Coordinated Fault Risk Prevention in Coupled Distribution and Transportation Networks Considering Flexible Travel Demands

Fuzhang Wu, Jun Yang, *Member*, *IEEE*, Song Ke, Hao Jiang, Muchao Xiang, Zaixun Ling, and Guiping Deng

***Abstract*—Large-scale development of electric vehicles (EVs) exposes power grids and transportation networks with limited capacity to increased fault risks. In this paper, a method to prevent fault risks in advance by using the flexibility of EV travel to coordinate the operation of distribution and transportation networks is proposed. Since EV travel decisions are influenced by the charging and travel time costs, adjusting charging price and travel time price can help guide behavior and enable coordinated operation of power and transportation networks. First, risk-based distribution locational marginal prices (RDLMPs) are established to restrain the distribution network risks. Second, traffic risks are formulated using origin-destination (OD) risk marginal prices (ODRMPs) considering the degree of traffic congestion fault risks. Under the guidance of the RDLMPs and ODRMPs, EV fleets optimize their travel plans to minimize overall costs, including charging and time costs. Finally, case studies verify that the proposed method can reduce the operational risks of both distribution and transportation networks.**

***Index Terms*—Coupled distribution and transportation networks, fault risk, flexibility of travel demand, OD risk marginal price (ODRMP), risk-based distribution locational marginal price (RDLMP).**

Received: August 22, 2024
Accepted: February 25, 2025
Published Online: July 1, 2025
Fuzhang Wu, Jun Yang (corresponding author), and Song Ke are with the Hubei Engineering and Technology Research Center for AC/DC Intelligent Distribution Network, the School of Electrical Engineering and Automation, Wuhan University, Wuhan 430072, China (e-mail: wfzhang@whu.edu.cn; JYang@whu.edu.cn; kesong1997@whu.edu.cn).

Hao Jiang is with the Electronic Information School, Wuhan University, Wuhan 430072, China (e-mail: jh@whu.edu.cn).

Muchao Xiang, Zaixun Ling, and Guiping Deng are with the Electric Power Research Institute of State Grid Hubei Electric Power Co., Ltd., Wuhan 430072, China (e-mail: 472319042@qq.com; lingzaixun@163.com; denggp8@hb.sgcc.com.cn).
DOI: 10.23919/PCMP.2024.000172

I. INTRODUCTION

Large-scale development of electric vehicles (EVs) has become a major strategic measure for most countries to achieve green development. However, the application of large-scale EVs increases fault risks in distribution and transportation networks with limited carrying capacity. In distribution networks, the "peak plus peak" brought by concentrated charging loads can push distribution lines to their capacity limits, making them more susceptible to faults from minor disturbances and potentially leading to widespread outages [1], [2]. Similarly, the growing travel demand for EVs will exacerbate traffic congestion and further strain or paralyze certain transportation links. Additionally, EV operation integrates the distribution and transportation networks, so faults in one network can spread between the two networks, potentially resulting in greater losses. On May 20, 2018, a peak load transfer operation failed in Shenzhen, China, led to power outages on several operating lines, rendering some charging stations (CSs) and traffic links inoperable. Although there are many preventive measures that can address power grid and transportation network fault risks, such as expanding power grid and transportation facilities and restricting users' electricity consumption and travel, these measures are uneconomical or harm the interests of users.

The common methods of fault suppression can be divided into three categories: advance prevention, intermediate prevention, and afterward prevention. One of the most economical and effective measures is to use the flexibility of users to prevent fault risks before accidents. Fortunately, EV operation offers great flexibility. For example, travel demand of EVs can often be shifted within a given time frame, as EV users primarily consider charging costs and travel time when making travel decisions. Risk control in distribution and transportation networks can be achieved by setting appropriate charging prices and publishing travel time costs to guide EV travel and charging. Therefore, it is of great practical significance to implement advance combined risk control of distribution and transportation networks by taking advantage of the flexibility of EV operation.

Fault risk prevention in coupled distribution and transportation networks inevitably involves three aspects. First, how can the impact of EV charging on the operation risk of the distribution network be reduced? Second, how can EV travel be guided to prevent traffic congestion fault risks? Third, how can the operational flexibility of EVs be used to coordinate the operational risks of both the distribution and transportation networks? Although large-scale applications of EVs have aroused wide interest and attention from researchers, most of the current researches focuse on distribution networks, such as the influences of the concentration and randomness of the EV charging load on distribution networks and the charging and discharging scheduling of EVs. There are a few studies that have emphasized the coupling of the power grid and transportation. For example, the stochastic security constrained unit commitment-traffic assignment problem is explored in [3], while references [4] and [5] propose an expansion planning methods for power and transportation networks considering the coupling characteristics of the two. In the recent years, some researchers have shifted their attentions to the resilience and fault problems of coupled distribution and transportation networks with large-scale EVs. Reference [6] proposes a cascading failure analysis framework for a coupled power grid and transportation network, while reference [7] investigates the impact of road capacity degradation on the transportation and power distribution networks based on the traffic assignment problem-optimal power flow framework. In [8], a power flow calculation method is proposed under N–1 contingency scenarios in the coupled distribution and transportation networks. A resilience assessment method for the electrified road networks is proposed in [9], though references [7]–[9] do not study the corresponding fault risk prevention strategy. In [10], a system resilience enhancement strategy is presented to protect the power distribution system coupled with the urban transportation system through traffic lights. Additionally, a method of using incentive electricity price to guide EV charging to deal with the potential security threat in coupled urban power-traffic networks is proposed in [11]. However, the fault prevention strategy developed in [10] and [11] is only implemented from a single network, such as power grid or transportation network, and does not involve the implementation of any coordinated prevention strategy for fault risks from the power and transportation networks simultaneously.

As mentioned above, a large number of researchers have focused on the impact of EV charging on distribution networks and proposed corresponding charging guidance strategies. Studies in [12] and [13] demonstrate that a significant amount of EV charging can cause possible branch congestion, and corresponding congestion management strategies are developed. Other analyses in [14] and [15] propose voltage control strategies for power systems with massive EV charging loads. Considering that large-scale EV charging can increase the peak–valley difference and reduce the operational economy of power grids, orderly charging models of EVs charging load transfer that take advantage of the flexibility of EVs are established [16]–[18]. However, current studies do not consider the fault risk caused by large-scale EV charging to power grids. With the large-scale increase in charging load, power distribution lines and other facilities may reach their transmission capacity limits, so fault propagation accidents can easily occur when power grids are subjected to equipment failure or maloperation. Therefore, it is necessary to consider the operating risks of distribution networks in the charging guidance of EVs.

In the field of traffic, studying the formation, dissipation and prevention of traffic congestion related faults is a key area of research. However, these studies have mainly focused on specific links. For example, a new car-following model is proposed in [19] to study the interval integration effect of a vehicle's self-delayed velocity information on traffic flow. Reference [20] proposes an approach to identify the underlying causes of recurrent congestion in tunnels, and analyzes the transmission and dissipation processes of congestion. In terms of traffic congestion fault management, reference [21] discusses the effects of odd-even plate measures on alleviating traffic congestion. By improving rings and optimizing the phase lengths of traffic lights, the problems and methods of optimizing congestion on roads are assessed in [22]. References [23]–[25] propose that charge policies for congested links can effectively reduce the congestion rate. Existing studies on traffic congestion fault management in the traffic field mainly take a certain link or node as the research object or maintain traffic order with the help of external equipment, such as odd-even plates and traffic lights, but fail to implement congestion management for all traffic. In addition, traffic managers and road users have different goals. Traffic managers pursue the entire traffic system operation optimization, that is, the system optimum (SO) [26]. However, road users only make travel decisions based on the maximization of their own interests, called user equilibrium (UE) [27]. To address the contradiction of these two interests, assessing the characteristics of EV users to achieve the optimization of an entire traffic system needs to be studied.

