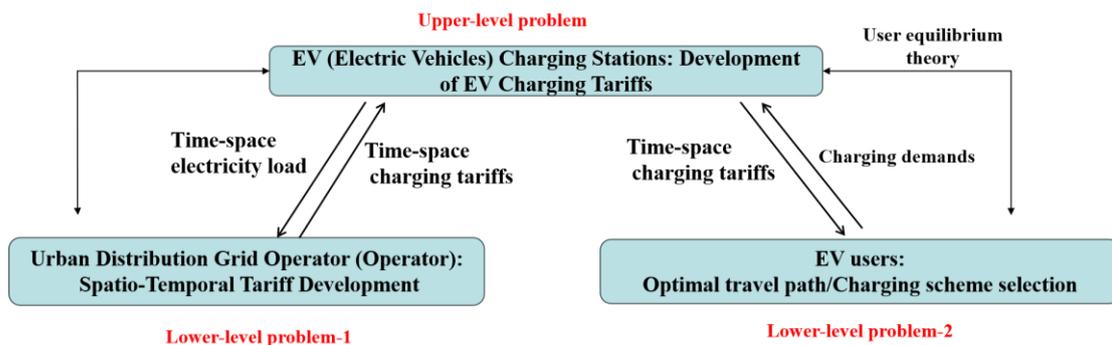
Figure 2

In the model proposed in this paper, the upper-level problem is the EVCS scheduling model, which minimizes the operation cost based on the time-space tariff set by DS and the time-space charging load of EV users, and also sets a reasonable EV charging tariff and reports the load profile to DS. Through this arrangement (arrange), the EVCS not only provides electric demand response service to DS, but also retains the flexibility of responding to changes

in users' demands. flexibility. The lower layer contains two independent sub-problems, in which sub-problem 1 is a city DS optimal dispatch model that aims to develop a time-space tariff to incentivize the EVCS to reshape its own load profile based on the electricity consumption loads of EVCS; sub-problem 2 is an optimal decision model for EV users, which aims to minimize the travel cost and formulate the optimal travel path and charging options based on the charging tariff of the EVCS. charging options) based on the charging tariff of the EVCS. Under this multi-layer iterative framework, EVCS, DS and EV users can make optimal decisions independently to capture the balance of interests among distribution network, EV charging station and EV users, and realize the effective solution of the model.

Through this design, a hierarchical model with coordinated interactions between parts is created to ensure that the charging behavior of EVs can be effectively interfaced with the strategies of the grid operator and the needs of EV users. Such a model can help optimize the overall performance of the grid and meet the charging demand of EV users.

3. Model Formulation

3.1 Upper-level problem: EVCS

The objective function：

$$\max \underbrace{\sum_{m\in\Omega^M}\sum_{t\in\Omega^T}\rho^{EV}_{m,t}P^{EVCS}_{m,t}\Delta t}_{\text{EV charging revenues}} - \underbrace{\sum_{m\in\Omega^M}\sum_{t\in\Omega^T}c^{ele}_{m,t}P^{EVCS}_{m,t}\Delta t}_{\text{electricity purchasing costs}} \tag{1}$$

$P^{EVCS}_{m,t}$ denotes the electric power of the charging station at the **m**-th traffic network node at time t.

$c^{ele}_{m,t}$ denotes the unit price of electricity bought by the **m**-th charging station at time t,

$\rho^{EV}_{m,t}$ denotes the buying tariff for EV users for the **m**-th charging station at time t.

Charging power limit constraint:

$$Q^{EVCS}_{m,t} = P^{EVCS}_{m,t}\tan\varphi^{EVCS}, \forall m\in\Omega^M, t\in\Omega^T \tag{2}$$

$$(P^{EVCS}_{m,t})^2 + (Q^{EVCS}_{m,t})^2 \le (S^{EVCS}_m)^2, \forall m\in\Omega^M, t\in\Omega^T \tag{3}$$

$Q^{EVCS}_{m,t}$ denotes the power used by the **m**-th charging station at time t.

$\tan\varphi^{EVCS}$ is the power factor angle of the corresponding EVCS.

S^{EVCS}_m denotes the power of the distribution transformer of the EVCS at the **m**-th node (i.e., rated apparent power).

