

Risk Assessment of Coupled Transportation Network and Distribution Network Considering Charging Power Restriction and Uncertainty Factors

Zhi Rui, Xiaoyuan Xu, Zheng Yan, Bin Qian, and Xiaoming Lin

Abstract—The increasing interdependence between transportation networks (TNs) and distribution networks (DNs) presents significant challenges for the analysis and risk assessment of coupled networks. This paper presents a risk assessment framework of coupled TN and DN (TDN) considering charging power restriction and uncertainty factors, simulating operations through a coordinated optimization model. The model incorporates charging power restrictions for fast charging stations (FCSSs). To enhance computation efficiency, nonlinear constraints are linearized, and an accuracy-aware adaptive piecewise linearization method is utilized. Random variables within the coupled TDN are employed as inputs to develop a surrogate model based on the Gaussian process regression method, complemented by suitable kernel functions designed for the scenarios with numerous discrete categorical variables. A global sensitivity analysis is conducted to identify the continuous and discrete uncertainty factors that significantly impact system performance. The proposed risk assessment framework serves as a valuable tool for evaluating the coupled TDN and facilitating the identification of continuous and discrete uncertainty factors affecting network operation while revealing risks associated with failures in the operation of coupled TDN.

Index Terms—Transportation network, distribution network, electric vehicle, charging power restriction, uncertainty, risk assessment.

I. INTRODUCTION

THE increasing integration of electric vehicles (EVs) into urban environments presents new challenges and opportunities for the interdependent transportation networks (TNs) and distribution networks (DNs). EV usage influences both electricity demand and urban traffic patterns [1], as their charging behavior creates a strong coupling between TNs and DNs, profoundly affecting traffic flow and load distribution in coupled TN and DN (TDN).

In the coupled TDN, the operation state of one network can substantially affect the other. For instance, road failures may lead to rerouting vehicles and altering charging demand, thereby impacting DN load distribution, while power outages can disrupt traffic flow. Consequently, interactions among system elements influence traffic flow, power distribution, and propagation of disturbances. Robust risk assessment is fundamental for system reliability, as it enables the identification of critical interdependencies and supports proactive management to ensure stable and secure operation of both networks.

For the risk assessment of the coupled TDN, [2] introduces a reliability assessment framework for integrated transportation and electrical power systems, analyzing how charging behaviors affect the reliability of TNs and DNs. Reference [3] investigates the effects of EV travel and charging patterns, including battery capacity, on DN reliability. Reference [4] presents a risk assessment framework for power systems with electrified transportation, quantifying the impact of traffic congestion on DN operations in New York State, USA. Reference [5] develops a vulnerability assessment for coupled power grid and EV traffic networks through a virtual EV energy network, enhancing system robustness. However, these studies primarily focus on specific influencing factors and largely overlook the role of uncertainty in system dynamics.

In practice, the coupled TDN faces significant uncertainty from renewable energy generation fluctuations, unpredictable user patterns, and potential component failures. Comprehensive risk assessment requires explicit probabilistic modeling of such stochastic factors since ignoring them may underestimate vulnerabilities and the likelihood of critical events.

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Consequently, recent studies increasingly advocate for probabilistic methods [6]–[8], which better support the evaluation of system resilience and inform effective risk mitigation strategies. Table I presents the research overview of coupled TDN risk assessment, summarizing the objectives, assessment methods, and types of uncertainty factor.

TABLE I
RESEARCH OVERVIEW OF COUPLED TDN RISK ASSESSMENT

Ref.	Objective	Assessment method	Type of uncertainty factor
[2]	TDN reliability	Quasi-sequential Monte Carlo	Charging load
[3]	DN reliability with EVs	Monte Carlo	Charging load
[4]	Traffic impact on DN	Non-sequential Monte Carlo	Traffic incident
[5]	TDN vulnerability	Virtual EV energy network	Load variation
[6]	TDN resilience in ice storm	Robust chance-constraint model	Line or road capacity
This paper	TDN risk assessment	Quasi Monte Carlo and Gaussian process regression (GPR)	Multiple continuous and discrete uncertainty factors

During risk assessment, uncertainty factors such as road capacity or load fluctuations are regarded as important considerations. To enhance risk assessment and effectively identify uncertainty factors, global sensitivity analysis is commonly employed as a valuable method for uncertainty quantification [9], concentrating on the identification of inputs that have the most significant influence. This method facilitates the prioritization of critical variables according to their contributions to response variability.

Among various sensitivity analysis methods, Sobol' indices based on analysis of variance theory have garnered significant attention. The Monte Carlo method and Quasi Monte Carlo method [10] are commonly employed to obtain the sensitivity indices. However, these methods may be impractical for time-consuming models. In such cases, surrogate models, which approximate the original model, offer a more suitable alternative.

Polynomial chaos expansion (PCE) is a widely used method when employing surrogate models. The core concept of PCE is to express the probabilistic response as a sum of orthogonal polynomial basis functions. In [11], PCE is utilized to construct a surrogate model for assessing the available delivery capability of DNs. However, PCE requires the knowledge of probability distribution of the input data. To address this limitation, [12] proposes a data-driven sparse PCE, which directly constructs the basis functions from input data. In addition, random forest (RF) can be employed to construct surrogate models, further enhancing computation efficiency [13].

However, when handling random variables in the coupled TDN, the computation time for individual scenarios tends to be long due to the numerous discrete categorical variables representing faults. In such cases, GPR [14], [15], which of-

fers flexibility in kernel design and requires relatively small amounts of data, is preferable because of striking the trade-off between computation cost and model accuracy. In this paper, a tailored kernel function is designed to accommodate the large number of scenarios involving discrete categorical variables.

This paper aims to propose a comprehensive risk assessment framework of the coupled TDN considering charging power restriction and continuous and discrete uncertainty factors. The main contributions are summarized as follows:

1) This paper establishes a coordinated optimization model for the coupled TDN that incorporates charging power restriction for fast charging stations (FCSs). The model accounts for uncertainty factors and identifies those with the most significant impact on operation performance, thereby enhancing risk assessment and decision-making process.

2) This paper introduces an accuracy-aware adaptive piecewise linearization (AAPWL) method that iteratively identifies the widest intervals under the maximum error constraint. This method minimizes breakpoints and integer variables and significantly reduces the computation burden of the optimization problem without sacrificing the fidelity of the system representation.

3) To address the challenges posed by numerous discrete categorical variables in the system, a custom GPR kernel is designed to effectively fuse continuous and discrete uncertainty factors. Besides, we establish a surrogate model based on GPR method, enabling a more robust and comprehensive sensitivity analysis.

The remainder of the paper is structured as follows. Section II presents the mathematical model of the coupled TDN. Section III introduces the risk assessment framework. Section IV explains the solution method. Numerical case studies are demonstrated in Section V. Finally, Section VI concludes the paper.

II. MATHEMATICAL MODEL OF COUPLED TDN

A. Model Assumption

1) Network Architecture and Control

This paper assumes a centralized TDN operator with the authority to monitor and regulate both networks for global optimization. The TN and DN are modeled as distinct yet interdependent networks, coupled via FCSs. The DN adopts a radial structure. All charging piles are intelligent and can respond to operator commands. Compensation for curtailment is feasible and enforced as needed.

2) User Behavior and Traffic Flow

Traffic flow follows the user equilibrium (UE) principle. The drivers equipped with real-time navigation systems can act as rational agents seeking to minimize their individual travel costs, considering both charging time and queuing time.

3) Uncertainty Representation

Network component failures, including roads, lines, distributed generators (DGs), loads, and FCSs, are modeled as independent random variables. Renewable energy generation and load fluctuations are represented using standard stochastic models.

B. TN Model

This paper adopts a modified TN model based on [16], formulated as a connected graph $G_T = (T_N, T_A)$, where $T_A = \{T_A^R, T_A^C, T_A^B\}$ and $T_N = \{T_N^R, T_N^V\}$ denote the sets of TN links and nodes, respectively. T_A^R , T_A^C , and T_A^B are the regular, charging, and bypass links, respectively. T_N^R and T_N^V are the regular and virtual nodes, respectively. FCSs are modeled through the introduction of virtual nodes and links. As illustrated in Fig. 1, each FCS is replaced by two virtual nodes, with links categorized into regular, charging, and bypass links. Bypass link is assumed to have negligible travel time for EVs not requiring charging.

