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Information Gap Decision Theory-Based Robust Economic Dispatch Strategy Considering the Uncertainty of Electric Vehicles

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Abstract: With the development of renewable energy power systems, electric vehicles, as an important carrier of green transportation, are gradually having an impact on the power grid load curve due to their charging behavior. However, the significant influx of electric vehicles (EVs) and distributed power sources has led to multiple uncertainties, increasing the difficulty in making grid scheduling decisions. Traditional robust scheduling strategies tend to be overly conservative, resulting in poor economic performance. Therefore, this paper proposes a robust and economic dispatch strategy for park power grids based on the information gap decision theory (IGDT). Firstly, based on the probabilistic characteristics of the spatial and temporal distribution of EVs charging, the Monte Carlo method is used to generate typical electricity usage scenarios for EVs. Simultaneously, an economic dispatch model for the park power grid is established with the objective of minimizing operating costs. Taking into account the uncertainty of renewable energy output, simulation analysis is conducted through the IGDT model. Finally, through the verification of the improved IEEE-33 node test system and comparison with other methods, the proposed approach in this paper can reduce decision conservatism and effectively reconcile the contradiction. Through analysis, the proposed method in this paper can reduce the total operational cost of the system by up to 3.2%, with a computational efficiency of only 8.9% of the traditional stochastic optimization time.

Keywords: power system; electric vehicles (EVs); information gap decision theory (IGDT); Monte Carlo method; decision conservatism

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1. Introduction

In recent years, the impact of electric vehicles (EVs) connecting to the power grid for charging has intensified on the load side of the grid, leading to increasingly severe issues such as shortages in traditional energy generation and environmental pollution. The integration of renewable energy with traditional thermal power units and the rapid construction of a new grid architecture with a high proportion of renewable energy penetration are regarded as optimal strategies for future development [1,2]. Against the backdrop of China's gradual implementation of the dual carbon targets and the focus on building a new power system with new energy as the mainstay, the installed capacity of new energy generation will continue to grow. However, new energy sources represented by wind power and photovoltaics exhibit strong randomness and volatility [3], posing greater challenges to the safe and stable operation of the grid and raising higher requirements for demand response management and the utilization of flexible resources. With the rapid development of the EV industry, the role of EVs in substituting for electricity in the transportation sector is continuously increasing. At the same time, their random and unordered mobile load characteristics will also have a certain impact on the safe and stable operation of the grid [4]. Therefore, studying the optimal management of EVs participating in regional power grids and avoiding their negative impacts on the grid is of great significance for ensuring the safe and stable operation of the grid and promoting the orderly development of the EV industry [5].