3.2 Lower-level problem-1: Urban distribution system

3.2.1 Objective function

The model aims to minimize system operations costs, as shown below.

$$\min \sum_{s\in\Omega^S}p_s\sum_{t\in\Omega^T}\left[c^e_t P^{GD}_{s,t}\Delta t + c^{aban}_t(P^{WT,max}_{s,t} - P^{WT}_{s,t})\Delta t\right] - \sum_{m\in\Omega^M}\sum_{t\in\Omega^T}c^{ele}_{m,t}P^{EVCS}_{m,t}\Delta t \tag{4}$$

Where: p_s is the corresponding probability of each scenario; $P^{WT}_{s,t}$ and $P^{WT,max}_{s,t}$ denotes the real-time output and

maximum predicted output for wind power; c_t^e 、 c_t^{aban} denotes the main grid purchased electricity tariff and the cost of the wind abandonment factor, respectively. $P_{s,t}^{GD}$ is the active power of the distribution transformer.

3.2.2 Distribution network operation constraints

Operation constraints of distribution network ensure the safe operation of power grid under different operation scenarios. Formula (5)-(6) means that the power of the distribution system to the main online shopping shall not exceed the rated capacity of the distribution transformer, and the polygon method is used for linearization here. Formula (7)-(8) is the active power and reactive power balance constraints of the distribution network. Equation (9) is the node voltage constraint. Formula (10)-(11) is the branch power flow constraint. Formula (12)-(13) is the wind power output constraint.

$$0 \le P_{s,t}^{GD}, Q_{s,t}^{GD} \le S^{TG}, \forall s \in \Omega^s, \forall t \in \Omega^T \tag{5}$$

$$0 \le P_{s,t}^{GD}, Q_{s,t}^{GD} \le \sqrt{2} S^{TG}, \forall s \in \Omega^s, \forall t \in \Omega^T \tag{6}$$

$$\begin{aligned}
&\sum_{l \in \Omega^L} K_{b,l}^{LN} P_{s,l,t}^{LN} = K_b^{GD} P_{s,t}^{GD} + K_b^{WT} P_{s,t}^{WT} \\
&\quad - P_{s,b,t}^{DE} - \sum_{m \in \Omega^M} K_{b,m}^{EVCS} P_{m,t}^{EVCS} \\
&\forall s \in \Omega^S, \forall b \in \Omega^B, \forall t \in \Omega^T
\end{aligned} \tag{7}$$

$$\begin{aligned}
&\sum_{l \in \Omega^L} K_{b,l}^{LN} Q_{s,l,t}^{LN} = K_b^{GD} Q_{s,t}^{GD} + K_b^{WT} Q_{s,t}^{WT} \\
&\quad - Q_{s,b,t}^{DE} - \sum_{m \in \Omega^M} K_{b,m}^{EVCS} Q_{m,t}^{EVCS} \\
&\forall s \in \Omega^S, \forall b \in \Omega^B, \forall t \in \Omega^T
\end{aligned} \tag{8}$$

$$\begin{aligned}
&\sum_{b \in \Omega^B} K_{b,l}^{LN} V_{s,b,t} - 2R_l P_{s,l,t}^{LN} / V_0 - 2X_l Q_{s,l,t}^{LN} / V_0 = 0, \\
&\quad \forall s \in \Omega^s, \forall l \in \Omega^L, \forall t \in \Omega^T
\end{aligned} \tag{9}$$

$$-S_l^{LN} \le P_{s,l,t}^{LN}, Q_{s,l,t}^{LN} \le S_l^{LN}, \forall s \in \Omega^S, \forall l \in \Omega^L, \forall t \in \Omega^T \tag{10}$$

$$-\sqrt{2} S_l^{LN} \le P_{s,l,t}^{LN} \pm Q_{s,l,t}^{LN} \le \sqrt{2} S_l^{LN}, \forall s \in \Omega^s, \forall l \in \Omega^L, \forall t \in \Omega^T \tag{11}$$

$$0 \le P_{s,t}^{WT} \le P_{s,t}^{WT,max}, \forall s \in \Omega^s, \forall t \in \Omega^T \tag{12}$$

$$Q_{s,t}^{WT} = P_{s,t}^{WT} tan\varphi^{WT}, \forall s \in \Omega^s, \forall t \in \Omega^T \tag{13}$$