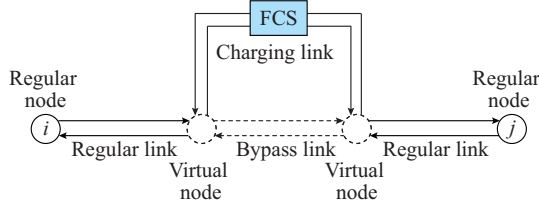


Fig. 1. Representation of an FCS in TN model.

Both gasoline vehicles (GVs) and EVs are incorporated into the TN model, since GV contribute to urban road congestion and travel time even though they do not utilize FCS directly [17]. GV are restricted to regular and bypass links, whereas EVs may access charging links if charging is required, or bypass links otherwise. Feasible paths for each vehicle type are pre-defined to ensure vehicles that only select links appropriate to their operation requirements.

The TN model, which incorporates both GV and EVs, is presented as:

$$\begin{cases} \sum_{k \in K_g^{rs}} f_{kg}^{rs} = q_g^{rs} \\ \sum_{k \in K_e^{rs}} f_{ke}^{rs} = q_e^{rs} \end{cases} \quad \forall (r, s) \quad (1)$$

$$x_a = \sum_{(r,s)} \sum_{k \in K_g^{rs}} f_{kg}^{rs} \delta_{akg}^{rs} + \sum_{(r,s)} \sum_{k \in K_e^{rs}} f_{ke}^{rs} \delta_{ake}^{rs} \quad \forall a \in T_A^R, \forall a \in T_A^B \quad (2)$$

$$x_a = \sum_{(r,s)} \sum_{k \in K_e^{rs}} f_{ke}^{rs} \delta_{ake}^{rs} \quad \forall a \in T_A^C \quad (3)$$

$$\begin{cases} c_{kg}^{rs} = \sum_a \omega_T t_a \delta_{akg}^{rs} \\ c_{ke}^{rs} = \sum_a \omega_T t_a \delta_{ake}^{rs} \end{cases} \quad (4)$$

$$\begin{cases} x_a \geq 0 \\ f_{kg}^{rs} \geq 0 \quad \forall k, \forall (r, s), \forall a \\ f_{ke}^{rs} \geq 0 \end{cases} \quad (5)$$

where a and k denote the indices of TN links and paths, respectively; (r, s) denotes an origin-destination (O-D) pair; K_g^{rs} and K_e^{rs} are the sets of available paths for GV and EV, respectively; q_g^{rs} and q_e^{rs} are the travel demands for GV and EV, respectively; f_{kg}^{rs} and f_{ke}^{rs} are the path flows for GV and EV, respectively; δ_{akg}^{rs} and δ_{ake}^{rs} denote whether link a is included in path k for GV and EV, respectively; c_{kg}^{rs} and c_{ke}^{rs} are the travel costs for GV and EV, respectively; ω_T is the mone-

tary value of travel time; and x_a and t_a are the traffic flow and travel time, respectively.

Equation (1) ensures that the total traffic flow across all paths connecting a given O-D pair matches the corresponding demand. Equations (2) and (3) define that the traffic flow on each link is the sum of the flows on all paths that traverse that link. The travel costs are defined in (4) as a function of travel time. The boundary constraints for the TN are outlined in (5).

Travel time on each link is characterized using a link performance function. For regular links, the Bureau of public road (BPR) model is adopted. For charging links, the total time cost comprises both charging time and queuing time, with the latter evaluated using queuing theory [18], which is well-suited for network-level equilibrium analysis.

$$t_a(x_a) = t_a^0 \left[1 + 0.15 \left(\frac{x_a}{c_a} \right)^4 \right] \quad \forall a \in T_A^R \quad (6)$$

$$t_a(x_a) = \frac{E_{ch}}{P_{ch}} + t_a^0 \left(\frac{x_a}{c_a^{ch}} \right)^3 \quad \forall a \in T_A^C \quad (7)$$

where t_a^0 is the free travel time; c_a is the link traffic capacity; c_a^{ch} is the number of operated charging piles; E_{ch} is the EV charging demand; and P_{ch} is the actual power of charging piles.

Queuing time will be negligible if the number of EVs passing through FCS is smaller than that of available charging piles. Otherwise, queuing time will significantly influence route choices and traffic assignment.

For a bypass link that represents the negligible internal distance within the FCS, the travel time is neglected.

$$t_a(x_a) = 0 \quad \forall a \in T_A^B \quad (8)$$

This paper adopts the UE principle, where travel costs across all utilized paths for each O-D pair are equal and no greater than those on unused alternatives. This principle is formulated via the following complementarity constraints.

$$0 \leq f_{kg}^{rs} \perp c_{kg}^{rs} - u_g^{rs} \geq 0 \quad \forall k \in K_g^{rs}, \forall (r, s) \quad (9)$$

$$0 \leq f_{ke}^{rs} \perp c_{ke}^{rs} - u_e^{rs} \geq 0 \quad \forall k \in K_e^{rs}, \forall (r, s) \quad (10)$$

where u_g^{rs} and u_e^{rs} are the minimum travel costs among all available routes for GV and EV, respectively.

The UE principle presumes that drivers have full knowledge of prevailing traffic conditions. TN cost F_T is expressed as being proportional to the total travel time of all vehicles within TN.

$$F_T = \omega_T \sum_a x_a t_a(x_a) \quad \forall a \in T_A \quad (11)$$

C. FCS Model

This paper assumes that charging piles in FCSs are smart charging units capable of dynamically adjusting their charging power based on commands from FCSs. The focus is exclusively on the active charging power of EVs.

The TDN operator can issue charging power restriction commands implemented by the charging piles at FCSs, ensuring that the actual charging power does not exceed the prescribed maximum allowable value. The charging power restriction at each charging pile is governed by the following

constraints.

$$P_{\text{ch}}^m = (1 - \zeta_{\text{ch}}^m) P_{\text{chm}}^m \quad \forall m \in E_{\text{FCS}} \quad (12)$$

$$0 \leq \zeta_{\text{ch}}^m \leq \zeta_{\text{max}} \quad \forall m \in E_{\text{FCS}} \quad (13)$$

where P_{ch}^m is the actual charging power of the m^{th} FCS; E_{FCS} is the set of FCSs; P_{chm}^m is the rated charging power of the m^{th} FCS; and ζ_{ch}^m is the power curtailment ratio of the m^{th} FCS with ζ_{max} as its upper bound.

These constraints collectively guarantee adequate FCS functionality while fulfilling the charging demands of EV owners. The aggregate charging load p^{ch} at each station is determined by the actual charging power and the number of charging piles, as expressed by:

$$p^{\text{ch}} = \min(x_a, c_a^{\text{ch}}) P_{\text{ch}} \quad \forall a \in T_A^C \quad (14)$$

The primary purpose of the charging power restriction is to enhance the safety and stability of the system. FCSs that comply with operator-initiated power curtailment will be compensated, as further detailed in the next section.

In this paper, the curtailment at FCSs is enacted by the system operator as a targeted operation measure to preserve DN security under conditions of uncertainty or elevated risk. The compensation strategy recognizes FCSs as controllable assets that are integral to risk mitigation, which promotes fairness to FCS operators and incentivizes their cooperation in system-level reliability management. While EV owners may incur temporary inconvenience due to curtailment, they ultimately benefit from enhanced network reliability and improved continuity of service.