Considerable research achievements have been made in the area of electric vehicle charging and discharging control strategies. Related studies have shown that by reasonably coordinating the charging and discharging of electric vehicles when they are connected to active distribution networks, it is possible to reduce the negative impact of their integration on the distribution network and improve the safety and stability of the power system. Reference [6] simulates the initial charging time and daily driving mileage of electric vehicles using the Monte Carlo algorithm. From the perspective of the benefits of the distribution network, an optimal scheduling model is established with the objectives of maximizing the economic efficiency of the active distribution network and minimizing the equivalent load variance. Reference [7] considers a bi-level optimization scheduling model that takes into account both the charging satisfaction of electric vehicle users and the safe and economic operation of the distribution network. The objective is to minimize the deviation between the two scheduling plans to achieve collaborative optimization. Reference [8] manages the charging power of each electric vehicle using linear programming techniques to obtain the total charging power of electric vehicles, allowing the distribution network to maximize the total charging power provided to vehicles. Reference [9] proposes a multi-stage optimal scheduling method for active distribution networks considering coordinated charging strategies for electric vehicles. By controlling the source side, network side, and demand side of the active distribution network, an optimal scheduling strategy is achieved, leading to the establishment of an ADN evaluation system that considers active controllability, active manageability, and active economy. References [10,11] reduce the negative impact of uncertainty by establishing a bi-level robust optimization model and a cost index system for distribution network safety effectiveness, respectively. Reference [12] addresses uncertainties on both the source and load sides by constructing a fuzzy chance-constrained programming optimization scheduling model, verifying the superiority of the scheduling model when considering energy storage devices. Reference [13] proposes a long-term charging and discharging scheduling strategy for electric vehicles under a joint demand response of pricing and incentives, aiming at minimizing the scheduling cost and psychological effects. Reference [14] adopts a time-of-use dynamic optimization approach, using the minimization of charging volume and charging cost as the objective function to verify the effectiveness of the model in load-side peak shaving and valley filling. Reference [15] considers an orderly charging and discharging strategy for EVs to establish a multi-objective model, demonstrating that the adoption of a multi-time-scale grouping scheduling strategy can effectively reduce the adverse impact of load fluctuations. Reference [16] introduces the pseudo-F-statistic indicator to judge the optimal reduced scenarios, which are used to handle source-load uncertainty and improve the economy and environmental friendliness of microgrids. Many of the above studies employ methods such as stochastic optimization, robust optimization, and multi-scenario optimization to handle uncertainty issues. In recent years, information gap decision theory (IGDT), as a non-probabilistic optimization method that does not require specific probability distributions or confidence intervals, has been better suited to uncertain scenarios and widely used in various optimization scheduling studies in power systems that consider uncertainty. Reference [17] considers factors such as line reactive power loss and generator voltage magnitude, employing IGDT to establish a combined framework model for generator units and a multi-objective reactive power planning model to enhance the robustness of the distribution network. Reference [18] uses IGDT to solve a multi-objective reactive power planning model with the objectives of minimizing reactive power loss and voltage stability index.

Currently, there are some relevant studies on the coordinated control between EVs and controllable units, but there are not many research studies on integrating EVs into the operation of industrial park VPPs. Reference [19] established a collaborative output optimization model for EVs and DG to achieve multi-objective optimization of power quality and economy. However, it only considered the load characteristics of EVs and did not leverage their energy storage capabilities. Reference [20] used electricity prices to guide EVs to participate in the optimal allocation of system energy storage capacity, enhancing the lifespan of the energy storage system. Nevertheless, it only considered the cost of the energy storage lifespan cycle and did not involve the overall operation of the power grid. Reference [21] involved gas turbines and EVs in the collaborative control of VPPs, analyzing the impact of EVs with different penetration rates on the economy of VPPs. However, it fixed the charging and discharging time periods of EVs, without considering the impact of their random travel patterns. Reference [22] analyzed the optimal scheduling of EVs participating in VPP carbon trading while satisfying the probability distribution of EV travel times. Nevertheless, it only considered the charging costs of EVs and did not involve subsidies for EVs. Reference [23] established a revenue model for EVs based on battery degradation to incentivize owners to participate in VPP operations. However, it only analyzed the scenario of wind power shortages and did not consider the impact of wind power fluctuations on VPPs containing EVs. In addition, while research has proposed optimization scheduling strategies for integrated energy systems in industrial parks that include electric vehicles, there may still be issues with insufficient coordination among energy systems in practical applications. This includes inadequate collaboration between electric vehicles and energy sources such as distributed photovoltaic systems and hydrogen energy equipment, resulting in low energy utilization efficiency.

Moreover, scholars currently often employ methods such as stochastic optimization and scenario optimization to incorporate uncertainty into the optimal scheduling of power systems [24,25]. However, when faced with uncertainty scenarios where specific probability distributions cannot be obtained, the IGDT method is often used to simulate uncertainty fluctuations and optimize models. Despite the numerous efforts to mitigate peak loads and valley filling issues resulting from EV integration into the grid through ordered charging and discharging strategies coupled with multi-time scale approaches, there is a scarcity of studies that incorporate the IGDT method with these strategies to address uncertainties in both supply and demand, while integrating them into the economic dispatch of the power grid. The proposed approach can significantly reduce the load peak-to-valley difference caused by EV integration into the grid, mitigate the increase in scheduling costs due to fluctuations in renewable energy generation, better coordinate the contradiction between robustness and economy, and seek a balance point. The innovations of this paper can be summarized as follows. Traditional robust dispatch strategies tend to be overly conservative in handling uncertainties such as renewable energy output and EV charging behavior, leading to poor economic performance. This paper innovatively proposes a robust and economic dispatch strategy for the campus power grid based on the IGDT. The IGDT model formulates decisions by optimizing the error range of uncertain quantities, without the need to know the specific probability distribution of uncertain factors beforehand. This allows the dispatch strategy to maintain robustness while reducing the conservativeness of decisions and improving economic performance.