In summary, a fault collaborative prevention strategy in coupled distribution and transportation networks based on the flexibility of EVs has not been studied. In terms of EV charging guidance, the influence of the charging load on the operating risk of the distribution network has not been considered. The travel flexibility of EVs has not been fully utilized in traffic network congestion fault management either. In practice, charging cost and travel time cost are the most important factors to be considered in EV users' travel decisions, and their initial travel time is transferable. Under the coupling of distribution and transportation networks, the operation risk control of the networks can be simultaneously realized by comprehensively utilizing the guiding role of charging cost and travel time cost to EVs.

In this paper, a fault risk advance coordinated prevention strategy in coupled distribution and transportation networks considering the flexibility of travel demand is proposed. This strategy fully considers the integration characteristics of the distribution and transportation networks and regards the two networks as the same stakeholder. The charging cost and the travel time cost of EVs are affected by setting the risk-based distribution locational marginal prices (RDLMPs) and the origin-destination risk marginal prices (ODRMPs) considering the coupled networks' risks. EV fleets optimize the travel arrangement with the goal of minimizing their comprehensive operating cost under the constraints of charging prices and travel time prices. In practice, charging piles with controllable charging power account for a relatively small proportion, such as approximately 1% in China, and EVs often start charging when they are connected to the grid. In addition, EVs tend to be parked for a long time in residential areas and working areas, while charging piles in commercial areas are mainly fast-charging. In this study, several appropriate assumptions are adopted: 1) The moment when the EV is connected to the grid is its charging start time; 2) The charging power is uncontrollable; and 3) When connected to the grid, EVs have enough time to obtain their required electricity. The main contributions of this paper are as follows.

1) A piecewise risk index quantitative model is proposed to describe the impact of the line load and traffic flow on the risk of distribution network lines and traffic network links.

2) RDLMPs, which can reflect the impact of the load increment of each node on the operation risk of the distribution network, are established to restrain the operation risk of the distribution network brought by the charging load.

3) The travel time cost is considered as an economic cost, and the economic risk scheduling model of transportation networks is constructed with the goal of minimizing the overall traffic operation costs under the traffic fault risk constraints. Based on this, ODRMPs are derived to reduce the risk of EV travel to the operation of transportation.

4) Under the constraints of RDLMPs and ODRMPs, a comprehensive optimal travel strategy for EV fleets considering charging costs and travel time costs is proposed.

The rest of the paper is organized as follows. Section II proposes the risk indicators of the distribution and transportation networks. Section III establishes an economic risk scheduling model of coupled distribution and transportation networks, while RDLMPs and ODRMPs are proposed. A comprehensive optimal travel strategy for EV fleets considering charging cost and travel time cost is developed in Section IV. Case studies and conclusions are presented in Sections V and VI, respectively.

II. Risk Indicators of Coupled Networks

The risk to distribution networks is mainly caused by the line load degree. In power systems, the power flow is often divided into three levels, such as normal, emergency and drastic, and the higher the power flow level of a certain line, the greater the risk of the line. Similarly, in a traffic system, traffic managers often divide traffic flow into different levels, unimpeded, congested and severely congested, according to the traffic flow of a link relative to its capacity. To quantify the influence of transmission line flow on system risk in security-constrained economic scheduling of transmission networks, a piecewise risk index function is set according to the line load rate. Compared with the risk management of transmission networks, this paper establishes the following risk indicators of distribution and transportation networks. The line or link risk index is composed of the line or link fault probability P_l and the line load rate severity or link traffic flow rate severity S_l, reflecting the severity of the line or link fault consequence.

The risk index of line or link l is shown as:

$$R_l = P_l S_l \tag{1}$$

The line load rate severity and link traffic flow rate severity are separately related to its load rate and traffic flow rate, which can be divided into three sections according to different load and traffic flow rates, as shown in Fig. 1.

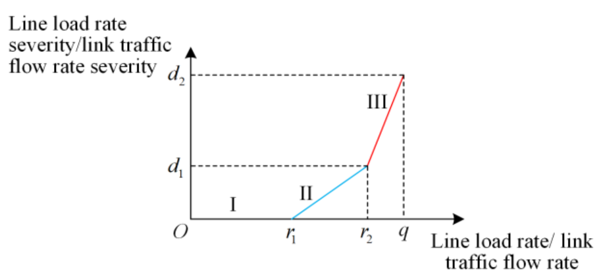

Fig. 1. The relationship between line load rate severity/link traffic flow rate severity and load rate/link traffic flow rate.

The line load rate severity or link traffic flow rate severity S_l of l is calculated by:

$$S_{a,t}=\begin{cases}0, & 0\leqslant r_{a,t}\leqslant r_1\\ \dfrac{d_1}{r_2-r_1}r_{a,t}-\dfrac{d_1 r_1}{r_2-r_1}, & r_1<r_{a,t}\leqslant r_2\\ \dfrac{d_2-d_1}{q-r_2}r_{a,t}+\dfrac{d_1 q-d_2 r_2}{q-r_2}, & r_2<r_{a,t}\leqslant q\end{cases} \tag{2}$$

where $S_{a,t}$ is the line load rate severity or the link traffic flow rate severity of line or link a at time t; $r_{a,t}$ is the line load rate or link traffic flow rate of line or link a at time t; q represents the maximum allowed line load rate or maximum allowed link traffic flow rate, for the power system, it is usually set to 1, while the value in the traffic system can be a constant greater than 1; r_1 and r_2 are the corresponding line load rate or link traffic flow rate parameters; while d_1 and d_2 are the corresponding line load rate severity or link traffic flow rate severity parameters, they can be set according to the degrees of importance on the line load rate severity and link traffic flow rate severity. In this paper, the typical modes are selected for the division of the line power flow and link traffic flow, and the typical values of parameters r_1, r_2 and q are adopted. It should be pointed out that the values of d_1 and d_2 depend on the importance that the system operator attaches to the severity of the power flow and traffic flow, and the larger the value of d_1 and d_2, the more sensitive of the system operator to excessive power flow and traffic flow.

Then, the total risk of the distribution network system or transportation system can be expressed as:

$$R_{\text{sys}}=\sum_{l\in L}R_l \tag{3}$$

where L is the set of all lines or links in the system.

III. RDLMPs and ODRMPs

The significance of setting the RDLMPs and ODRMPs is to clearly reflect the influence of the slight increment of the nodal load or OD travel demand on the distribution network risk and the transportation risk, respectively. This needs to be obtained by analyzing the risk-based security-constrained economic scheduling model.

A. Risk-based Security-constrained Economic Scheduling of Coupled Networks

In the risk-based security-constrained economic scheduling of coupled distribution and transportation networks, the operation economy and risk constraints of the distribution and transportation networks should be considered. The goal of a distribution system is to minimize its energy purchasing cost from an independent system operator (ISO) under certain risk constraints, and the objective function is shown as:

$$\min f_{\text{dis}}=\sum_{k\in W}\sum_{t\in T}a_k P_{Wk,t}^2+b_k P_{Wk,t}+c_k \tag{4}$$

where f_{dis} is the energy purchasing cost of the distribution network; T is the set of scheduling times; W is the number of tie-lines; a_k, b_k and c_k are the cost coefficients of the distribution system purchasing power from the ISO; and $P_{Wk,t}$ is the purchased electric energy in time period t through tie-line k.