$l(\Omega^L)$, $ss(\Omega^{ss})$, $b(\Omega^B)$ is the indexing and correspondence sets for distribution network branches, distribution

transformers and distribution network nodes; S_{ss}^{TG} is the expansion capacity of the transformer; $P_{s,t}^{GD}$ and $Q_{s,t}^{GD}$ is the active and reactive power of the distribution transformer; $P_{s,l,t}^{LN}$ and $Q_{s,l,t}^{LN}$ denote the active and reactive power transmitted by branch l; $V_{s,b,t}$ denote the square of the node voltage amplitude; $K_{b,l}^{LN}$、$K_{b,d}^{DE}$ denote the corresponding elements of distribution network node-branch correlation matrix and node-load correlation matrix; The 0-1 parameters K_b^{GD}、K_b^{WT} indicates whether node b is connected to a distribution transformer or a wind farm; K_m^{EVCS} indicates if node m is an EVCS pending node; $P_{s,d,t}^{DE}$ and $Q_{s,d,t}^{DE}$ denote the node load power. $P_{s,d,t}^{DE,curt}$ denotes the loss of load; V_0 denotes the reference voltage; R_l and X_l 为 denotes the resistance and reactance values of the branch l after the expansion. S_l^{LN} denotes the rated capacity; φ^{WT} denotes the factor angle of wind farm.

3.3 Lower-level problem-2: EV users

For each trip, the EV will start from the start node r and reach the end node s, i.e., the start-destination O-D pair r-s. The set of O-D pairs is denoted by Ω_{OD}. The TN traversed by the EV is represented by the connected directed graph $\Omega_{TN} = (\Omega^A, \Omega^N)$, which consists of a series of nodes $m \in \Omega^N$ and arcs $a \in \Omega^A$. The arcs symbolize the roads within the transportation network (TN), while the nodes at their intersections denote the locations of electric vehicle charging stations (EVCSs). Pairs can be linked through various sequences of numerically ordered arcs and nodes, creating a path designated as q. The set of paths of rs is denoted by Ω^{OD}. The path traffic is denoted by $w_{q,rs}$.

An EV seeks the lowest cost path based on the current traffic conditions including travel time on the road $t_{a,t}$, charging price ρ_m^{evcs} and node charging $t_{m,q,rs,t}$, which can be formulated as an EV routing and charging problem.

Accumulation of electric vehicle (EV) traffic on a single road leads to congestion, and simultaneous charging at a singular EV charging station results in increased waiting times and a shortage of power supply. EVs vie for roadway and EV charging station (EVCS) resources through the optimization of their charging and routing decisions. Path costs for EVs $c_{q,rs,t}$ include driving and waiting times (translated into monetary costs through the parameter κ) and charging costs:

$$\min \sum_{q \in \Omega^{rs}} \sum_{rs \in \Omega^{OD}} \sum_{t \in \Omega^T} c_{q,rs,t}^{\min} \tag{14}$$

$$c_{q,rs,t} = \sum_{a \in \Omega^A} \kappa t_{a,t} \delta_{a,q,rs} + \sum_{m \in \Omega^M} (\kappa t_{m,q,rs,t} \gamma_{m,q,rs,t} + h_{m,q,rs,t} \rho_{m,t}^{EV}) \tag{15}$$

$$e_{m,q,rs,t} - e_{n,q,rs,t} + D_a - h_{m,q,rs,t} = \phi_{a,q,rs,t}, \forall (n,m) = a \in \Omega^A \tag{16}$$

$$-M\left(1-\delta_{a,q,rs}\right) \leq \phi_{a,q,rs,t} \leq M\left(1-\delta_{a,q,rs}\right), \forall (n,m)=a \in \Omega^A \tag{17}$$

$$E^{\min} \leq e_{m,q,rs,t} \leq E^{\max}, \forall m \in \Omega^M \tag{18}$$

$$e_{m,q,rs,t} = E_0^{rs}, \forall m \in \Omega^{A,s} \tag{19}$$

$$h_{m,q,rs,t} \leq a_m^{evcs} h_m^{\max}, \forall m \in \Omega^M \tag{20}$$

$$h_{m,q,rs,t} \leq \gamma_{m,q,rs,t} h_m^{\max}, \forall m \in \Omega^M \tag{21}$$