The organizational framework of the full text is as follows. In Section 2, EV charging scenarios are generated by Monte Carlo method. Then, IGDT-based dispatch mathematical models are given in Section 3 and a corresponding solution method is provided in Section 4. In Section 5, By comparing with other methods, the feasibility of the proposed method in this paper has been verified in the modified IEEE-33 system. Finally, Section 6 concludes the whole paper.

2. Generation Method of EV Charging Scenarios Based on Monte Carlo Method

2.1. Parameters for EV Charging

Based on the travel habits of residents, the driving mileage and travel time of household vehicles conform to the patterns of lognormal distribution and piecewise normal distribution. This paper refers to the probability density in reference [23] to calculate the probability distributions of driving mileage and grid connection/disconnection time, which serve as the basis for Monte Carlo sampling. The probability density of driving mileage for electric vehicles is shown in Equation (1).

$$f_L = \frac{1}{\sqrt{2\pi} L\sigma_L} \exp[-\frac{(\ln L - \mu_L)^2}{2\sigma_L^2}] \tag{1}$$

In the above formula, μ_L and σ_L represent the expected value and variance, which are set to 3.18 and 0.90, respectively. L refers to the daily driving mileage of EVs. The probability density of grid connection time for EVs can be expressed as (2):

$$f_{in} = \begin{cases} \frac{1}{\sqrt{2\pi} L\sigma_{in}} \exp[\frac{(\ln t - \mu_{in})^2}{2\sigma_{in}^2}], \mu_{in} - 12 < t \le 24 \\ \frac{1}{\sqrt{2\pi} L\sigma_{in}} \exp[\frac{(\ln t + 24 - \mu_{in})^2}{2\sigma_{in}^2}], 0 < t \le \mu_{in} - 12 \end{cases} \tag{2}$$

where μ_{in} and σ_{in} represent the expected value and variance, which are set to 17.9 and 3.40, respectively. The probability density of grid disconnection time for electric vehicles can be calculated using Formula (3):

$$f_{out} = \begin{cases} \frac{1}{\sqrt{2\pi} L\sigma_{out}} \exp[\frac{(\ln t - \mu_{out})^2}{2\sigma_{out}^2}], 0 < t \le \mu_{out} + 12 \\ \frac{1}{\sqrt{2\pi} L\sigma_{out}} \exp[-\frac{(\ln t - 24 - \mu_{out})^2}{2\sigma_{out}^2}], \mu_{out} + 12 < t \le 24 \end{cases} \tag{3}$$

In the formula, μ_{out} and σ_{out} represent the expected value and variance, which are set to 9.25 and 3.18, respectively.

2.2. Monte Carlo Sampling Method

Although each EV is not representative when charging and discharging, the charging patterns of EVs can be derived by studying the characteristics of charging for a large number of EVs. In the previous section, the probability distribution related to EV charging was obtained. Firstly, one EV is selected as a representative to calculate its charging load, and then the total charging load of all EVs can be obtained through superposition calculation. The total charging load of all EVs can be calculated using the Monte Carlo method. The initial time and disconnection time are random variables and can be generated using random numbers based on their probability density functions (PDFs) according to Equations (2) and (3), and then the difference between them shows the charging duration, as shown in (4).The charging duration of a single EV can be expressed as

$$\Delta T = T_{\text{out}} - T_{in} \tag{4}$$

ΔT represents the charging duration of a single EV; T_{out} and T_{in} represent the time when the electric vehicle disconnects and connects, respectively.