D. DN Model

The DN power flow equations are formulated using the DistFlow model which is appropriate for radial networks as:

$$\sum_{i \in O(j)} (P_{ij} - r_{ij} I_{ij}) + p_j^g = \sum_{i' \in I(j)} P_{ji'} + p_j^L + p_j^{\text{ch}} - p_j^S \quad \forall i, j \in E_B \quad (15)$$

$$\sum_{i \in O(j)} (Q_{ij} - x_{ij} I_{ij}) + q_j^g = \sum_{i' \in I(j)} Q_{ji'} + q_j^L - q_j^S \quad \forall i, j \in E_B \quad (16)$$

$$U_j = U_i - 2(r_{ij} P_{ij} + x_{ij} Q_{ij}) + (r_{ij}^2 + x_{ij}^2) I_{ij} \quad \forall (i, j) \in E_L \quad (17)$$

$$I_{ij} U_i \geq P_{ij}^2 + Q_{ij}^2 \quad \forall (i, j) \in E_L \quad (18)$$

where i and j are the indices of DN buses; E_B and E_L are the sets of buses and lines, respectively; $O(j)$ and $I(j)$ are the parent and child bus sets of bus j , respectively; P_{ij} , Q_{ij} , r_{ij} , x_{ij} , and I_{ij} are the active power flow, reactive power flow, resistance, reactance, and squared current magnitude of line ij , respectively; $P_{ji'}$ is the active power flow from bus j to its child bus i' ; U_j is the squared voltage magnitude; p_j^g and q_j^g are the DG active and reactive power outputs, respectively; and p^L and q^L are the active and reactive power loads, respectively.

These equations characterize the balance of active and reactive power at nodes, voltage drop, and apparent power at each line, respectively, where (18) is the convex relaxation of line apparent power. The DistFlow formulation assumes a radial topology and continuous state variables. For weakly meshed networks, validity can be ensured by adding con-

straints for voltage consistency.

The constraints of DN model are defined as:

$$\begin{cases} p_{\min}^g \leq p_j^g \leq p_{\max}^g \\ q_{\min}^g \leq q_j^g \leq q_{\max}^g \end{cases} \quad \forall j \in E_G \quad (19)$$

$$U_{\min} \leq U_j \leq U_{\max} \quad \forall j \in E_B \quad (20)$$

$$P_{ij}^2 + Q_{ij}^2 \leq S_{\max}^2 \quad \forall (i, j) \in E_L \quad (21)$$

$$\begin{cases} 0 \leq p_j^S \leq p_j^L \\ q_j^S = p_j^S \tan \phi_j^L \end{cases} \quad \forall j \in E_B \quad (22)$$

where p_j^S and q_j^S are the active and reactive load sheddings, respectively; ϕ_j^L is the load power factor angle; $p_{\min}^g$ and $q_{\min}^g$ are the lower bounds of DG active and reactive power outputs, respectively; $p_{\max}^g$ and $q_{\max}^g$ are the upper bounds of DG active and reactive power outputs, respectively; E_G is the set of DG-connected buses; $U_{\min}$ and $U_{\max}$ are the lower and upper bounds of squared nodal voltage, respectively; and $S_{\max}$ is the maximum apparent power flow.

Constraint (19) establishes the upper and lower bounds on the DG output. Constraints (20) and (21) delineate the permissible ranges for nodal voltages and line flows, respectively. Constraint (22) implicitly constrains the power shortage to not exceed the load demand. Given the high resistance-to-reactance ratio of the DN, the network is predominantly sensitive to active power, and reactive power shedding provides minor relief for voltage constraints but incurs additional penalty costs. Therefore, the power factor of the shed load is set to be 1, ensuring that load curtailment is performed solely through effective active power reduction.

The operation cost of DN F_E is calculated as:

$$F_E = \rho \sum_{j \in I(0)} p_{0j} + \sum_{j \in E_G} \left(a_j (p_j^g)^2 + b_j p_j^g \right) + \omega_{\text{sp}} \sum_{j \in E_B} p_j^S + \omega_{\text{sq}} \sum_{j \in E_B} q_j^S + \omega_{\text{chr}} \sum_{j \in E_{\text{ch}}} p_j^{\text{chr}} \quad (23)$$

$$p^{\text{chr}} = c_a^{\text{ch}} P_{\text{ch}} \zeta_{\text{ch}} \quad (24)$$

where ρ and p_{0j} are the contract price and power supplied from the main grid, respectively; a_j and b_j are the DG cost coefficients; ω_{sp} and ω_{sq} are the penalty costs for active and reactive power shortages, respectively; ω_{chr} is the compensation rate for charging curtailment; $I(0)$ is the set of child buses directly connected to the root bus (bus 0) of the DN; and p^{chr} is the total curtailed charging power.

In (23), on the right-hand side, the first term represents the power purchase cost from the grid; the second term is the generation cost of DGs; the third term denotes the compensation cost for load shedding; the fourth term quantifies the compensation paid to FCS operators for participating in demand response by curtailing their charging power upon the TDN operator's request; and the last term incentivizes FCSs to function as controllable assets, ensuring their financial motivation to provide ancillary services that bolster grid stability and mitigate security risks.

E. Coordinated Optimization Model

This paper assumes a centralized system operator within the coupled TDN, who is empowered to issue power curtail-

ment directives to FCSs, with compliant stations receiving compensation. Operator-initiated adjustments to FCS charging power impact both power flow in DNs and EV charging durations, which in turn influence route selection and traffic distribution. As critical interconnections between TNs and DNs, FCSs play a pivotal role in optimizing the joint operation of both networks via charging power regulation.

System uncertainties, encompassing variables related to the TNs, DNs, and FCSs, are modeled as random inputs, with detailed formulations provided in Supplementary Material A.

The optimization objective is to minimize the total integrated operation cost, subject to the constraints that ensure safe and stable network operation. The coordinated optimization model consolidates electricity procurement and generation costs, penalties for power shortages, travel costs, time costs, and compensation to FCS operators for mandated curtailment.

$$\begin{aligned} \min F = F_T + F_E = & \omega_T \sum_a x_a t_a(x_a) + \rho \sum_{j \in O(0)} p_{0j} + \\ & \sum_{j \in E_G} \left(a_j (p_j^g)^2 + b_j p_j^g \right) + \omega_{sp} \sum_{j \in E_B} p_j^s + \\ & \omega_{sq} \sum_{j \in E_B} q_j^s + \omega_{chr} \sum_{j \in E_{ch}} p_j^{chr} \end{aligned} \quad (25)$$

where $O(0)$ denotes the set of outgoing neighbor buses of the root bus; and p_j^{chr} is the total curtailed charging power.

The objective function balances the economic loss of travel delays against the severe penalties of power outages, enabling the system to strategically curtail EV charging loads to preserve grid reliability. This comprehensive model provides a realistic and implementable framework for risk-aware network management and planning. Overall, the mathematical model of the coupled TDN is established, as the constraints are specified as: (1)-(10) for TNs; (12)-(14) for FCSs; and (15)-(22) for DNs.

III. RISK ASSESSMENT FRAMEWORK

Based on the mathematical model of the coupled TDN, a global sensitivity analysis is performed to identify the key uncertainty factors influencing the safe and stable operation of the system. Additionally, reliability indices will be calculated.

A. Global Sensitivity Analysis with Sobol' Indices

Sobol' indices are utilized in this paper for global sensitivity analysis. Based on variance decomposition, the Sobol' indices quantify the contribution of each input variable and its interactions to the variance of the output of the coordinated optimization model [19]. Denoting the output as $y=f(\mathbf{z})$, where $\mathbf{z}$ is the vector of independent input variables, the total output variance can be decomposed into components attributable to individual variables and their interactions. The first-order sensitivity index (FSI) and total sensitivity index (TSI) are denoted as S_i and S_i^T to measure these effects, respectively.

$$\begin{cases} S_i = \frac{V_i}{V} \\ S_i^T = \frac{V_i^T}{V} \end{cases} \quad (26)$$

where V_i denotes the contribution of the i^{th} input variable to the total variance V ; and V_i^T denotes the total effect of the i^{th} input variable including its interactions with other variables. To improve computation efficiency, S_i^T can be approximated as [20]:

$$S_i^T = 1 - V_{-i} \quad (27)$$

where V_{-i} is the variance of the conditional expectation of y given all inputs except the i^{th} input variable.