$$P_{m,t}^{EVCS} = \sum_{rs \in \Omega^{OD}} \sum_{q \in \Omega^{rs}} w_{q,rs,t} h_{m,q,rs,t}, \forall m \in \Omega^M, \forall t \in \Omega^T \tag{22}$$

$$\sum_{q \in \Omega^{rs}} w_{q,rs,t} = W_{rs,t}^{\mathrm{mod}}, \forall rs \in \Omega^{OD} \tag{23}$$

$$r_{rs,t} = \sum_{q \in \Omega^{rs}} \frac{w_{q,rs,t} c_{q,rs,t}^0}{\tau} \tag{24}$$

$$c_{q,rs,t}^0 = \sum_{a \in \Omega^A} \kappa t_{a,t} \delta_{a,q,rs} + \sum_{m \in \Omega^M} \kappa t_{m,q,rs,t} \gamma_{m,q,rs,t} \tag{25}$$

$$W_{rs,t}^{\mathrm{mod}} = W_{rs,t} + \xi r_{rs,t-1} - \xi r_{rs,t} \tag{26}$$

$$x_{a,t} = \sum_{rs \in \Omega^{OD}} \sum_{q \in \Omega^{rs}} w_{q,rs,t} \delta_{a,q,rs}, \forall a \in \Omega^A, t \in \Omega^T \tag{27}$$

$$x_{m,t} = \sum_{rs \in \Omega^{OD}} \sum_{q \in \Omega^{rs}} w_{q,rs,t} \gamma_{m,q,rs,t}, \forall m \in \Omega^M, t \in \Omega^T \tag{28}$$

where $\delta_{a,q,rs}$ is the section-path association element, $\delta_{a,q,rs}$ is 1 when section a is on path q of the rs pair and 0 otherwise; $\gamma_{m,q,rs,t}$ is a 0-1 variable representing the charging decision; $h_{m,q,rs,t}$ is the charging power. D_a is the energy consumption of arc a, and ϕ_a^q is an auxiliary variable. $P_{m,t}^{EVCS}$ is the charging power at the charging station m at moment t. M is a very large positive constant. the availability of the EVCS is represented by the binary parameter a_m^{evcs}, which limits the charging behavior of the EV. γ_m^q is the binary variable for the charging decision at node m. $w_{q,rs,t}$ is the traffic flow rate between pairs of paths q, rs at moment t. $W_{rs,t}^{\mathrm{mod}}$ is the travel demand between pairs O-D. The traffic flow on arc a and node m are denoted as $x_{a,t}$ and $x_{m,t}$, respectively.

According to the BPR function, the arc time is given by

$$t_{a,t} = t_a^0(1+0.15(x_{a,t}/u_a)^4), \forall a \in \Omega^A \tag{29}$$

where t_a^0 is the free passage time, u_a is the road capacity, and the travel time $t_{a,t}$ reflects the congestion effect on the road. Nodal time is charging time:

$$t_{m,q,rs,t} = h_{m,q,rs,t}/h_m^{\max}, \forall m \in \Omega^M \tag{30}$$

$$0 \le w_{q,rs,t} \perp (c_{q,rs,t} - c_{q,rs,t}^{\min}) \ge 0, \forall q \in \Omega^{rs}, rs \in \Omega^{OD} \tag{31}$$

$h_m^{\max}$ is the rated power of the charging pile at m. $c_{q,rs,t}$ is the total cost of path q. $c_{q,rs,t}^{\min}$ denotes the minimum cost of traveling in all paths. For each O-D pair, the path cost of all used/active paths is equal to and less than the path cost of unused/active paths (i.e., $w_{q,rs,t} =0$).

4. Methodology

The Figure 3 demonstrates the flowchart of solution framework for our proposed Stackelberg game-based coordinative dispatch of EV charging stations and urban distribution systems. The solution framework is arranged as two levels. In the upper-level, we generate the initial group of charging prices, i.e., determining customized charging price for each EVCS. The lower-level is further divided into two sub-problems. The first sub-problem is traffic assignment problem, which involves assigning EV users to different charging stations. In this process, the charging load curves of EVCSs are generated, and the objective function corresponding to each individual is calculated. Then, these charging power curves will be transmitted to the distribution network for subsequent power distribution. The second sub-problem is to solve the optimal space-time electricity price. In this part, by constructing and solving the corresponding model, we can find the optimal space-time electricity price that can make the game equilibrium between the electric vehicle charging station and the distribution network. Then, this optimal price will be sent to EVCSs to update the position of individual population and get new population. In the whole process, the results of the lower-level problems will be continuously fed back to the upper-level problems, so as to continuously adjust and improve the charging price strategy in the optimization process. Through the above iterative process, the equilibrium of EVCS, urban distribution network and EV users can be obtained. The step-by-step description of the solution procedures is presented below.