To calculate the charging load of a single EV, a random number is first generated based on the distribution of the initial charging time and the SOC before charging begins. Using the above formula, the duration of charging required for that particular EV is calculated. Multiplying this duration by the charging power yields the charging demand for that EVs within a day. The behavior of different EVs is independent of each other, allowing the charging loads of all EVs to be directly added together for the calculation of the total charging load. Assuming that there are a total of N EVs that need to be charged within a certain power grid area, the total charging load during the t-th time period can be expressed as

$$P_t^{c,cha} = \sum_{n=1}^{N} P_{n,t}^{c,cha} \tag{5}$$

In the formula, $P_t^{c,cha}$ represents the total charging load of N EVs during the t-th time period; $P_{n,t}^{c,cha}$ represents the charging load of the n-th EV during the t-th time period.

The randomness of EV loads primarily stems from owners' charging behaviors, including factors such as charging time, location, and duration. These factors are influenced by various elements like owners' daily activity patterns, electricity price fluctuations, and the availability of charging facilities, thus exhibiting significant uncertainty. Traditional distribution network load curves are primarily affected by overall power demand, seasonal changes, differences between weekdays and holidays, as well as the electricity consumption patterns of large industrial users. While they also demonstrate a certain level of randomness, this randomness tends to be more stable and predictable through historical data. The purpose of the new economic dispatch method is to optimize based on these differences. For example, it can take into account the dynamic and unpredictable nature of EV loads, balancing network loads through intelligent charging strategies, demand response measures, or coordination with other energy systems, thus reducing grid fluctuations and costs. Furthermore, the new method can harness the potential of EVs as distributed energy storage devices, providing flexibility and stability to the power grid. Based on the Monte Carlo method calculation steps mentioned earlier, the process used in this paper to calculate the total charging demand of a large number of EVs within a day using this method is summarized in Figure 1. The specific calculation steps can be outlined as follows:

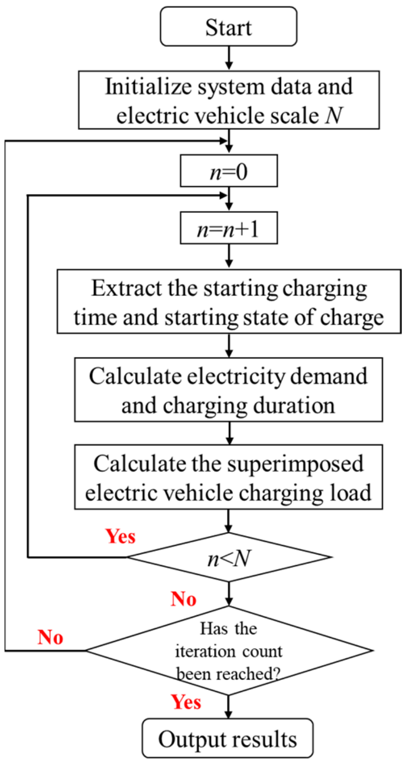

Figure 1. Flowchart of calculating EV charging load using monte carlo method.

(**Step 1**) Determine the total number of electric vehicles in the simulation, the rated capacity of the battery, the charging power, and the number of iterations for the simulation.

(**Step 2**) Randomly generate a starting charging time that satisfies the normal distribution specified in Formulas (2) and (3).

(**Step 3**) Randomly generate a daily driving mileage that satisfies the lognormal distribution specified in Formula (1).

(**Step 4**) Substitute the generated random numbers into Formula (4) to calculate the charging duration.

(**Step 5**) Obtain the charging load curve for a single electric vehicle within a day.

(**Step 6**) Accumulate all charging loads to obtain the total charging load for all electric vehicles in the simulation.

The charging load of EVs exhibits uncertainty in both time and space, primarily due to the randomness of factors such as EV users' travel habits, driving distances, and charging times. By introducing PDFs to model these random factors, we can more accurately reflect the uncertainty of EV charging loads.