In this paper, the Quasi Monte Carlo method based on Sobol' sequences is used to generate training samples, which offers a faster convergence rate and ensures a more uniform coverage of the high-dimensional uncertainty space. The details can be found in Supplementary Material B.

B. Surrogate Model Based on GPR Method

In this paper, the GPR method is employed to construct a surrogate model. GPR is a non-parametric Bayesian method that describes the output $y=f(\mathbf{x})$ as a Gaussian process (GP) with a mean function $m(\mathbf{x})$ and covariance (kernel) function $k(\mathbf{x}, \mathbf{x}')$ [21].

$$f(\mathbf{x}) \sim GP(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')) \quad (28)$$

The covariance function is determined based on the expected smoothness and patterns in the data. The squared exponential kernel k_{SE} is a widely used choice for smooth and stationary functions.

$$k_{SE}(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}'\|^2}{2l^2}\right) \quad (29)$$

where σ_f^2 and l are the signal variance and length-scale parameter of the GPR kernel, respectively.

Given that $\mathbf{x}_i$ and $\mathbf{f}_i$ denote the input and predictive output of the testing dataset, the joint distribution of the training output $\mathbf{y}$ and $\mathbf{f}_i$ is expressed as:

$$\begin{bmatrix} \mathbf{y} \\ \mathbf{f}_i \end{bmatrix} \sim GP\left(\begin{bmatrix} m(\mathbf{x}) \\ m(\mathbf{x}_i) \end{bmatrix}, \begin{bmatrix} k(\mathbf{x}, \mathbf{x}) + \sigma_e^2 \mathbf{I} & k(\mathbf{x}, \mathbf{x}_i) \\ k(\mathbf{x}_i, \mathbf{x}) & k(\mathbf{x}_i, \mathbf{x}_i) \end{bmatrix}\right) \quad (30)$$

where $\mathbf{I}$ is the identity matrix; and σ_e^2 is the observation noise variance, which also improves numerical stability.

Based on the conditional distribution of the joint Gaussian distribution, the posterior distribution of $\mathbf{f}_i$ can be derived as:

$$\mathbf{f}_i \sim GP(\mathbf{m}_i, \mathbf{K}_i) \quad (31)$$

$$\mathbf{m}_i = k(\mathbf{x}_i, \mathbf{x}) (k(\mathbf{x}, \mathbf{x}) + \sigma_e^2 \mathbf{I})^{-1} \mathbf{y} \quad (32)$$

$$\mathbf{K}_i = k(\mathbf{x}_i, \mathbf{x}_i) - k(\mathbf{x}_i, \mathbf{x}) (k(\mathbf{x}, \mathbf{x}) + \sigma_e^2 \mathbf{I})^{-1} k(\mathbf{x}, \mathbf{x}_i) \quad (33)$$

where $\mathbf{m}_i$ and $\mathbf{K}_i$ are the posterior mean and covariance of the predicted output $\mathbf{f}_i$, respectively.

Numerous discrete categorical variables emerge due to the necessity of accounting for faults in system elements. Consequently, the mixed kernel k_{mix} is designed as a combination of an approximate squared exponential kernel for continuous

variables and a Hamming distance kernel for discrete categorical variables.

$$k_{\text{mix}}(\mathbf{x}, \mathbf{x}') = \sigma^2 \exp\left(-\gamma_{\text{cont}} \|\mathbf{x} - \mathbf{x}'\|^2\right) + \gamma_{\text{cat}} \delta_d(\mathbf{x}, \mathbf{x}') \quad (34)$$

where σ^2 is the variance parameter; γ_{cont} and γ_{cat} are the length-scale and weight parameters for continuous and categorical variables, respectively; and $\delta_d(\mathbf{x}, \mathbf{x}')$ is the Hamming distance function. $\delta_d(\mathbf{x}, \mathbf{x}')$ applies the scalar-valued categorical matching function $\delta_d(x_i, x_j)$, which is defined as:

$$\delta_d(x_i, x_j) = \begin{cases} 1 & x_i = x_j \\ 0 & x_i \neq x_j \end{cases} \quad (35)$$

where x_i and x_j are two categorical variables in input samples.

The customized kernel significantly outperforms standard SE kernels as the number of discrete categorical variables increases, offering superior robustness for mixed-type datasets. The positive definiteness of the combined kernel is inherited from its SE and discrete components, ensuring its validity within the GPR. Hyperparameters are optimized by maximizing the log-marginal likelihood for each output, enabling the surrogate model to adaptively capture distinct sensitivity patterns. The accuracy of the fitted surrogate model is assessed by the coefficient of determination R^2 .

GPR is specifically chosen due to the flexibility of its kernel-based framework, which is essential for handling the mix of continuous and discrete categorical variables in the coupled TDN. This choice is validated against the models of GPR-SE, RF, PCE, and support vector regression (SVR) using a synthetic benchmark. As summarized in Table II, the GPR-Custom model demonstrates superior predictive accuracy, achieving the highest R^2 score. Crucially, the GPR-Custom model provides a substantial performance uplift over the GPR-SE model, confirming its necessity for this problem. While RF and PCE offer less computation time, the superior fidelity of the GPR-Custom model justifies the trade-off, ensuring the reliability of subsequent risk and sensitivity analysis.

TABLE II

COMPARATIVE PERFORMANCE OF SURROGATE MODELS ON SYNTHETIC BENCHMARK PROBLEM

Model	R^2	Computation time (s)
GPR-Custom	0.9643	5.47
GPR-SE	0.9165	1.43
RF	0.7071	1.27
PCE	0.8799	1.02
SVR	0.9035	47.69

C. Reliability Indices of Coupled TDNs

To conduct a comprehensive risk assessment, the reliability of the coupled TDN is quantified using several indices computed by the Quasi Monte Carlo method. These indices are chosen to provide a balanced and holistic assessment of the network performance by capturing the distinct reliability concerns of both transportation and power domains.

1) Travel Time Reliability (TTR)

TTR is chosen to evaluate the quality of service from the

perspective of TN. It measures the proportion of vehicles that can complete their travel within a predetermined time threshold, reflecting the efficiency of travelling.

$$q_R^{rs} = q^{rs} \{t_{rs} \leq \theta_R t_{rs}^0\} \quad (36)$$

$$TTR = \frac{1}{N_s} \sum_{i=1}^{N_s} \left(\sum_{rs} q_R^{rs} / \sum_{rs} q^{rs} \right) \quad (37)$$

where q^{rs} and q_R^{rs} are the total and satisfied travel demands, respectively; t_{rs} and t_{rs}^0 are the actual and free travel time, respectively; θ_R is the time threshold coefficient; and N_s is the number of Monte Carlo samples.

2) Bus Load Power Shortage (BLPS)

BLPS refers to the total power shortage in DN, which characterizes the power shortage experienced by users.

$$BLPS = \frac{1}{N_s} \sum_{i=1}^{N_s} \sum_{j \in E_B} p_j^s \quad (38)$$

3) Electric Power Not Supplied (EPNS)

EPNS characterizes the power shortage experienced by consumers due to charging power restrictions or failures in DNs.

$$EPNS = \frac{1}{N_s} \sum_{i=1}^{N_s} \sum_{j \in E_B} (p_j^s + p_j^L \delta_j) \quad (39)$$

where δ_j is a binary indicator of complete load loss.

BLPS and EPNS are selected as they are standard indices for quantifying the reliability of DNs.

The Quasi Monte Carlo procedure is terminated when either the maximum number of iterations is reached or the following convergence criterion is satisfied.

$$\beta = \frac{\sqrt{\text{Var}(\psi_n)}}{E[\psi_n]} \leq \varepsilon_{\text{MC}} \quad (40)$$

where ψ_n is the reliability index after n iterations; β is the coefficient of variation; ε_{MC} is the convergence threshold; and $\text{Var}(\cdot)$ and $E[\cdot]$ are the variance and expectation operators, respectively.