Step 1) Load the model parameters and initialize the iteration counter *iter*=1.

Step 2) Generate the initial population of EV charging prices for EVCSs.

Step 3-1) Set number of individuals *v*=1

Step 3-2) pass the EV charging prices corresponding to individual *v* to EV users.

Step 3-3) Solve lower-level problem-2 (Traffic assignment problem), and obtain and charging power curves of EVCSs, which is further transferred to the distribution network.

Step 3-4) Solve lower-level problem-1 (Optimal dispatching and pricing of urban distribution system), and obtain the optimal spatiotemporal electricity price, which is further passed to EVCSs.

Step 3-5) Calculate the objective function corresponding to each individual.

Step 3-6) Judge whether all individual have been traversed. If so, continue; otherwise, set *v*=*v*+1 and go to Step 3-2).

Step 4) Judge whether the game equilibrium is achieved. If so, Output the price information and scheduling results

corresponding to the equilibrium solution. The procedure is terminated. Otherwise, set *iter=iter+1* and go to Step 3-1).
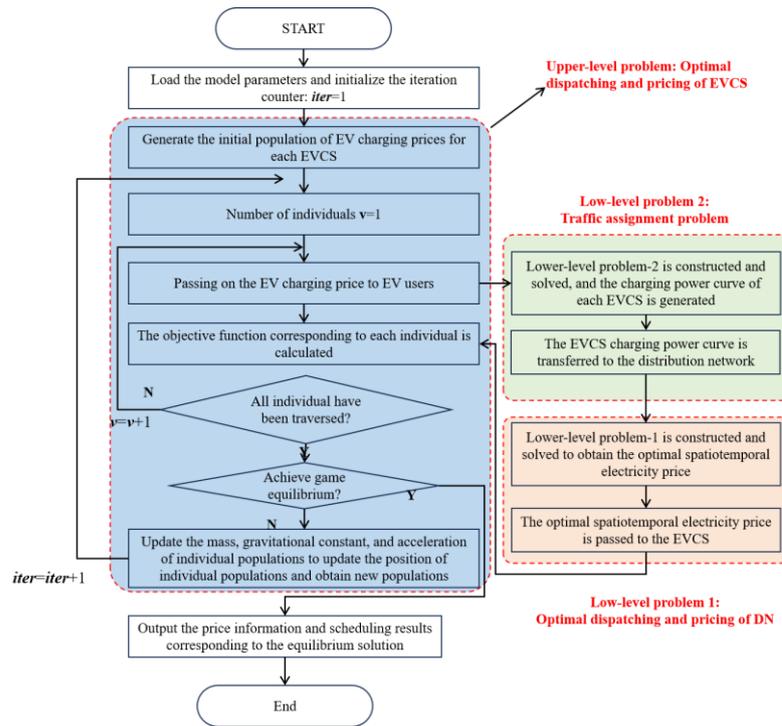
Figure 3 Flowchart of the solution procedures.

5. Numerical Studies

5.1 Description of the Arithmetic Example

In order to verify the effectiveness of the above coordinated scheduling model of electric vehicle charging stations (EVCSs) and urban distribution system (UDS) considering the spatio-temporal dynamic traffic flow on the experimental balance of interests, this paper constructs a coupled distribution network-transportation system, and selects the IEEE-33 node as the test distribution network model for the algorithmic analysis, and selects the road network of the urban area as the test of the algorithmic example for transportation network model as shown in Figure 4.
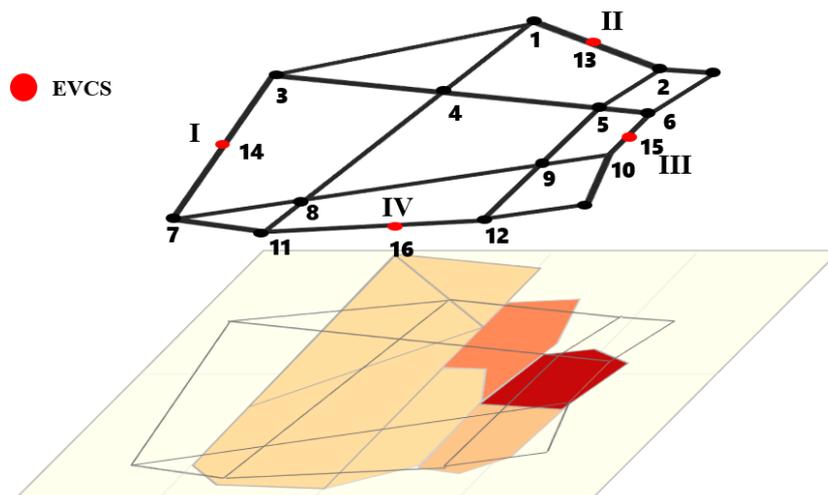
Figure 4 Traffic network topology and charging station location distribution diagram