The constraint conditions are given in (5)–(14) as:

$$-\sum_{j=1}^{D}P_{Dj,t}+\sum_{k=1}^{W}P_{Wk,t}-M_t=0,\quad \forall t \tag{5}$$

$$h_{l,t}=-\sum_{j=1}^{D}H_{l-j,t}P_{Dj,t}+\sum_{k=1}^{W}G_{l-k,t}P_{Wk,t},\quad \forall t,l \tag{6}$$

$$r_{l,t}=h_{l,t}\big/F_l^{\max},\quad \forall t,l \tag{7}$$

$$0\leqslant h_{l,t}\leqslant F_l^{\max},\quad \forall t,l \tag{8}$$

$$S_{l,t}\geqslant 0,\quad \forall t,l \tag{9}$$

$$S_{l,t}\geqslant a_{1l,t}r_{l,t}-b_{1l,t},\quad \forall t,l \tag{10}$$

$$S_{l,t}\geqslant a_{2l,t}r_{l,t}-b_{2l,t},\quad \forall t,l \tag{11}$$

$$P_{l,t}\cdot S_{l,t}\leqslant K_{l,t}R_{l,t}^{\max},\quad \forall t,l \tag{12}$$

$$P_{Wk}^{\min}\leqslant P_{Wk,t}\leqslant P_{Wk}^{\max},\quad \forall t,k \tag{13}$$

$$P_{Dj,t}^{\min}\leqslant P_{Dj,t}\leqslant P_{Dj,t}^{\max},\quad \forall t,j \tag{14}$$

where D is the number of distribution network nodes; $P_{Dj,t}$ is the load demand of node j at time t, which includes the charging load of CSs; M_t represents the distribution network loss at time t; while $h_{l,t}$ and $r_{l,t}$ are the power flow and load rate on line l at time t, respectively; $H_{l-j,t}$ and $G_{l-k,t}$ refer to the power transfer distribution factors, which represent the sensitivity relationship between the power flow of line l and the load at node j and the power of tie-line k, respectively; $F_l^{\max}$ is the maximum transmission capacity of line l; $P_{Wk}^{\min}$ and $P_{Wk}^{\max}$ limit the power transmitted to the system by tie-line k, for node j with CS, its load is flexible; $P_{Dj,t}^{\max}$ and $P_{Dj,t}^{\min}$ represent the upper and lower load limits at time t, respectively; $K_{l,t}R_{l,t}^{\max}$ is the load risk indicator threshold set for line l, the value of $K_{l,t}R_{l,t}^{\max}$ will affect the formulation of the risk scheduling plan, $R_{l,t}^{\max}$ can be set as the line risk level under traditional security-constrained economic dispatch, and $K_{l,t}$ ($K_{l,t}<1$) can be adjusted according to the degrees of importance on operation risks; the fault probability and load rate severity of line l at time t are $P_{l,t}$ and $S_{l,t}$ respectively; the correlation coefficient between line load rate severity and load rates $a_{1l,t}$, $a_{2l,t}$, $b_{1l,t}$, $b_{2l,t}$ are calculated by:

$$\begin{cases} a_{1l,t} = \dfrac{d_1}{r_2 - r_1} \\ b_{1l,t} = \dfrac{d_1 r_1}{r_2 - r_1} \\ a_{2l,t} = \dfrac{d_2 - d_1}{q - r_2} \\ b_{2l,t} = \dfrac{d_1 q - d_2 r_2}{q - r_2} \end{cases} \tag{15}$$

where d_1, d_2, r_1, r_2, and q depend on the importance that the system operator attaches to different power flow levels.

Traffic managers pursue the minimum operation time cost of the entire transportation, that is, the SO. The objective function of the traffic manager can be denoted as:

$$\min f_{\text{tra}} = \sum_{t\in T}\sum_{a\in A} x_{a,t} t_{a,t}(x_{a,t}) \tag{16}$$

where the traffic link set is A; $x_{a,t}$ is the traffic flow on link a ($a\in A$) at time t; and $t_{a,t}$ is the travel time needed of link a at time t.

According to traffic characteristics, the link travel time is a monotonic function of the traffic flow, which can be described by the Bureau of Public Roads (BPR) model, as:

$$t_{a,t}(x_{a,t}) = t_a^0\left[1 + 0.15(x_{a,t}/C_a)^4\right], \quad \forall t, a \tag{17}$$

where t_a^0 and C_a reflect the free flow time and traffic capacity of link a, respectively.

Meanwhile, equation (16) should be subject to the following constraints:

$$d_{w,t} = \sum_{p\in R_w} f_{p,t}^w, \quad \forall t, w \tag{18}$$

$$x_{a,t} = \sum_{w\in \Gamma}\sum_{p\in R_w} \delta_{a,p}^w f_{p,t}^w, \quad \forall t, a \tag{19}$$

$$r_{a,t} = x_{a,t}/C_a, \quad \forall t, a \tag{20}$$

$$S_{a,t} \geqslant 0, \quad \forall t, a \tag{21}$$

$$S_{a,t} \geqslant a_{1a,t} r_{a,t} - b_{1a,t}, \quad \forall t, a \tag{22}$$

$$S_{a,t} \geqslant a_{2a,t} r_{a,t} - b_{2a,t}, \quad \forall t, a \tag{23}$$

$$P_{a,t} S_{a,t} \leqslant K_{a,t} R_{a,t}^{\max}, \quad \forall t, a \tag{24}$$

$$D_w^{\min} \leqslant d_{w,t} \leqslant D_w^{\max}, \quad \forall t, w \tag{25}$$

$$f_{p,t}^w \geqslant 0, \quad \forall t, w, p \tag{26}$$

where $\delta_{a,p}^w$ is a link coefficient, $\delta_{a,p}^w = 1$ if link a belongs to path p, otherwise, $\delta_{a,p}^w = 0$; Γ is defined as the set of OD pairs, and w is one of the OD pairs in Γ; R_w is the set of routes for w; p denotes any route in the traffic network; $f_{p,t}^w$ represents the traffic flow of route p as assigned by the travel demand of OD pair w at time t; $d_{w,t}$ is the travel demand of w at time t; the fault probability of link a at time t is $P_{a,t}$; the link parameters $K_{a,t}$ and $R_{a,t}^{\max}$ have similar physical meanings to $K_{l,t}$ and $R_{l,t}^{\max}$ in distribution networks, respectively; $D_w^{\max}$ and $D_w^{\min}$ limit the travel demand upper and lower of OD pair w at time t; $a_{1a,t}$, b_{1at}, $a_{2a,t}$ and b_{2at} are calculated by:

$$\begin{cases} a_{1a,t} = \dfrac{d_1}{r_2 - r_1} \\ b_{1a,t} = \dfrac{d_1 r_1}{r_2 - r_1} \\ a_{2a,t} = \dfrac{d_2 - d_1}{q - r_2} \\ b_{2a,t} = \dfrac{d_1 q - d_2 r_2}{q - r_2} \end{cases} \tag{27}$$

In (18), the travel demand of OD pair w at time t is the sum of the traffic flow of all the routes of w. Equation (19) shows that the traffic flow of link a at time t is the sum of the traffic flow of the routes that include link a. Equations (20)–(23) are risk constraints corresponding to individual traffic links. In (20)–(23), according to Fig. 1 in Section II, the values of the relevant parameters are denoted as (27). Although these parameters have similar forms with (15), they have different meanings and values in power system and transportation system.

Considering the coupling relationship between the distribution and transportation networks, to minimize the total operation cost, the distribution and transportation networks will gradually form a fusion system managed by the same central operator (CO) [28], [29]. Therefore, the risk-based security-constrained economic scheduling problem considering the coupling of the two networks can be expressed as follows:

$$\begin{aligned} \min f = \alpha&\left(\sum_{k\in W}\sum_{t\in T} a_k P_{Wk,t}^2 + b_k P_{Wk,t} + c_k\right) + \\ \beta&\left(\sum_{t\in T}\sum_{a\in A} x_{a,t} t_{a,t}\right), \text{ s.t. } (5)-(14) \text{ and } (17)-(26) \end{aligned} \tag{28}$$

where α and β ($a \geqslant 0, \beta \geqslant 0, a + \beta = 1$) represent the operation cost weights of the distribution network and transportation network, respectively. When $a = 1$ and $\beta = 0$, the system degenerates into a risk-based security-constrained economic scheduling of the distribution network under EV charging; when $a = 0$ and $\beta = 1$, the system degenerates into a risk-based security-constrained economic scheduling model of transportation.