IV. SOLUTION METHOD

A. Linearization of Constraints

In problem (25), nonlinearity arises from two components within $t_a(x_a)$. The first is the polynomial function of traffic flow x_a , and the second is the charging duration $E_{\text{ch}}/P_{\text{ch}}$. To address both sources of nonlinearity, this paper employs a piecewise linearization (PWL) approximation using Special Ordered Sets of type 2 (SOS2) variables to handle the nonlinearities. The SOS2 property ensures that at most two adjacent variables are nonzero in the optimal solution [22]. For clarity, the application of PWL approximation using SOS2 variables is detailed below using $t_a(x_a)$ as an illustrative example. The same procedure is applied to linearize the charging duration function.

The feasible range of traffic flow x_a is divided into subintervals, within which $t_a(x_a)$ is locally approximated by linear segments. The resulting constraints can be expressed as:

$$\begin{cases} x_a = \sum_m x_a^m \lambda_a^m \\ t_a = \sum_m t_a(x_a^m) \lambda_a^m \\ \sum_m \lambda_a^m = 1 \\ 0 \leq \{\lambda_a^m, \forall m\} \in SOS2 \quad \forall a \end{cases} \quad (41)$$

where x_a^m is the m^{th} breakpoint of the traffic flow range; and λ_a^m is the *SOS2* weight variable corresponding to the m^{th} breakpoint.

The UE complementarity constraints (9) and (10) are reformulated as a linear constraint set via the Big- M method, which are presented as:

$$\begin{cases} 0 \leq f_{kg}^{rs} \leq M(1 - v_{kg}^{rs}) \\ 0 \leq c_{kg}^{rs} - u_g^{rs} \leq Mv_{kg}^{rs} \end{cases} \quad \forall k, \forall(r, s) \quad (42)$$

$$\begin{cases} 0 \leq f_{ke}^{rs} \leq M(1 - v_{ke}^{rs}) \\ 0 \leq c_{ke}^{rs} - u_e^{rs} \leq Mv_{ke}^{rs} \end{cases} \quad \forall k, \forall(r, s) \quad (43)$$

where v_{kg}^{rs} and v_{ke}^{rs} are the binary auxiliary variables for linearizing the UE complementarity constraints for GV and EV, respectively; and M is a sufficiently large constant based on the largest possible travel cost.

For the PWL approximation, the AAPWL method is employed to minimize the number of breakpoints while satisfying a predefined requirement [23]. Based on the property that the maximum approximation error of continuous monotonic functions arises at the point where the slopes of the original function and its linear approximation are equal, AAPWL method iteratively solves an optimization problem to insert new breakpoints solely in necessary regions.

$$\begin{cases} \max x^{w+1} \\ \text{s.t.} \quad \frac{g(x^*) - h(x^w)}{x^* - x^w} = \frac{h(x^{w+1}) - h(x^w)}{x^{w+1} - x^w} \\ h'(x^*) = \frac{h(x^{w+1}) - h(x^w)}{x^{w+1} - x^w} \\ g(x^*) - h(x^*) \leq \varepsilon \\ x_a^w \leq x_a^{w+1} \leq x_a^{\max} \end{cases} \quad (44)$$

where x^w and x^{w+1} are the start and end of the w^{th} interval, respectively; $h(\cdot)$ and $h'(\cdot)$ are the original nonlinear function and its derivative, respectively; $g(\cdot)$ is the linear approximation over the current interval; x^* is the point of the maximum approximation error; $x_a^{\max}$ is the maximum feasible traffic flow; and ε is the maximum allowable error. This method effectively reduces the number of integer variables.

To further validate the AAPWL method, it is compared with uniform PWL and tangent PWL methods in linearizing x^s over $[0, 1.5]$ with a 0.01 error tolerance. As shown in Table III, AAPWL method achieves the target accuracy with fewer breakpoints, yielding a more compact and efficient formulation without significant computation overhead.

The minimization function (14) is replaced by the following linear constraints with the Big- M method.

TABLE III
COMPARISON OF LINEARIZATION METHODS

Method	Number of breakpoints	Computation time (s)
AAPWL	19	1.43
Uniform PWL	41	0.21
Tangent PWL	80	0.47

$$\begin{cases} d_a^{\text{ch}} \leq x_a \\ d_a^{\text{ch}} \leq c_a^{\text{ch}} \\ d_a^{\text{ch}} \geq x_a - M(1 - \mu_a^{\text{ch}}) \\ d_a^{\text{ch}} \geq c_a^{\text{ch}} - M\mu_a^{\text{ch}} \end{cases} \quad (45)$$

where d_a^{ch} is an auxiliary variable representing $\min(x_a, c_a^{\text{ch}})$; and μ_a^{ch} is an auxiliary binary variable enforcing linearization.

B. Risk Assessment Process of Coupled TDN

The risk assessment process for the coupled TDN is illustrated in Fig. 2.

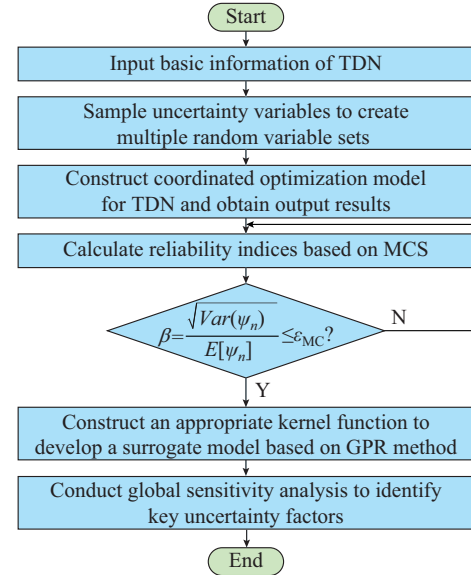


Fig. 2. Risk assessment process of coupled TDN.

A sample size of 15000 scenarios is selected to ensure the convergence of variance-based Sobol' indices, facilitated by the high efficiency of the surrogate model.

This paper also compares risk assessments for coupled and single networks. For the single TN and DN, only domain-specific uncertainty factors are considered. Specifically, for the single DN, charging load distributions are generated via kernel density estimation (KDE) based on single TN outputs, while the remaining steps remain consistent across all scenarios.

The key difference between the analysis of coupled network and single network lies in their implementation. The coupled network framework jointly optimizes TNs and DNs, enabling real-time exchange of charging and power data to capture interdependencies. In contrast, the single network framework analyzes each network in isolation without accounting for internetwork feedback.

V. CASE STUDIES

A. Simulation Setups

The proposed risk assessment framework is tested on the coupled TDN. Figure 3 depicts the topology of the coupled TDN, comprising a ring-structured TN and an IEEE 33-bus DN. Relevant TN link parameters and travel demands are detailed in Supplementary Material A Tables SAI and SAIL, respectively. The maximum linearization error tolerance of AAPWL method is set to be 0.01 to ensure high computation fidelity. Each charging pile operates at a nominal power of 50 kW.

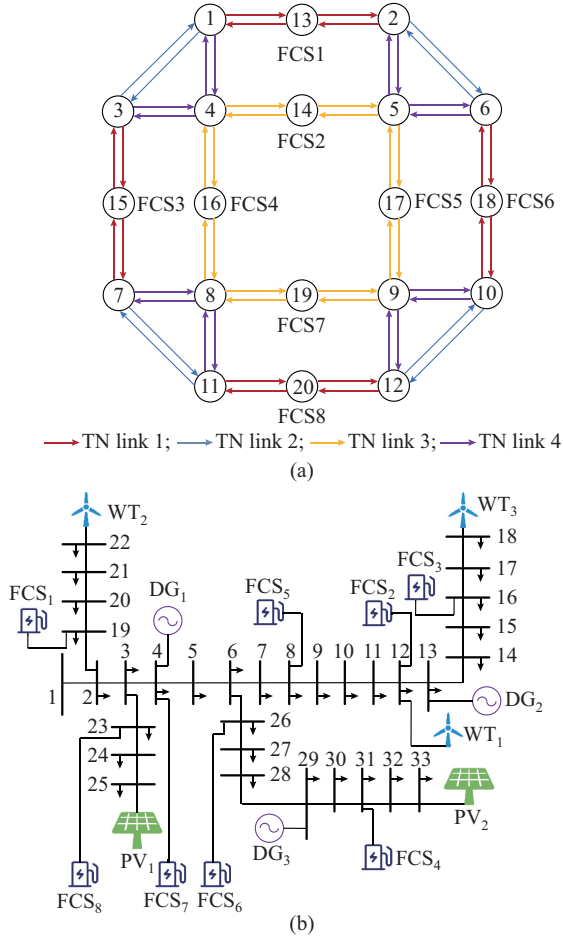


Fig. 3. Topology of coupled TDN. (a) Ring-structured TN. (b) IEEE 33-bus DN.