5.2 Simulation results

During the run of the arithmetic example, we carried out many iterations, and in the game of GSA optimization for the three subjects, as shown in Figure 5, the initial objective function of CASE4 is solved higher, and as the game proceeds, the value of the objective function continues to rise, which indicates the effectiveness of the game, and the objective function of CASE4 is solved the best, which indicates the effectiveness of the solving strategy.

Tab 1

	Distribution grid tariffs	traffic flow theory
CASE1	Price Fixed	No consideration of residuals
CASE2	Price Fixed	Consideration of residual flow
CASE3	Perform game pricing	Not considering residual flow
CASE 4	Perform game pricing	Consideration of residual flow
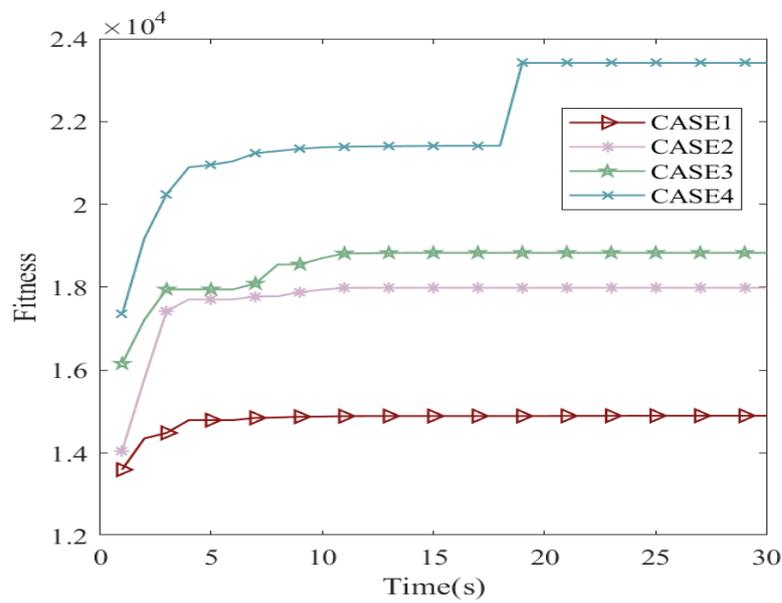
Figure 5

And through the calculation, we get the specific value of the electricity price, as shown in Tab 2 and demonstrated by Figure 6