B. RDLMPs

By taking the partial derivative of Lagrange function F of the risk-based security-constrained economic scheduling model proposed in this paper, the RDLMPs are obtained. $\lambda_{1,t}$, $\lambda_{2l,t}$ and $\lambda_{3l,t}$ are defined as the Lagrangian multipliers of equality constraints (5)–(7); $\mu_{1l,t} \geqslant 0$, $\mu_{2l,t} \geqslant 0$, $\mu_{3k,t} \geqslant 0$, $\mu_{4k,t} \geqslant 0$, $\mu_{5j,t} \geqslant 0$, $\mu_{6j,t} \geqslant 0$, $\delta_{1l,t} \geqslant 0$, $\delta_{2l,t} \geqslant 0$, $\delta_{3l,t} \geqslant 0$, and $\tau_{l,t} \geqslant 0$ are defined as the Lagrangian multipliers of inequality constraints (8)–(14). According to the Kuhn–Tucker (KKT) condition, conditions (29)–(32) should be satisfied at the optimal solution.

$$\partial F / \partial h_{l,t} = -\lambda_{2l,t} + \lambda_{3l,t} / F_l^{\max} + \mu_{1l,t} - \mu_{2l,t} = 0 \quad (29)$$

$$\lambda_{2l,t} = \lambda_{3l,t} / F_l^{\max} + \mu_{1l,t} - \mu_{2l,t} \quad (30)$$

$$\partial F / \partial S_{l,t} = -\delta_{1l,t} - \delta_{2l,t} - \delta_{3l,t} + \tau_{l,t} P_{l,t} = 0 \quad (31)$$

$$\partial F / \partial r_{l,t} = -\lambda_{3l,t} + \delta_{2l,t} a_{1l,t} + \delta_{3l,t} a_{2l,t} = 0 \quad (32)$$

Since at most one of $\delta_{1l,t}$, $\delta_{2l,t}$, and $\delta_{3l,t}$ in (32) is not zero:

$$\lambda_{3l,t} = \delta_{2l,t} \times 0 + \delta_{2l,t} a_{1l,t} + \delta_{3l,t} a_{2l,t} = \tau_{l,t} P_{l,t} a_{ml,t}, \quad \forall l \quad (33)$$

where $a_{ml,t}$ is the micro increment rate of the line load rate severity to the line load rate, which is determined by section m in Fig. 1, where line l is located at this time.

The partial derivative of the Lagrange function to the load of node j is calculated, and the risk-based distribution locational marginal price $A_{j,t}$ of node j can be obtained by integrating (30) and (33):

$$\begin{aligned} & A_{j,t} = \partial F / \partial P_{Dj,t} = \\ & \lambda_{1,t} + \lambda_{1,t} \frac{\partial M_t}{\partial P_{Dj,t}} - \sum_{l=1}^{L} \lambda_{2l,t} H_{1-j,t} + \mu_{5j,t} - \mu_{6j,t} = \\ & \lambda_{1,t} + \lambda_{1,t} \frac{\partial M_t}{\partial P_{Dj,t}} - \sum_{l=1}^{L} \mu_{1l,t} H_{1-j,t} + \sum_{l=1}^{L} \mu_{2l,t} H_{1-j,t} + \\ & \mu_{5j,t} - \mu_{6j,t} - \sum_{l=1}^{L} \tau_{l,t} P_{l,t} a_{ml,t} H_{1-j,t} \end{aligned} \quad (34)$$

According to (34), the risk-based distribution locational marginal price includes the energy price, loss price, congestion price and risk price. The risk price is obtained by multiplying the power transfer distribution factors, line failure probability, parameter $a_{ml,t}$ and Lagrange multiplier of the risk constraint. By introducing risk price, the RDLMP model proposed in this paper can reflect the risk level of the distribution network caused by EV charging.

C. ODRMPs

Similarly, ODRMPs can be obtained by taking the partial derivative of the Lagrange function F with respect to $d_{w,t}$; $\pi_{1,t}$, $\pi_{2a,t}$ and $\pi_{3a,t}$ are the Lagrangian multipliers of equality constraints (18)–(20), respectively; $\sigma_{1a,t} \geqslant 0$, $\sigma_{2a,t} \geqslant 0$, $\sigma_{3a,t} \geqslant 0$, $\kappa_{a,t} \geqslant 0$, $\vartheta_{1w,t} \geqslant 0$, $\vartheta_{2w,t} \geqslant 0$, and $\upsilon_{w,p,t} \geqslant 0$ are defined as the Lagrangian multipliers of inequality constraints (21)–(26), respectively. To obtain the optimal solution, the following KKT conditions should be satisfied:

$$\begin{cases} \dfrac{\partial F}{\partial x_{a,t}} = \beta t_a^0 + \dfrac{0.75\beta}{C_a^4} t_a^0 x_{a,t}^4 + \pi_{2a,t} + \dfrac{\pi_{3a,t}}{C_a} = 0 \\ \pi_{2a,t} = -\dfrac{\pi_{3a,t}}{C_a} - \beta t_a^0 - \dfrac{0.75\beta}{C_a^4} t_a^0 x_{a,t}^4 \\ \dfrac{\partial F}{\partial S_{a,t}} = -\sigma_{1a,t} - \sigma_{2a,t} - \sigma_{3a,t} + \kappa_{a,t} P_{a,t} = 0 \\ \dfrac{\partial F}{\partial r_{a,t}} = -\pi_{3a,t} + \sigma_{2a,t} a_{1a,t} + \sigma_{3a,t} a_{2a,t} = 0 \\ \pi_{3a,t} = \sigma_{1a,t} \times 0 + \sigma_{2a,t} a_{1a,t} + \sigma_{3a,t} a_{2a,t} = \kappa_{a,t} P_{a,t} a_{ma,t} \\ \dfrac{\partial F}{\partial f_{p,t}^w} = -\pi_{1,t} - \sum_{a \in A} \pi_{2a,t} \delta_{a,p}^w - \upsilon_{w,p,t} = 0 \\ \pi_{1,t} = -\sum_{a \in A} \pi_{2a,t} \delta_{a,p}^w - \upsilon_{w,p,t} \end{cases} \quad (35)$$

$$\begin{aligned} B_{w,t} = \frac{\partial F}{\partial d_{w,t}} = & \left[\frac{1}{|R_w|} \sum_{p \in R_w} \sum_{a \in A} \left(\beta t_a^0 + \frac{0.75\beta}{C_a^4} t_a^0 x_{a,t}^4 \right) \delta_{a,p}^w \right] - \\ & \frac{1}{|R_w|} \sum_{p \in R_w} \upsilon_{w,p,t} - \vartheta_{1w,t} + \vartheta_{2w,t} + \frac{1}{|R_w|} \sum_{p \in R_w} \sum_{a \in A} \kappa_{a,t} P_{a,t} a_{ma,t} \delta_{a,p}^w \end{aligned} \quad (36)$$

where $B_{w,t}$ is the ODRMP of the EVs travel of the OD pair w at time t; $a_{ma,t}$ is the micro increment rate of link traffic flow rate severity to link traffic flow. Based on the KKT conditions listed in (35), the ODRMP of OD pair w can be denoted by (36).

The marginal time price of OD pair w at time t includes the travel base time price, congestion time price and risk time price.