The DN is supplied by the main grid at bus 1 and includes three DGs (DG₁-DG₃), each with the maximum active and reactive outputs of 1.5 MW and 1.5 Mvar, respectively. It also integrates three wind turbines (WTs) (WT₁-WT₃), each with a rated capacity of 2.5, 1.5, and 2.5 MW, respectively, and two photovoltaic (PV) arrays (PV₁ and PV₂), each with a capacity of 1 MW. The system operates with a 10 MVA base power and a 12.66 kV base voltage. The nodal voltage limits are set between 0.93 p.u. and 1.07 p.u.. Key economic parameters include the electricity price of 1400 \$/p.u., a monetary value of travel time at 0.2 \$/min, compensation rates for active and reactive power shortages

at 300 \$/MW and 300 \$/Mvar, respectively, and a compensation rate for charging power curtailment at FCS of 180 \$/MW. Given the high resistance-to-reactance characteristics of the distribution lines, the load curtailment is configured to operate at unity power factor to maximize the cost-effectiveness of voltage support. Uncertainty factors are categorized into continuous and discrete types, with detailed formulations provided in Supplementary Material A. Continuous uncertainty factors include link capacity fluctuation ξ_{ca} , EV charging ratio ξ_{ch} , state of charge (SoC) after charging ξ_{so} , WT output P_{WT} , PV output P_{PV} , and conventional load ξ_{CL} . The outputs of WTs and PVs are calculated based on wind speed and solar irradiance [24], [25]. Discrete uncertainty factors are represented by fault state variables δ , with fault rates for TN links δ_R , DN lines δ_L , DN loads δ_{con} , FCSs δ_{FCS} , and DGs δ_{DG} , which are set to be 0.25%, 0.5%, 0.4%, 0.3%, and 0.1%, respectively. Failed components are assumed unavailable for the duration of the scenario. Different types of faults are independent of each other.

B. Result Analysis

1) Network Cost Comparison

Figures 4 and 5 compare the DN and TN costs in coupled (i.e., TDN) and single networks (i.e., DN or TN), respectively. Both results indicate that network costs stabilize after 1000 iterations.

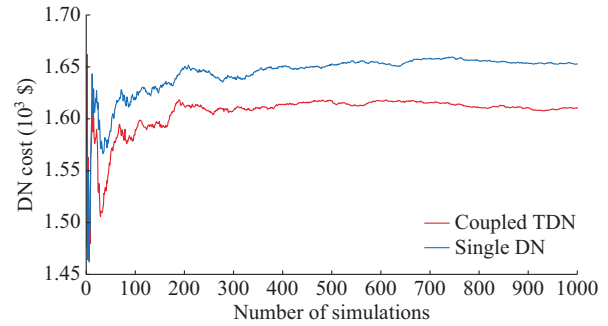


Fig. 4. DN cost in coupled TDN and single DN.

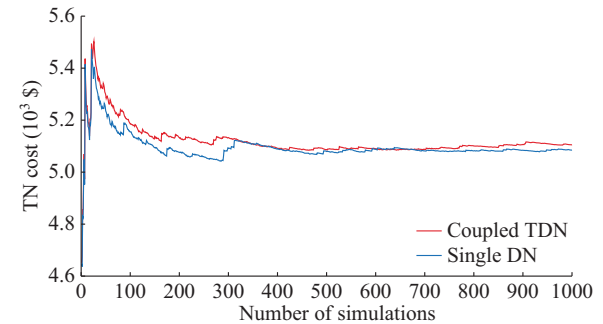


Fig. 5. TN cost in coupled TDN and single DN.

Relative to single network calculations, DN costs in the coupled TDN decrease due to charging power restrictions, which decrease the aggregate charging load and alleviate power shortages within the DN.

In contrast, TN costs remain largely unchanged. The increase in EV charging time under power constraints, along with subsequent adjustments in route choices and travel

time, redistributes traffic flow but incurs only marginal cost variations. Notably, GV travel is largely insensitive to changes in charging power, resulting in minor fluctuations in TN costs between the coupled and single networks.

2) Impacts of Charging Power Restriction

Figure 6 shows boxplots comparing charging power distributions at each FCS in the coupled TDN and single TN. When charging power restrictions are applied in the coupled TDN, the distribution becomes significantly more dispersed, with increased variation both among FCSs and across networks. This highlights the enhanced flexibility and dynamic allocation of charging loads in response to network constraints.

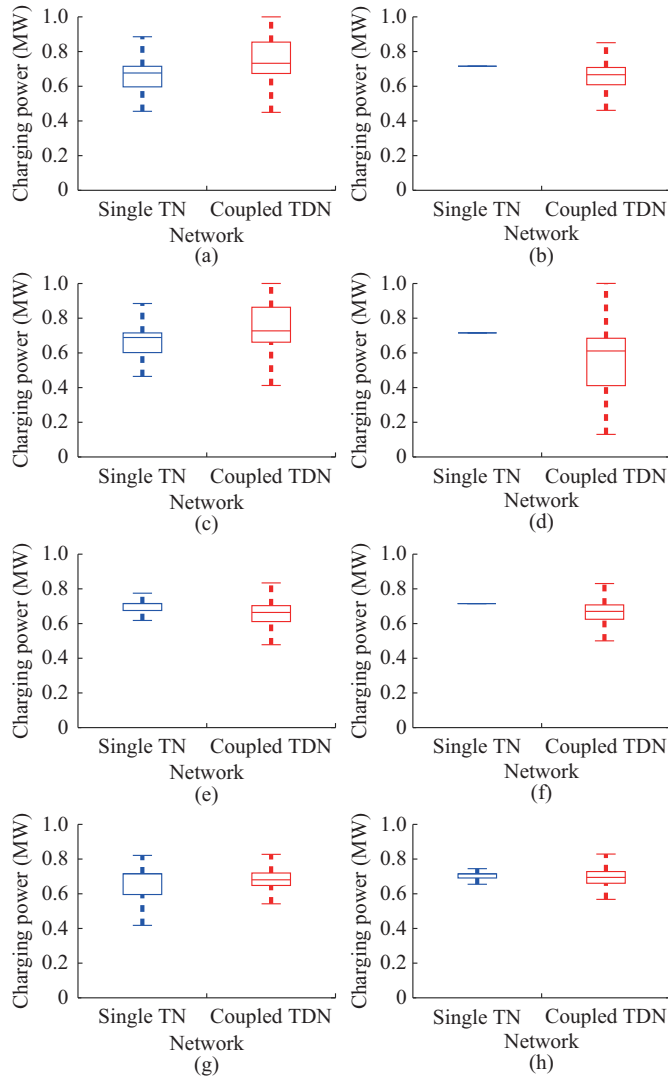


Fig. 6. Comparison of charging power distributions at each FCS in coupled TDN and single TN. (a) FCS1. (b) FCS2. (c) FCS3. (d) FCS4. (e) FCS5. (f) FCS6. (g) FCS7. (h) FCS8.

In contrast, in single TN without explicit charging power restrictions, charging power at each FCS remains stable and shows little variation between the networks. Here, the distribution is mainly dictated by travel demand, resulting in more uniform station utilization and limited adaptability to changing conditions.