3. Economic Dispatch Model of a Park Power Grid with the Participation of EVs

3.1. Objective Function

For the power grid and EVs, as they belong to different stakeholders, in other words, both parties hope to minimize their respective operating costs. To balance the interests of both sides, this paper establishes dispatch models from the perspectives of the distribution network and the user side. By using the weight assignment method, the multi-objective optimization problem is transformed into a single-objective optimization problem. In this paper, the objective functions of the grid operator and EV owners are combined through the weighted sum method because there exists a mutual dependency and interaction between the stable operation of the power grid and the charging needs of EVs in the power system. Grid operators typically focus on grid operation costs, while EV owners are concerned about charging costs. Both of these costs are economic objectives and can be addressed through the weighted sum method. Combining them helps find a solution that balances the interests of all parties. By utilizing the weighted sum method, we can allocate weights between different objectives based on actual conditions and policy goals, thus satisfying the grid operation requirements while also considering the interests of EV owners. This integration benefits multiple parties. Firstly, it helps ensure the stable operation and reliability of the power grid, reducing the risk of grid failures and outages. Secondly, it improves the convenience and service quality of EV charging, promoting the promotion and use of EVs. Additionally, by comprehensively considering the interests of all parties, it optimizes the allocation and utilization of power resources, enhancing the overall efficiency and economic benefits of the power system. Furthermore, when both parties agree to tilt the benefits towards one side, this can be achieved by adjusting the weight factors, further enhancing the flexibility of the solution.

The objective of the distribution network dispatch is to minimize the daily operating cost of the system. The daily operating cost of the distribution network includes the operation and maintenance cost of distributed generation, energy storage cost, line loss penalty cost, and electricity purchase cost. The specific mathematical expression is as follows:

$$\min F_1 = \sum_{t=1}^{T}\sum_{i=1}^{I}(C_{i,t}^{om} + C_{i,t}^{es} + C_{i,t}^{loss}) + \sum_{t=1}^{T} C_t^{grid} \tag{6}$$

Here, I represents the total number of system nodes; $C_{i,t}^{om}$, $C_{i,t}^{es}$, and $C_{i,t}^{loss}$ represent the equipment operation and maintenance cost, energy storage operating cost, and network loss penalty cost, respectively; C_t^{grid} represents the cost of purchasing electricity from the main grid by the distribution network at time t. Detailed calculation formulas for each cost component are given as follows:

$$C_{i,t}^{om} = C_{om}^{wind} P_t^{wind} + C_{om}^{pv} P_t^{pv} \tag{7}$$

$$C_{i,t}^{es} = C_{om}^{stor}(P_t^{cha} + P_t^{dis}) \tag{8}$$

$$C_{i,t}^{loss} = C_{loss} P_{i+1,t}^{loss} \tag{9}$$

Here, C_{om}^{wind} and C_{om}^{pv} represent the unit operation and maintenance costs for wind power and photovoltaic power, respectively; P_t^{wind} and P_t^{pv} represent the wind power and photovoltaic power outputs at time t, respectively; C_{om}^{stor} represents the unit operating cost of the energy storage device; P_t^{cha} and P_t^{dis} represent the charging and discharging power of the energy storage device at time t, respectively; $P_{i+1,t}^{loss}$ represents the loss of the branch leading to the (i + 1)-th node; C_{loss} represents the unit cost equivalent for distribution network line loss.

The objective function for user-side scheduling aims to minimize the total charging cost of EVs, which is shown in (10).

$$\min F_2 = \sum_{t=1}^{\Delta t} \sum_{n=1}^{N} (\lambda_t^{cha} P_{n,t}^{c,cha} - \lambda_t^{dis} P_{n,t}^{c,dis}) \tag{10}$$

Here, λ_t^{cha} and λ_t^{dis} respectively represent the charging unit price and discharge subsidy for the n-th EV. $P_{n,t}^{c,dis}$ represents the discharge power of the n-th EV at time t. The discharge subsidy is a fixed value, unaffected by external conditions, and is generally set by the grid company to incentivize flexible and orderly charging and discharging of EVs.