Tab 2

	Case-1 (benchmark)	Case-2	Case-3	Case-4
Optimal objective function (best)	**1.876E+04**	**2.065E+04**	**2.173E+04**	**2.448E+04**
Objective function mean (mean)	1.662E+04	1.859E+04	1.903E+04	2.215E+04
Standard Deviation (SD)	1.570E+03	1.488E+03	1.320E+03	9.346E+02
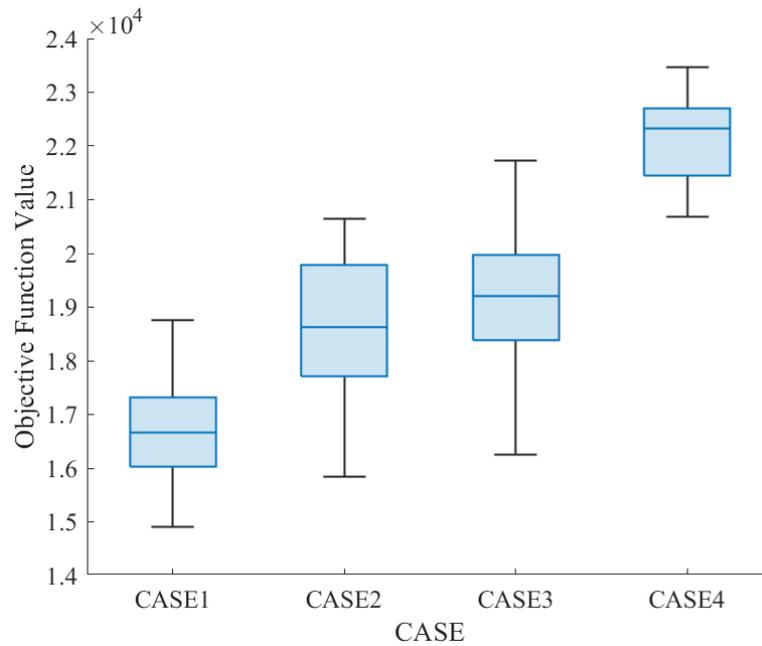
Figure 6

From the results, it can be seen that the method proposed in this paper to solve the model model shows good performance in the arithmetic cases.

5.2 Sensitivity analysis

Through comparative analysis, we found that certain parameters in the arithmetic examples have a significant effect on the results. In order to assess the degree of influence of different parameters on the model performance, we performed a sensitivity analysis by varying the values of κ and ξ, respectively, which are taken as shown in Table Tab 3. The generated results are shown in Tab 4 and demonstrated by Figure 7. When ξ decreases, the optimal value and mean of the objective function increase, and the standard deviation decreases, and when κ increases, the optimal value and mean of the objective function decrease, and the standard deviation also decreases.

Tab 3

	κ	ξ
Case-1	100	0.6
Case-2	100	0.5
Case-3	150	0.6
Case-4	150	0.5

Tab 4

	Case-1 (benchmark)	Case-2	Case-3	Case-4
Optimal objective function (best)	**2.364E+04**	**2.665E+04**	**2.149E+04**	**2.486E+04**
Objective function mean (mean)	2.099E+04	2.371E+04	1.882E+04	2.258E+04
Standard Deviation (SD)	1.754E+03	1.473E+03	1.247E+03	1.482E+03
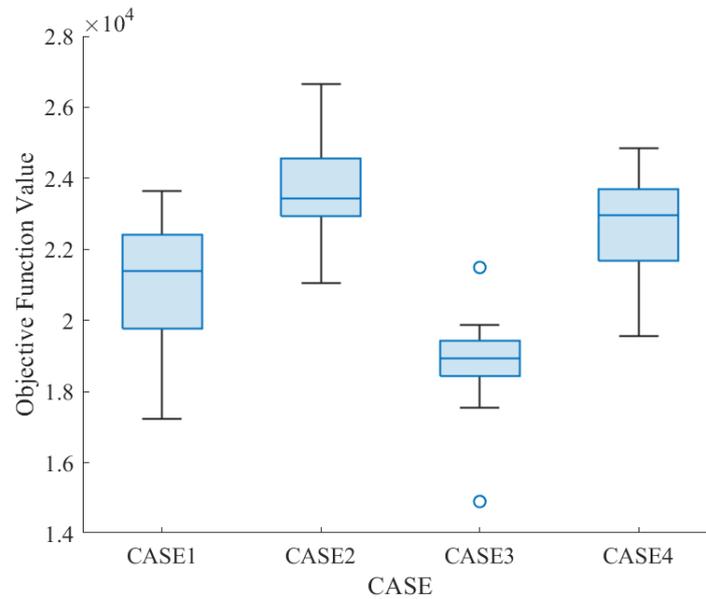
Figure 7

6. Conclusion

In this paper, a coordinated scheduling model of electric vehicle charging station and urban distribution system based on the Stackelberg game is proposed, and a multi-layer iterative framework is designed to realize the effective solution of the model. Based on IEEE-33-bus distribution network and 16-node traffic network, an example is analyzed. The conclusions are as follows: (1) The method proposed in this paper effectively reduces the operating cost of distribution network and transportation network while respecting the balance of interests among distribution network, electric vehicle charging station and electric vehicle users. (2) Residual current coefficient ξ and delay time cost κ will have a significant impact on the scheduling results.