The analysis of the voltage and charging power constraints indicates that voltage violation are the primary driver for load curtailment, particularly affecting downstream nodes due to cumulative voltage drops along the feeder. Power limits may restrict flow on upstream lines during topological re-configuration. In the coordinated optimization, the reactive power curtailment naturally converges to zero even without explicit constraints. This behavior is attributed to the high R/X ratio of DN, where active power dominates voltage support. Consequently, the optimizer prioritizes active power shedding as the most cost-effective strategy, given the negligible voltage relief provided by reactive power curtailment.

Overall, incorporating charging power restrictions within the coupled TDN not only redistributes charging loads more flexibly but also introduces greater variability in FCS usage, which can better adapt to fluctuating network states. This highlights a critical operation trade-off that, while the coupled TDN enhances grid reliability, it induces service inequity across the networks. Network operators must consider this effect when designing the compensation strategy.

3) Global Sensitivity Analysis

A GP surrogate with a customized kernel is built for global sensitivity analysis, trained on 1000 Sobol' sequence samples and validated on 200 independent samples, achieving $R^2 \geq 0.98$ for every output. The normalized root mean square error (RMSE) and mean absolute error (MAE) for risk indices remain below 2%. This low prediction error confirms the fidelity of the surrogate model for risk assessment.

While the physical optimization model requires approximately 22.5 s per sample, the surrogate model reduces the inference time to just 0.002 s per sample. The entire process, including training, is completed within 6.5 hours, making large-scale risk assessment feasible.

Figure 7 presents the TSI of network cost. Note that numerical subscripts in the index variables in this paper denote the indices of different individual components (e. g., WTs, PV units, load nodes, road links, and FCSs) in the network. The analysis reveals that DN costs are predominantly influenced by renewable energy output, failures of critical power lines, and fluctuations in EV charging demand. In contrast, TN costs are mainly driven by variations in road capacity, failures of critical roads, and power line outages that impact charging availability.

Notably, the results indicate that TN-related uncertainty factors exert a greater overall influence on the coupled TDN cost. This disparity arises because disruptions in TN tend to propagate rapidly, affecting a large number of users and triggering widespread changes in route selection, which incur high network-wide costs. Conversely, while uncertainty factors in the DN do impact TN through charging restriction, the distributed structure and operation flexibility of DN allow it to absorb and localize these effects more effectively, thereby mitigating their network-wide financial impact.

The analysis also highlights the interplay between the two networks. Stochastic EV charging demand, originating from the TN, affects both traffic distribution and charging loads, thereby influencing DN performance. Conversely, line failures in the DN can cause FCS outages, alter available charging paths, and subsequently impact TN costs.

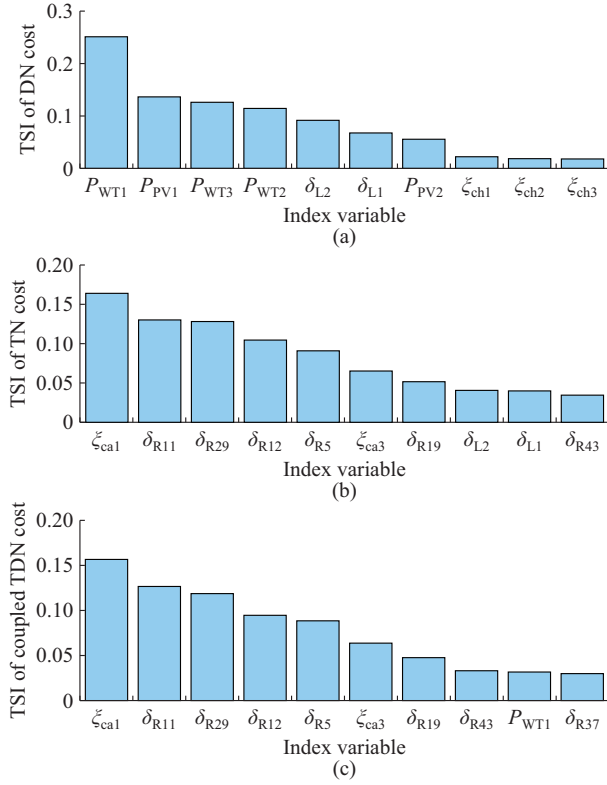


Fig. 7. TSI of network cost. (a) DN cost. (b) TN cost. (3) Coupled TDN cost.

As illustrated in Fig. 8, line failures are identified as the most critical uncertainty factor affecting traffic flow at FCSs, as they can disrupt operation and influence EV users' decisions. Failures within FCSs or on connecting roads have similar effects, further shaping vehicle route selection.

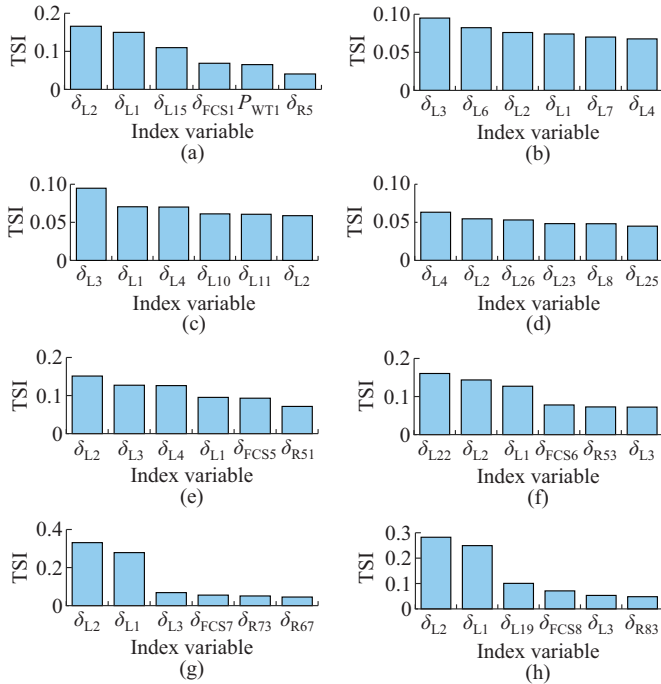


Fig. 8. TSI of traffic flow at FCSs in coupled TDN. (a) FCS1. (b) FCS2. (c) FCS3. (d) FCS4. (e) FCS5. (f) FCS6. (g) FCS7. (h) FCS8.

Figure 9 presents the TSI of traffic flow at FCSs in single TN. It reveals that the primary influencing factors on traffic flow at FCSs are the fault states of FCSs and the conditions of adjacent roadways. Additionally, the demand for EV charging has a notable impact on traffic flow at these FCSs.

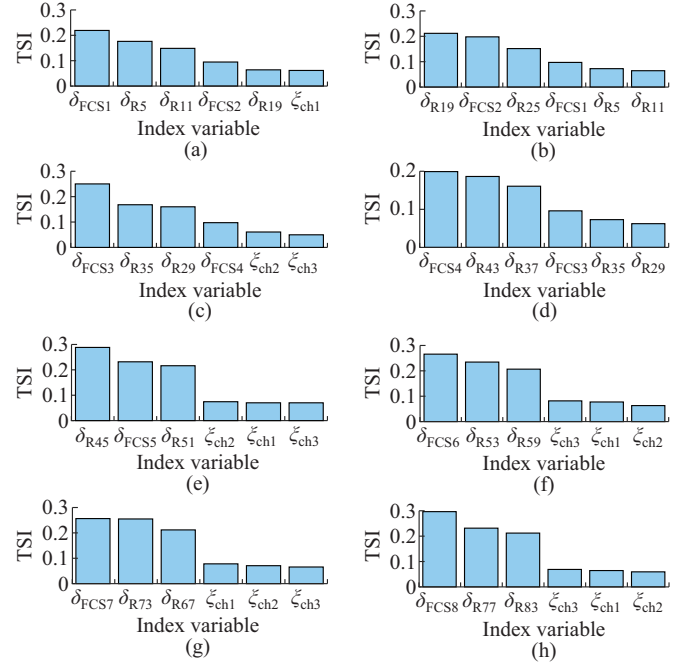


Fig. 9. TSI of traffic flow at FCSs in single TN. (a) FCS1. (b) FCS2. (c) FCS3. (d) FCS4. (e) FCS5. (f) FCS6. (g) FCS7. (h) FCS8.