Since the objective functions of the park distribution network and EV users are not consistent, as shown in (11), the weighted assignment method is adopted to transform the multi-objective optimization problem into a single-objective optimization problem for solving.

$$\min F = \sigma F_1 + (1 - \sigma) F_2 \tag{11}$$

Here, σ represents the weight factor. Its specific value can be determined through negotiation between the power grid decision maker and the user. Currently, power grids and EV users often cooperate through negotiation or signing agreements. Power grid companies offer certain electricity price discounts or compensation to guide EVs to consume electricity in an orderly manner [26,27]. This article also considers the discharge compensation for EVs in (10) to avoid affecting the self-interest of EV users. Under the framework of the achieved cooperation, the power grid and users can negotiate to determine the weighting factor. In fact, by introducing the weighting factor, the multi-objective optimization problem is transformed into a single-objective optimization problem to reduce computational complexity. Adjusting the value of the weighting factor allows the decision maker to choose which side to optimize. Both the power grid and users are pursuing the maximization of their own interests. From the perspective of the user side, the weight factor in (11) is often zero. At this time, the response behavior of EVs mainly depends on the charging unit price and discharge subsidy in the objective function (10). These subsidy coefficients are formulated by the power grid company before scheduling, taking into account peak shaving demand and capacity, in order to guide the orderly participation of the load side in demand response. The objective functions (10) and (11) have been determined through negotiations and agreements on related coefficients before scheduling.

3.2. Constraint Condition

(1) Power flow constraints in distribution network branches

The typical branch power flow model is shown in Figure 2. The constraint conditions that should be satisfied by the power flow [16] in this branch are

$$U_{j,t}^2 = U_{i,t}^2 - 2(r_{ij} P_{ij,t} + x_{ij} Q_{ij,t}) + (r_{ij}^2 + x_{ij}^2) I_{ij,t}^2 \tag{12}$$

$$P_{j,t} = P_{ij,t} - r_{ij} I_{ij,t}^2 - \sum_{k:j \to k} P_{jk,t} \tag{13}$$

$$Q_{j,t} = Q_{ij,t} - x_{ij} I_{ij,t}^2 - \sum_{k:j \to k} Q_{jk,t} \tag{14}$$

$$I_{ij,t}^2 = \frac{P_{ij,t}^2 + Q_{ij,t}^2}{U_{i,t}^2} \tag{15}$$

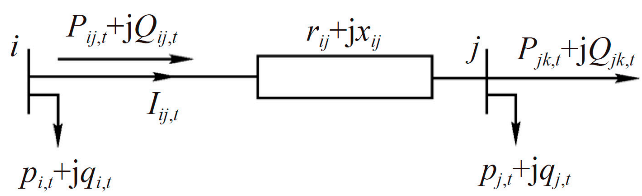

Figure 2. The typical branch power flow model.

In the equation, $U_{i,t}$ and $U_{j,t}$ represent the voltages at nodes i and j, respectively; $P_{i,t}$ and $P_{j,t}$ represent the active power injection at nodes i and j, respectively; $Q_{i,t}$ and $\overline{Q_{j,t}}$ represent the reactive power injection at nodes i and j, respectively; $P_{ij,t}$ and $Q_{ij,t}$ represent the active and reactive power at the sending end of branch ij; $r_{ij} + jx_{ij}$ represents the impedance of branch ij; $P_{jk,t}$ and $Q_{jk,t}$ represent the active and reactive power at the sending end of branch jk; and k: $j \rightarrow k$ represents the set of child nodes with node j as the parent node.

Observing the above equation, it can be found that the power flow constraint conditions contain quadratic terms, making this optimal power flow problem a nonlinear programming problem. Conventional algorithms and intelligent optimization algorithms may not perform well in solving it. Therefore, this paper utilizes second-order cone relaxation to transform the model into a standard second-order cone programming problem that can be efficiently solved.