REFERENCES

[1] Ray S, Kasturi K, Patnaik S, et al. Review of electric vehicles integration impacts in distribution networks: Placement, charging/discharging strategies, objectives and optimisation models[J]. Journal of Energy Storage, 2023, 72: 108672.

[2] Yuvaraj T, Devabalaji K R, Thanikanti S B, et al. Minimizing the electric vehicle charging stations impact in the distribution networks by simultaneous allocation of DG and DSTATCOM with considering uncertainty in load[J]. Energy Reports, 2023, 10: 1796-1817.

[3] X. Jiang, S. Wang, Q. Zhao and X. Wang, "Optimized Dispatching Method for Flexibility Improvement of AC-MTDC Distribution Systems Considering Aggregated Electric Vehicles," in Journal of Modern Power Systems and Clean Energy, vol. 11, no. 6, pp. 1857-1867, November 2023, doi: 10.35833/MPCE.2022.000576.

[4] J. Fan, P. He, C. Li and Y. Ji, "A Sequential Repair Crew Dispatch Strategy for Distribution Systems Coordinated With Transportation Systems," in IEEE Systems Journal, vol. 17, no. 4, pp. 5866-5876, Dec. 2023, doi: 10.1109/JSYST.2023.3283556.

[5] Y. Xu, Z. Liu, C. Zhang, J. Ren, Y. Zhang and X. Shen, "Blockchain-Based Trustworthy Energy Dispatching Approach for High Renewable Energy Penetrated Power Systems," in IEEE Internet of Things Journal, vol. 9, no. 12, pp. 10036-10047, 15 June15, 2022, doi: 10.1109/JIOT.2021.3117924.

[6] J. Jian, M. Zhang, Y. Xu, W. Tang and S. He, "An Analytical Polytope Approximation Aggregation of Electric Vehicles Considering Uncertainty for the Day-Ahead Distribution Network Dispatching," in IEEE Transactions on Sustainable Energy, vol. 15, no. 1, pp. 160-172, Jan. 2024, doi: 10.1109/TSTE.2023.3275566.

[7] Y. Tao, J. Qiu and S. Lai, "A Data-Driven Management Strategy of Electric Vehicles and Thermostatically Controlled Loads Based on Modified Generative Adversarial Network," in IEEE Transactions on

Transportation Electrification, vol. 8, no. 1, pp. 1430-1444, March 2022, doi: 10.1109/TTE.2021.3109671.

[8] Li, Yanbin, et al. "Dynamic pricing based electric vehicle charging station location strategy using reinforcement learning." Energy 281 (2023): 128284.

[9] Lee, Woongsup, Robert Schober, and Vincent WS Wong. "An analysis of price competition in heterogeneous electric vehicle charging stations." IEEE Transactions on Smart Grid 10.4 (2018): 3990-4002.

[10] Li, Ke, et al. "Strategic pricing of electric vehicle charging service providers in coupled power-transportation networks." IEEE Transactions on Smart Grid (2022).

[11] Lai, Shuying, et al. "Pricing for electric vehicle charging stations based on the responsiveness of demand." IEEE Transactions on Smart Grid 14.1 (2022): 530-544.

[12] Lee, Sangyoon, and Dae-Hyun Choi. "Dynamic pricing and energy management for profit maximization in multiple smart electric vehicle charging stations: A privacy-preserving deep reinforcement learning approach." Applied Energy 304 (2021): 117754.

[13] Zhou, Zhe, et al. "Integrated pricing framework for optimal power and semi-dynamic traffic flow problem." IET Renewable Power Generation 14.18 (2020): 3636-3643.

[14] Zhou, Suyang, et al. "Dynamic EV charging pricing methodology for facilitating renewable energy with consideration of highway traffic flow." IEEE Access 8 (2019): 13161-13178.

[15] Li, Michael ZF. "The role of speed–flow relationship in congestion pricing implementation with an application to Singapore." Transportation Research Part B: Methodological 36.8 (2002): 731-754.

[16] Wie, Byung-Wook, and Roger L. Tobin. "Dynamic congestion pricing models for general traffic networks." Transportation Research Part B: Methodological 32.5 (1998): 313-327.

[17] Li, Kun, and Petros Ioannou. "Modeling of traffic flow of automated vehicles." IEEE Transactions on Intelligent Transportation Systems 5.2 (2004): 99-113.