Therefore, calculations conducted on the coupled network enhance the effectiveness of risk assessment compared with analyses based on a single network.

4) Reliability Indices

To facilitate a comprehensive risk assessment of the coupled TDN, this paper computes the reliability indices of the network and conducts a comparative analysis of the reliability differences between the coupled TDN and single DN. The indices converge after 1000 simulations, and the variance coefficient exhibits a monotonic downward trajectory. The simulation is terminated as the variance coefficient for all indices dropped below the threshold of 0.005, demonstrating the sufficiency of the simulation count for risk assessment.

1) DN reliability indices

Figures 10 and 11 present a comparison of BLPS and EPNS between the coupled TDN and single DN, respectively. The BLPS in the coupled TDN is significantly reduced. This reduction is attributed to the charging power restriction within the coupled TDN. When the power supply is insufficient, the restriction on charging loads decreases the power shortage observed in the single DN.

2) TN reliability indices

Figure 12 presents a comparison of TTR between the coupled TDN and single TN. The travel time threshold is set to be 1.8. The TTR of the coupled TDN is found to be comparable to that of the single TN. This is attributable to the reallocation of traffic flow and the significant presence of GVs, which mitigates the potential decline in TN reliability.

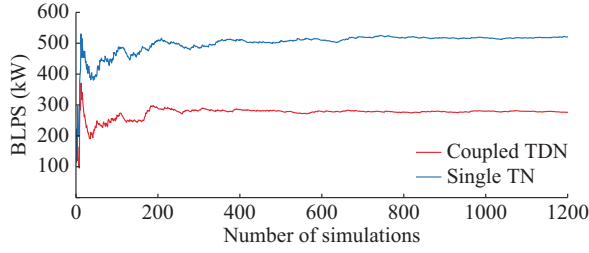


Fig. 10. Comparison of BLPS between coupled TDN and single TN.

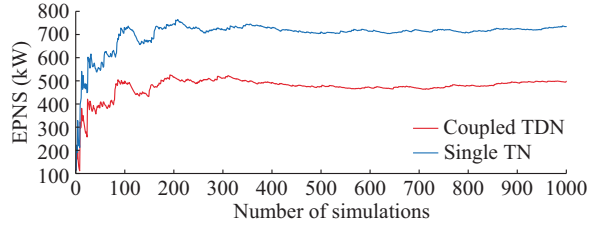


Fig. 11. Comparison of EPNS between coupled TDN and single TN.

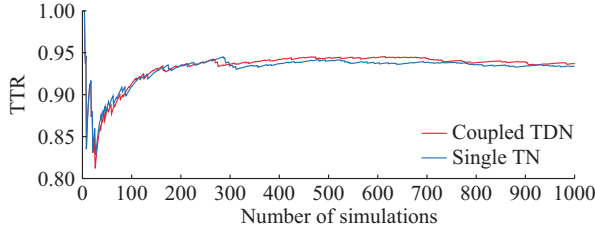


Fig. 12. Comparison of TTR between coupled TDN and single TN.

Additionally, the reliability of the power supply for users in the single DN has significantly improved through the optimization of the coupled TDN. Although the charging power at FCSs may be constrained, the TN reliability remains largely unaffected due to its traffic flow allocation.

5) Comparative Discussion

1) Deterministic and uncertainty-aware scenarios

To illustrate the value of uncertainty modeling, Fig. 13 compares the system performance in deterministic and uncertainty-aware scenarios. The deterministic scenario underestimates network costs and misses potential load shedding, while explicitly modeling uncertainty factors yields higher and more realistic risk assessment. This underscores the necessity of uncertainty factor consideration for accurate risk and cost assessment in the coupled network.

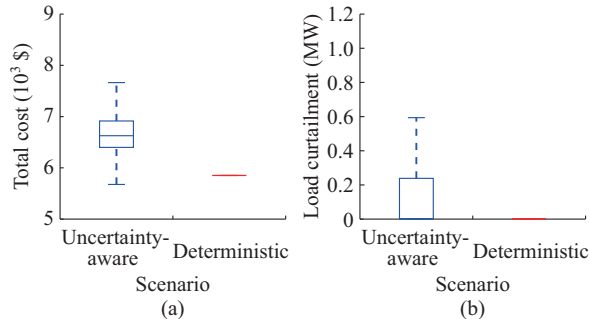


Fig. 13. Comparison of system performance in deterministic and uncertainty-aware scenarios. (a) Total cost. (b) Load curtailment.

2) Impact of different EV ratio

Table IV shows that as the EV ratio rises from 10% to 40%, the average FCS traffic flow quadruples, though charging load increases modestly due to station limits, longer queues, and curtailment responses.

This result provides a key insight that, while increasing EV adoption significantly raises the demand for charging infrastructure, the impact on the peak load of DN is nonlinear and can be actively managed. It highlights that the primary initial bottleneck is traffic congestion and queuing at FCSs, rather than a direct, unmanageable surge in total electricity consumption, suggesting that traffic management and smart charging strategies are as crucial as grid reinforcement.

TABLE IV
RESULTS UNDER DIFFERENT EV RATIO

EV ratio (%)	Average FCS traffic flow (p.u.)	Charging load (MW)
10	4.1	3.21
16	6.6	4.99
30	12.3	5.89
40	16.4	5.97

3) Impact of monetary value of travel time

Figure 14 indicates that increasing the monetary value of travel time shifts network priorities toward minimizing travel costs. As a result, more load is curtailed and charging power is less restricted, lowering total travel cost when network faults occur.

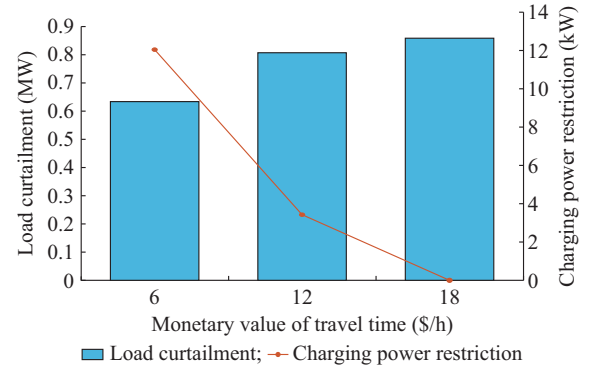


Fig. 14. Results of different monetary value of travel time.

In this sensitivity analysis, the curtailment compensation is fixed to isolate the impact of monetary value of travel time. In practical policy design, parameter co-variation should be considered. As the monetary value of travel time increases, the compensation price should be adjusted to cover the rising opportunity costs and maintain effective demand response incentives.

VI. CONCLUSION

This paper proposes a risk assessment framework of the coupled TDNs, employing a coordinated optimization model with FCSs as coupling elements and incorporating the charging power restriction. Nonlinear constraints are linearized for computation efficiency. Uncertainty factors are addressed by incorporating stochastic variables into surrogate model based

on GPR method with tailored kernels for numerous discrete categorical variables. The global sensitivity analysis then identifies the dominant sources of uncertainty factors affecting network performance. Comparative reliability analysis between the coupled TDN and each single network further elucidates their distinct risk profiles.

Simulation results demonstrate that, compared with the single DN, the coupled TDN achieves lower DN costs and improved reliability, while charging load distribution becomes more heterogeneous and the overall charging demand declines. TN costs and reliability exhibit minimal change. Sensitivity results reveal that key uncertainty factors in one subsystem can significantly impact the other, underscoring the importance of integrated assessment.

The risk assessment framework offers a versatile tool for risk evaluation and management in the coupled TDN. Future work will focus on incorporating vehicle-to-grid (V2G) technologies to evaluate the trade-offs between grid support and battery degradation, adopting data-driven user behavior models to capture realistic charging responses, and extending the framework to assess resilience under spatially correlated failure scenarios.

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