IV. TRAVEL STRATEGY FOR EV FLEET

CO obtains RDLMPs and ODRMPs based on the predicted results of the charging power of each node in the distribution network and traffic flow on each traffic link through problem (28) and issues them to the EV fleets. Under the guidance of RDLMPs and ODRMPs, EV fleets aim to make travel plans with an optimal overall cost of travel time cost and charging cost. The RDLMPs can be fitted by a linear function or a quadratic function [13]. In this paper, the quadratic function shown in (37) is adopted, and the corresponding parameters are obtained by the data-driven method. The travel cost optimization objective of the EV fleets is denoted in (38). In this problem, considering that the charging power of EVs is uncontrollable and the charging process is divided into three stages, of which the main stage is constant power charging, it can be assumed that the charging power of EVs of OD pair w is constant power P_w. Meanwhile, the charging period is divided into time slots with equal time intervals, and the interval of each charging slot is Δt. The charging energy demand of EVs of OD pair w at their destination is Q_w, and the number of charging time slots required is n.

$$A_{j,t} = A_{j,t_1} + a(t-t_1) + b(t-t_1)^2, \quad t \in T = [t_1, t_2] \tag{37}$$

where $A_{j,t}$ and A_{j,t_1} are the ODRMPs' fitting values at node j at time t and time t_1 respectively; t_1 and t_2 are the starting and ending times of travel period T, respectively; a and b are fitting coefficients.

The travel planning goals of the EV fleet of OD pair w are as follows:

$$\min f_w = \xi \sum_{t\in T} B_{w,t} d_{w,t} + \varphi \sum_{t\in T}\sum_{i=1}^{n} A_{d,t+t_{p,t}+i\Delta t} P_w d_{w,t} \Delta t \tag{38}$$

$$\text{s.t.} \begin{cases} \sum_{t\in T} d_{w,t} = D_w, & \forall w \\ d_{w,t} \geqslant 0, & \forall t, w \\ t_1 \leqslant t \leqslant t_2, & \forall w \\ t_{p,t} = \sum_{a\in A_R} \delta_{a,p}^{w} t_{a,t}, & \forall t, p \\ n = Q_w / P_w \Delta t \\ (17),(18),(19) \end{cases} \tag{39}$$

where $A_{d,t+t_{p,t}+i\Delta t}$ represents the RDLMP of EVs charging at the end point d at time t; $\xi > 0$ and $\varphi > 0$ are the travel time cost and charging cost coefficients of the EV fleet, respectively; $t_{p,t}$ represents the total time required for the EVs to choose path p for travel at time t. Problems (38) and (39) comprehensively optimize the travel time cost and charging cost of the EV fleet travel under the constraints of RDLMPs and ODRMPs and is a convex optimization problem.

V. CASE STUDIES

In this section, regional transportation in Nanjing, China, and three IEEE 33-node distribution networks are used to analyze the effectiveness of coordinated fault risk prevention in coupled distribution and transportation networks. The regional transportation covers a total area of approximately 50 km^2, including 60 traffic nodes and 97 traffic links. Figure 2 shows the traffic topology of this region, which includes residential, commercial and work areas.

The locations of the CSs at OD points in the transportation and distribution networks are presented in Table I. This region has good charging facilities, with sufficient slow charging piles in residential and work areas and a large number of fast charging piles in commercial areas. The evening travel peak period is taken as an example to carry out case studies. According to the traffic flow and resident travel rules in Nanjing, the evening travel peak period is from 17:00 to 19:00, and the travel demand of each travel starting point is approximately 2016. Their starting points are in work areas, while 60% and 40% of the travel demand endpoints are evenly distributed in residential areas and commercial areas, respectively. In the absence of charging price and travel time price guidance, the travel and charging of EV fleets are in a disordered state. Figure 3 shows the distribution of travel demand for OD pair 62-8 during the evening travel peak period and the distribution of charging load at CS1 from 17:00 to 22:00 under disordered travel and charging. The cost coefficients of the distribution system purchasing energy from the ISO are set as $a_k = 0$, $b_k = 0.23$ ¥/kWh and $c_k = 0.08$ ¥/(kWh)^2.

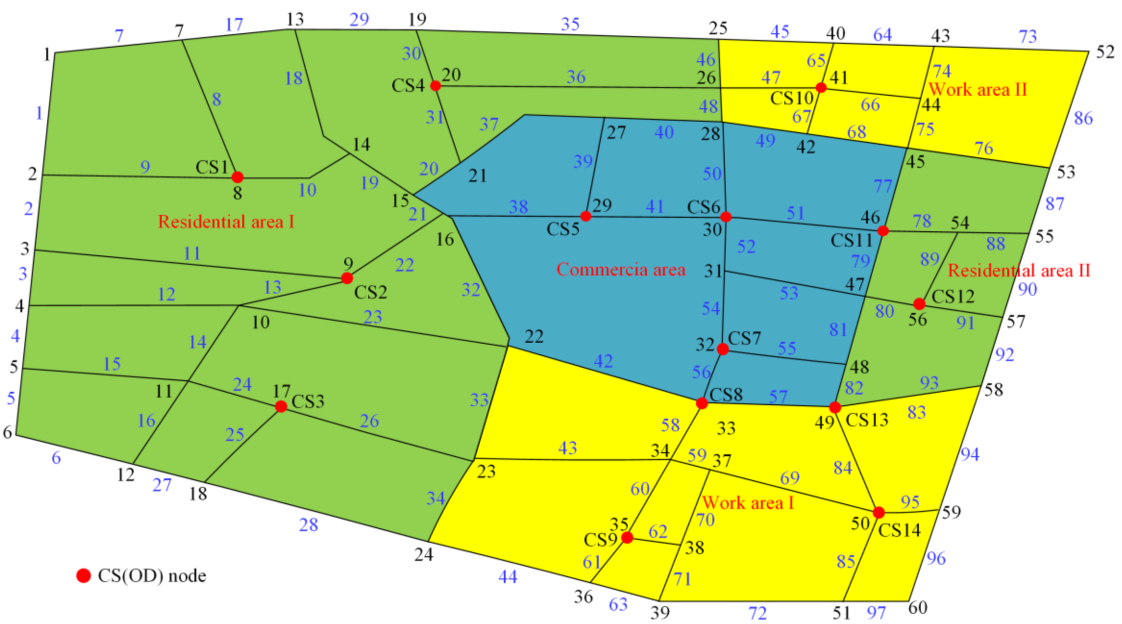

Fig. 2. Traffic topology of regional transportation.

TABLE I
RELATED PARAMETERS OF THE CSs

CS	Distribution network number	D-node	T-node
1	1	4	8
2	1	8	9
3	1	11	17
4	1	15	20
5	2	4	29
6	2	11	30
7	2	23	32
8	2	26	33
9	3	5	35
10	3	11	41
11	1	23	46
12	1	26	56
13	1	30	49
14	3	23	50

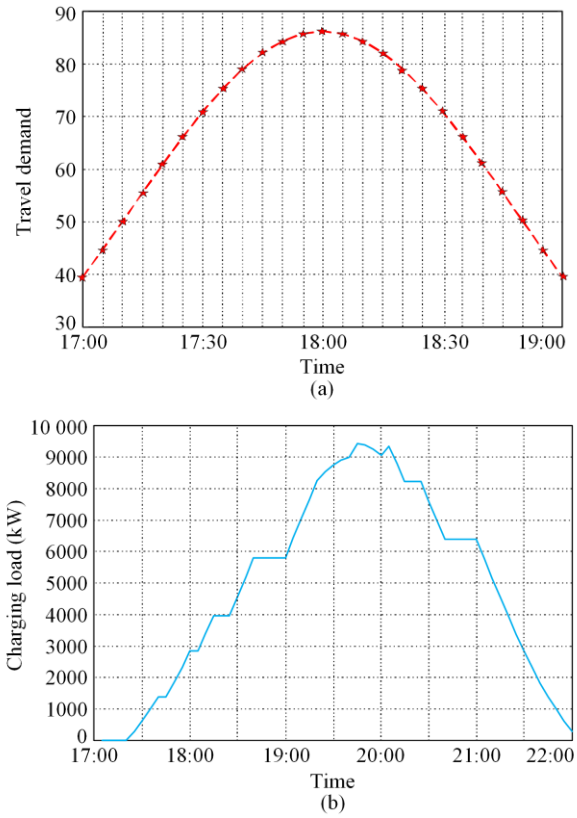

Fig. 3. Distribution of travel demand for OD pair 62-8 and charging load at CS1 under disordered travel and charging. (a) Distribution of travel demand for OD pair 62-8 from 17:00 to 19:00 under no guidance. (b) Distribution of charging load at CS1 from 17:00 to 22:00 under no guidance.