First, auxiliary variables are introduced through Equations (16) and (17), that is,

$$a_{ij,t} = U_{i,t}^2 \tag{16}$$

$$\beta_{ij,t} = I_{ij,t}^2 \tag{17}$$

In the equation, $\alpha_{j,t}$ and $\beta_{ij,t}$ represent the squares of the voltage at node i and the square of the current on branch ij, respectively. By introducing auxiliary variables, the original power flow Constraints (12)–(15) can be transformed into (18)–(22).

$$a_{j,t} = a_{i,t} - 2(r_{ij}P_{ij,t} + x_{ij}Q_{ij,t}) + (r_{ij}^2 + x_{ij}^2)\beta_{ij,t} \tag{18}$$

$$P_{j,t} = P_{ij,t} - r_{ij}\beta_{ij,t} - \sum_{k:j\rightarrow k} P_{jk,t}\beta_{ij,t} \tag{19}$$

$$Q_{j,t} = Q_{ij,t} - x_{ij}\beta_{ij,t} - \sum_{k:j\rightarrow k} Q_{jk,t} \tag{20}$$

$$\beta_{ij,t} = \frac{P_{ij,t}^2 + Q_{ij,t}^2}{a_{j,t}} \tag{21}$$

$$U_{i,t,\min}^2 \leq \beta_{ij,t} \leq U_{i,t,\max}^2 \tag{22}$$

At this point, Equation (21) remains a nonlinear constraint. With the help of second-order cone relaxation, Equation (21) can be transformed into a second-order cone constraint.

$$\beta_{ij,t} \geq \frac{P_{ij,t}^2 + Q_{ij,t}^2}{a_{j,t}} \tag{23}$$

After equivalent transformation, Formula (23) can be written as the standard second-order cone form, that is,

$$\left\| \begin{matrix} 2P_{ij,t} \\ 2Q_{ij,t} \\ \beta_{ij,t} - a_{j,t} \end{matrix} \right\|_2 \leq \beta_{ij,t} + a_{j,t} \tag{24}$$

(2) Constraints on the output of renewable energy sources

$$\begin{cases} 0 \leq P_t^{wind} \leq P_{t,\max}^{wind} \\ 0 \leq P_t^{pv} \leq P_{t,\max}^{pv} \end{cases} \tag{25}$$

Here, $P_{t,\max}^{wind}$ and $P_{t,\max}^{pv}$ represent the maximum power generation of wind power and photovoltaics at time t, respectively.

(3) Constraint on electricity purchase amount

$$0 \leq P_t^{grid} \leq P_{\max}^{grid} \tag{26}$$

Here, $P_{\max}^{grid}$ represents the maximum allowed power purchase amount.

(4) Constraints on the charging and discharging status of EVs

$$\begin{cases} P_{\min}^{c,cha} \leq P_{n,t}^{c,cha} \leq P_{\max}^{c,cha} \\ P_{\min}^{c,dis} \leq P_{n,t}^{c,dis} \leq P_{\max}^{c,dis} \\ P_{n,t}^{c,cha} P_{n,t}^{c,dis} = 0 \end{cases} \tag{27}$$

Here, $P_{\min}^{c,cha}$ and $P_{\max}^{c,cha}$ represent the minimum and maximum charging power allowed by the charging station, respectively; $P_{\min}^{c,dis}$ and $P_{\max}^{c,dis}$ represent the minimum and maximum discharging power allowed by the charging station. Additionally, constraints related to the state of charge also need to be satisfied, as shown in (28).

$$\begin{cases} SOC_n(t_{over}) \geq SOC_{n,set} \\ SOC_n(t+1) = SOC_n(t) + \frac{\eta_c P_{n,t}^{c,cha}}{E_{cap}} h_{state} \Delta t_{ch,n} \\ + \frac{\eta_d P_{n,t}^{c,dis}}{E_{cap}} h_{state} \Delta t_{d,n} \end{cases} \tag{28}$$