The parameters of the severity functions are set as follows. In power systems, when the line power flow is less than 90% of the line capacity, the line has abundant capacity, which is called normal state. So r_1 is 0.9, and according to the common division of the power flow severity, $r_2 = 1.1 r_1$, and $q = 1$ are selected. In the traffic field, the operation state of the traffic flow less than the link capacity is often defined as unimpeded, while the traffic flow is higher than the link capacity but less than 1.5 times of the link capacity is defined as congested, whereas the traffic will fail to run when the traffic flow is greater than twice the link capacity. So, $r_1 = 1$, $r_2 = 1.5$, and $q = 2$ are set in the traffic flow rate severity function. In addition, considering that the system can operate for a short time under the condition of the emergency operation of the line and the congested operation of the link, $d_1 = 1$ is taken in this study. As long as the slope of the third segment in the piecewise severity function shown in Fig. 1 is greater than that of the second segment, the value of d_2 can be selected as 10, which highlights that the operator shows lower tolerance to higher power flow rate and traffic rate.

A. Effectiveness of Coordinated Fault Risk Prevention

To prove the effectiveness of the RDLMP and ODRMP models proposed in this paper, their composition is analyzed. Additionally, taking the distribution network node where CS1 is located and OD pair 62-8 as examples, Fig. 4 shows the RDLMPs and ODRMPs at different times. As seen, the RDLMP is composed of the energy price, loss price, congestion price and risk price, and the ODRMP is composed of the travel base time price, congestion time price and risk time price. When the distribution network node load or traffic travel demand is low, there is no congestion price or risk price in the RDLMP and ODRMP. The RDLMP increases sharply in the period of high node load, and the ODRMP increases rapidly in the period of high travel demand. In addition, the proportion of increases in congestion price and risk price is larger. This is because the risk of distribution network lines and traffic links is high under peak load and travel conditions, and a small load or travel demand increase will exacerbate their risks.

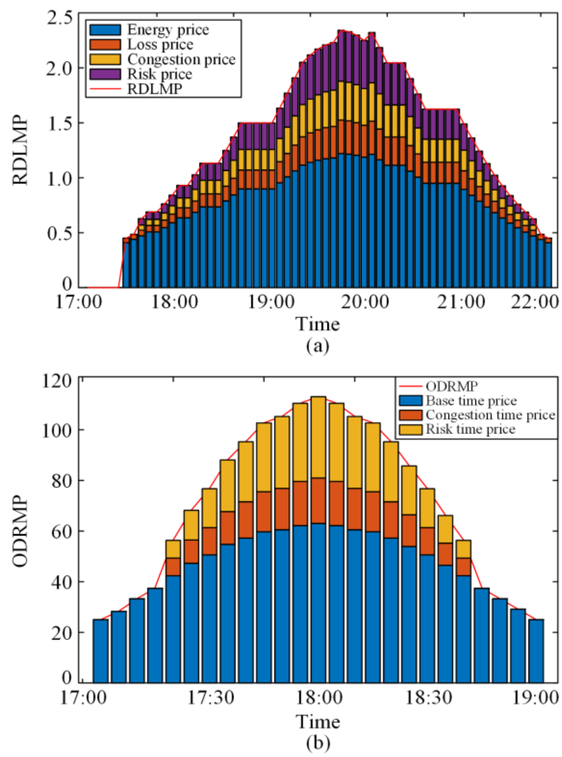

Fig. 4. RDLMP of the distribution network node where CS1 is located and the ODRMP of OD pair 62-8. (a) RDLMP of the distribution network node where CS1 is located from 17:00–22:00. (b) ODRMP of OD pair 62-8 from 17:00–19:00.

The travel arrangement of EV fleets and the distribution of charging loads in the coupled networks are analyzed under the guidance of the RDLMPs and ODRMPs. Figure 5 shows the travel demand distribution of OD pair 62-8 and the charging load distribution of CS1 under the guidance strategy. As shown in Fig. 5, to reduce travel and charging costs, the EV fleet transfers travel and charging during peak hours to trough hours, realizing reasonable travel planning. The reason is that after the introduction of the risk price, the RDLMPs and ODRMPs in the travel demand and charging load peak periods increase sharply, resulting in higher travel and charging costs in these periods, while the travel and charging costs in the trough periods are lower, and there is no congestion price or risk price.

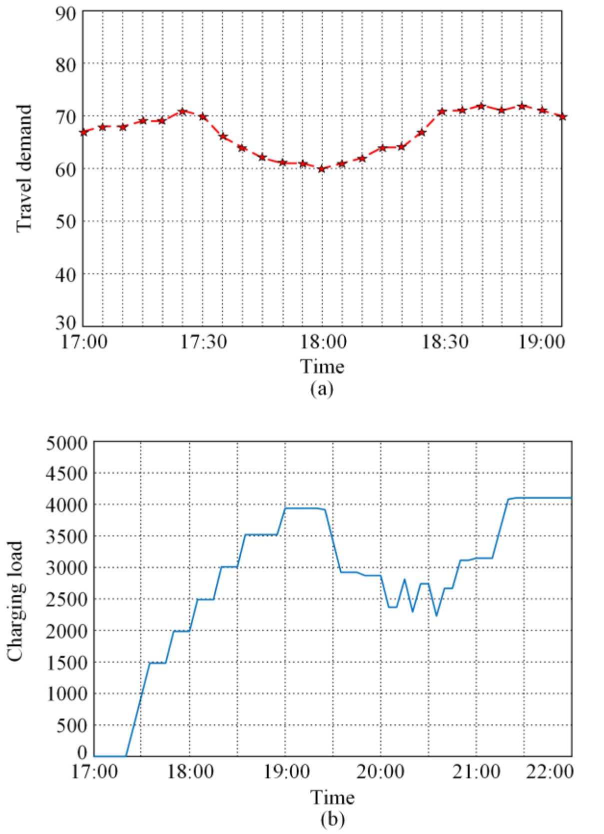

Fig. 5. Distribution of travel demand for OD pair 62-8 and charging load at CS1 under the guidance strategy. (a) Distribution of travel demand for OD pair 62-8 from 17:00 to 19:00. (b) Distribution of charging load at CS1 from 17:00 to 22:00.

Furthermore, the operation risk and traffic flow rate of power grid lines and traffic links before and after the guidance of the RDLMPs and ODRMPs are analyzed. Taking line 3–4 of distribution network 1 and traffic links 8, 9 and 10 connecting CS1 as examples, Figs. 6 and 7 show the operation risks of line 3–4 of distribution network 1 and the traffic flow rates of traffic links 8, 9 and 10 before and after the implementation of the guidance strategy, respectively.

In the scenario of disordered travel and charging, the travel and charging of EVs have obvious clustering characteristics, which leads to greater fault risks in the operation of distribution networks and relatively higher traffic flow rate of links in traffic networks. After the implementation of the guidance strategy, both the distribution network operation risk and traffic flow rate of traffic networks are effectively reduced, and the operation of the coupled networks can be ensured within the safe range. This study demonstrates that the proposed RDLMPs and ODRMPs are effective in alleviating fault risks in coupled distribution and transportation networks.

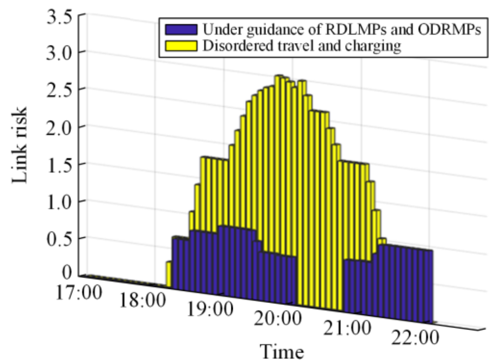

Fig. 6. Operation risks of line 3–4 of distribution network 1 before and after the implementation of the guidance strategy.

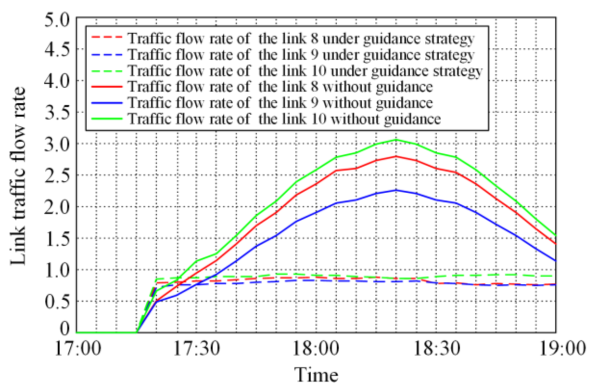

Fig. 7. Traffic flow rate of links 8, 9, and 10 from 17:00 to 19:00 before and after the implementation of the guidance strategy.

B. Comparative Studies

To further verify the benefits of coordinating distribution and transportation network operations in the development of the fault risk prevention strategy, the operation of EVs is guided separately by considering only the distribution network operation risk (Case 1) and only the transportation network operation risk (Case 2). In the two cases, EVs aim to minimize their charging cost and their travel time cost. In Case 1, which only considers the operation risk of the distribution network, the scheduling model of the CO is (4)–(14), and the operation of the transportation network without guidance strategies will follow the user optimal principle of (38) and (39). In Case 2, which only considers the operation risk of the transportation network, the scheduling model of the CO is (16)–(26), and the charging price of the distribution network is obtained by the optimal power flow model without considering the operation risk. Figures 8 and 9 show the operation risk of line 3–4 of distribution network 1 and the traffic flow rates of traffic links 8, 9 and 10 under Case 1 and Case 2, respectively.

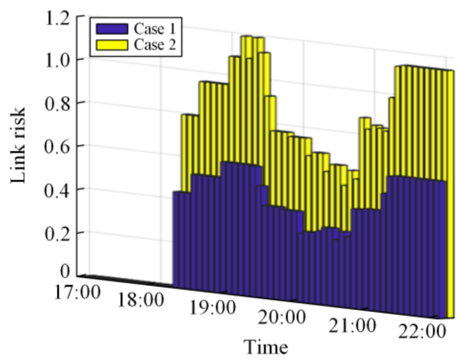

Fig. 8. Operation risks of line 3–4 of distribution network 1 under Case 1 and Case 2.

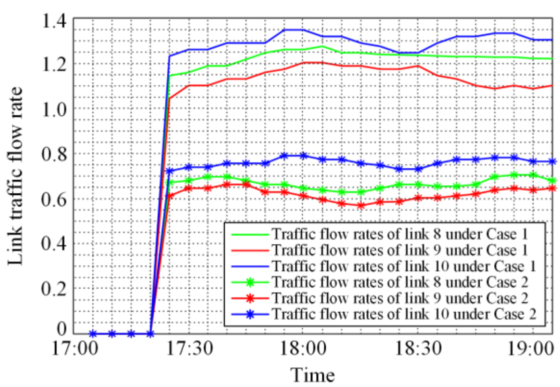

Fig. 9. Traffic flow rates of traffic links 8, 9 and 10 under Case 1 and Case 2.

Under the guidance strategy that only considers the risks of distribution networks, although the operation risks of the distribution networks are lower than that under the fault risk coordinated prevention strategy in coupled distribution and transportation networks, the traffic congestion is more severe. Similarly, under the guidance strategy that only considers traffic risks, the congestion rate of the transportation network is improved, but the distribution network faces greater fault risks. Therefore, although considering the risks of the distribution network and transportation network simultaneously cannot guarantee the optimality of the risk management and control of the individual distribution and transportation networks, collaborative optimization can ensure that both distribution and transportation networks operate within the safe range of risks.

VI. Conclusions

This paper studies a fault risk coordinated prevention strategy in coupled distribution and transportation networks by taking full advantage of EVs' travel and charging flexibilities. With the increasing penetration of EVs and further strengthening of the coupling depth between distribution and transportation networks, network risk management becomes an important issue in the development of EVs. This research can provide a means of risk control for distribution network and transportation network management agencies. The main conclusions of the paper include the following:

1) A risk-based security-constrained economic scheduling model is established by considering the operation risk of distribution network lines and transportation links in a traditional economic dispatching model of distribution and transportation networks, which can effectively reflect the risks brought by EV charging and travel to distribution and transportation networks.

2) The flexibility of EV travel and charging is utilized for fault risk coordinated prevention in coupled distribution and transportation networks, which can effectively reduce the operation risk or traffic flow rate of distribution and transportation networks simultaneously and ensure that both networks operate within the safety range.

3) Although guidance measures that only consider the operation risk of a single network can reduce the operation risk of this network to a greater extent, but the operation risk of another network can increase, thereby posing great operation risk for the whole coupled distribution and transportation system.

In this paper, it is assumed that the distribution and transportation networks have the same central operator, which is relatively rare in reality. In other scenarios, there is only partial information interaction between the distribution and transportation networks. In addition, the line load is considered in the risk indicator definition of distribution networks, while the fault risk of distribution networks may also be affected by other factors such as voltage. Therefore, future work will focus on how to develop collaborative fault risk prevention strategies by considering various factors, and when there is only limited information interaction between the distribution and transportation networks.

Acknowledgment

Not applicable.

Authors' Contributions

Fuzhang Wu: conceptualization, methodology, software, writing-original draft preparation, writing-review & editing, and visualization. Jun Yang: project administration. Song Ke: investigation, resources, and data curation. Hao Jiang: formal analysis. Muchao Xiang, Zaixun Ling, and Guiping Deng: data curation. All authors read and approved the final manuscript.

FUNDING

This work is supported by the Project of State Grid Corporation of China (No. 5108-202299265A-1-0-ZB).

AVAILABILITY OF DATA AND MATERIALS

Please contact the corresponding author for data material request.

DECLARATIONS

Competing interests: 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 article.

AUTHORS' INFORMATION

Fuzhang Wu received the B.S. and Ph.D. degrees from the School of Electrical Engineering and Automation, Wuhan University, Wuhan, China in 2015 and 2020, respectively. He then joined Wuhan University, Wuhan, China, where he is currently a postdoctoral researcher. His research interests include electric vehicles and grid integration of renewable energy.

Jun Yang received the Ph.D. degree from the Huazhong University of Science and Technology, China, in 2006. He then joined Wuhan University, Wuhan, China, where he is currently a professor. His research interests include power system security, electrical vehicles, and smart grid.

Song Ke received his B.E. degree from the North China Electric Power University, Baoding, China in 2019. He is currently pursuing his doctoral degree in the School of Electrical Engineering and Automation, Wuhan University. His research interest is electrical vehicles.

Hao Jiang received the B.Eng. degree in 1999 in communication engineering from Wuhan University, Wuhan, China, where he received the M.Eng. and Ph.D. degrees in communication and information systems in 2001 and 2004, respectively. From 2004 to 2005, he was a postdoctoral researcher with LIMOS, Clermont-Ferrand, France, and was a visiting professor with the University of Calgary, AB, Canada, and ISIMA, Blaise Pascal University, France. He is currently a professor with Wuhan University. His research interests include mobile ad hoc network and mobile big data.

Muchao Xiang received the B.E. degree from the Huazhong University of Science and Technology, China, in 2018. He is currently a researcher in Electric Power Research Institute of State Grid Hubei Electric Power Co., Ltd., Wuhan, China. His research interest is power system operation.

Zaixun Ling received the Ph.D. degree from the Huazhong University of Science and Technology, China, in 2015. He is currently a researcher in Electric Power Research Institute of State Grid Hubei Electric Power Co., Ltd., Wuhan, China. His research interest is power system operation.

Guiping Deng received the Ph.D. degree from the Huazhong University of Science and Technology, China, in 2008. She is currently a researcher in Electric Power Research Institute of State Grid Hubei Electric Power Co., Ltd., Wuhan, China. His research interest is power system operation.

REFERENCES

[1] B. Xu, G. Zhang, and K. Li *et al.*, "Reactive power optimization of a distribution network with high-penetration of wind and solar renewable energy and electric vehicles," *Protection and Control of Modern Power Systems*, vol. 7, no. 4, pp. 1-13, Oct. 2022.

[2] A. N. Sheta, G. M. Abdulsalam, and B. E. Sedhom *et al.*, "Comparative framework for AC-microgrid protection schemes: challenges, solutions, real applications, and future trends," *Protection and Control of Modern Power Systems*, vol. 8, no. 2, pp.1-40, Apr. 2023.

[3] Y. Sun, Z. Chen, and Z. Li *et al.*, "EV charging schedule in coupled constrained networks of transportation and power system," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 4706-4716, Sep. 2019.

[4] S. Xie, Z. Hu, and J. Wang, "Two-stage robust optimization for expansion planning of active distribution systems coupled with urban transportation networks," *Applied Energy*, vol. 261, Mar. 2020.

[5] S. Xie, Z. Hu, and J. Wang, "Scenario-based comprehensive expansion planning model for a coupled transportation and active distribution system," *Applied Energy*, vol. 255, Dec. 2019.

[6] F. Wu, J. Yang, and H. Jiang *et al.*, "Cascading failure in coupled networks of transportation and power grid," *International Journal of Electrical Power and Energy Systems*, vol. 140, Sep. 2022.

[7] W. Wei, J. Wang, and L. Wu, "Quantifying the impact of road capacity loss on urban electrified transportation networks: an optimization based approach," *International Journal of Transportation Science and Technology*, vol. 5, no. 4, pp. 268-288, Dec. 2016.

[8] S. Lü, S. Chen, and Z. Wei *et al.*, "Security-constrained optimal traffic-power flow with adaptive convex relaxation and contingency filtering," *IEEE Transactions on Transportation Electrification*, vol. 9, no. 1, pp. 1605-1617, Mar. 2023.

[9] K. Sun, W. Chen, and J. Chen *et al.*, "A resilience enhancement strategy for multi-microgrid in extreme scenarios based on electric vehicles," *Power System Protection and Control*, vol. 51, no. 24, pp. 53-65, Dec. 2023. (in Chinese)

[10] X. Wang, M. Shahidehpour, and C. Jiang *et al.*, "Resilience enhancement strategies for power distribution network coupled with urban transportation system,"

IEEE Transactions on Smart Grid, vol. 10, no. 4, pp. 4068-4079, Jul. 2019.

[11] Y. Sheng, Q. Guo, and T. Yang *et al*., "A potential security threat and its solution in coupled urban power-traffic networks with high penetration of electric vehicles," *CSEE Journal of Power and Energy Systems*, vol. 8, no. 4, pp. 1097-1109, Jul. 2022.

[12] A. Asrari, M. Ansari, and J. Khazaei *et al*., "A market framework for decentralized congestion management in smart distribution grids considering collaboration among electric vehicle aggregators," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1147-1158, Mar. 2020.

[13] Z. Liu, Q. Wu, and S. S. Oren *et al*., "Distribution locational marginal pricing for optimal electric vehicle charging through chance constrained mixed-integer programming," *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 644-654, Mar. 2018.

[14] Y. O. Assolami, A. Gaouda, and R. El-shatshat, "Impact on voltage quality and transformer aging of residential prosumer ownership of plug-in electric vehicles: assessment and solutions," *IEEE Transactions on Transportation Electrification*, vol. 8, no. 1, pp. 492-509, Mar. 2022.

[15] M. Bayati, M. Abedi, and G. Gharehpetian *et al*., "Short-term interaction between electric vehicles and microgrid in decentralized vehicle-to-grid control methods," *Protection and Control of Modern Power Systems*, vol. 4, no. 1, pp. 1-11, Jan. 2019.

[16] Z. Moghaddam, I. Ahmad, and D. Habibi *et al*., "A coordinated dynamic pricing model for electric vehicle charging stations," *IEEE Transactions on Transportation Electrification*, vol. 5, no. 1, pp. 226-238, Mar. 2019.

[17] R. L. Hu, R. Skorupski, and R. Entriken *et al*., "A mathematical programming formulation for optimal load shifting of electricity demand for the smart grid," *IEEE Transactions on Big Data*, vol. 6, no. 4, pp. 638-651, Dec. 2020.

[18] Y. Zhu, W. Chang, and D. Wu *et al*., "A Stackelberg game optimization scheduling strategy considering the interaction between a charging-discharging-storage integrated station and an electric vehicle," *Power System Protection and Control*, vol. 52, no. 7, pp. 157-167, Apr. 2024. (in Chinese)

[19] G. Zhang, Y. Zhang, and D. Pan *et al*., "Study on the interval integration effect of vehicle's self-delayed velocity on traffic stability in micro traffic modeling," *Physica A: Statistical Mechanics and its Applications*, vol. 533, no. 1, Nov. 2019.

[20] A. Tympakianaki, H. N. Koutsopoulos, and E. Jenelius,"Anatomy of tunnel congestion: causes and implications for tunnel traffic management," *Tunnelling and Underground Space Technology*, vol. 83, pp. 498-508, Jan. 2019.

[21] M. Farda and C. Balijepalli, "Exploring the effectiveness of demand management policy in reducing traffic congestion and environmental pollution: car-free day and odd-even plate measures for Bandung city in Indonesia," *Case Studies on Transport Policy*, vol. 6, no. 4, pp. 577-590, Sep. 2018.

[22] A. Stupin, L. Kazakovtsev, and A. Stupina, "Control of traffic congestion by improving the rings and optimizing the phase lengths of traffic lights with the help of anylogic," *Transportation Research Procedia*, vol. 63, pp. 1104-1113, Nov. 2022.

[23] K. Geng, Y. Wang, and E. Cherchi, "Commuter departure time choice behavior under congestion charge: Analysis based on cumulative prospect theory," *Transportation Research Part A: Policy and Practice*, vol. 168, Feb. 2023.

[24] Y. Sun, "Research on urban road traffic congestion charging based on sustainable development," *Physics Procedia*, vol. 24, pp. 1567-1572, Feb. 2012.

[25] E. Tvinnereim, H. Haarstad, and A. Rodeseike *et al*., "Explaining public acceptance of congestion charging: The role of geographical variation in the Bergen case," *Case Studies on Transport Policy*, vol. 8, no. 3, pp. 992-1001, Sep. 2020.

[26] X. Shi, X. Xu, and J. Cao, "A collective neurodynamic approach for solving distributed system optimum dynamic traffic assignment problems," *Neurocomputing*, vol. 483, no. 28, pp. 411-422, Apr. 2022.

[27] G. Ferro, R. Minciardi, and M. Robba, "A user equilibrium model for electric vehicles: Joint traffic and energy demand assignment," *Energy*, vol. 198, no. 1, May 2020.

[28] W. Wei, S. Mei, and L. Wu *et al*., "Optimal traffic power flow in urban electrified transportation networks," *IEEE Transactions on Smart Grid*, vol. 8, no. 1, pp. 84-95, Jan. 2017.

[29] S. Xie, Z. Hu, and J. Wang, "Scenario-based comprehensive expansion planning model for a coupled transportation and active distribution system," *Applied Energy*, vol. 255, Dec. 2019.