In the above equation, $SOC_n(t_{over})$ and $SOC_{n,set}$ represent the actual battery state of charge (SOC) when the n-th vehicle leaves the charging station and the expected SOC set by the user, respectively. To meet the travel needs of EV users, the actual SOC when leaving should be no lower than the expected value. Additionally, $SOC_n(t)$ and $SOC_n(t+1)$ represent the SOC of the battery at times t and t + 1, respectively. h_{state} is a binary variable used to indicate the charging and discharging status. Furthermore, $\Delta t_{ch,n}$ and $\Delta t_{d,n}$ represent the duration of charging and discharging for the n-th EV, respectively. In this paper, Constraint (28) should always be satisfied because (28) is the active constraint. In the practical application, Constraint (28) can be checked through the following approaches: (1) Implementing user-side information aggregation through load aggregators. Since the potential of a single EV participating in the demand response is limited, they are often aggregated into a single interest entity, namely, unified scheduling by load aggregators. The status information of EVs is transmitted and aggregated through the vehicle's on-board system. (2) Some smart meters and charging piles installed in the power grid will also provide charging records and related data of the vehicles.

4. IGDT Based Robust Model and Its Solution Methodology

During actual operation, environmental factors can lead to Knightian uncertainty (risks that cannot be measured by expected values or calculated probabilities) in the power generation fluctuations of renewable energy units. Compared to stochastic optimization and traditional robust optimization, IGDT does not require the probability distribution functions of uncertain parameters that are difficult to obtain, nor the membership functions required by fuzzy methods, and it can better adapt to Knightian uncertainty scenarios. Therefore, this section adopts the IGDT method to simulate the uncertainty in the power generation fluctuations of renewable energy units and considers the following optimization problem:

$$\begin{cases} \max\limits_{d} f(X, d) \\ s.t. \quad h(X, d) = 0 \\ g(X, d) \leq 0 \end{cases} \tag{29}$$

In the equation, $f(X, d)$ represents the objective function; $h(X, d)$ represents the equality constraint; $g(X, d)$ represents the inequality constraint; d is the decision variable; X is the uncertain variable. For deterministic models, the value of the uncertain parameter is equal to its predicted value $X = \widetilde{X}$. Therefore, the objective function can be rewritten as

$$B_0 = \max\limits_{d} f(\widetilde{X}, d) \tag{30}$$

Based on the IGDT fractional uncertainty model, the fluctuations of the actual value of the uncertain variable X around its predicted value $\widetilde{X}$ can be expressed as

$$U(a, \widetilde{X}) = \left\{ X : \left| \frac{X - \widetilde{X}}{\widetilde{X}} \right| \right\} \leq a \Bigg\}, a \geq 0 \tag{31}$$

In the equation, U represents the set of possible values for X, and α represents the deviation coefficient. By assigning corresponding weights to the deviation coefficients of each uncertain variable, multiple uncertain variables can be normalized:

$$U(a^w, \widetilde{P}_t^{wind}) = \left\{ P_t^{wind} : \left| P_t^{wind} - \widetilde{P}_t^{wind} \right| \leq a^w \widetilde{P}_t^{wind} \right\}, a^w \geq 0 \tag{32}$$

$$U(a^p, \widetilde{P}_t^{pv}) = \left\{ P_t^{pv} : \left| P_t^{pv} - \widetilde{P}_t^{pv} \right| \leq a^p \widetilde{P}_t^{pv} \right\}, a^p \geq 0 \tag{33}$$

$$\begin{cases} a^w = \xi^w a \\ a^p = \xi^p a \end{cases}, \xi^w, \xi^p \in (0,1) \tag{34}$$

$$\xi^w + \xi^p = 1 \tag{35}$$

Here, $\widetilde{P}_t^{wind}$ and $\widetilde{P}_t^{pv}$ are the predicted values of wind power and photovoltaic output, respectively; a^w and a^p are the deviation coefficients of charging demand and grid injection power, respectively; ξ^w and ξ^p are the corresponding weights of a^w and a^p, which can be determined by methods such as the Analytic Hierarchy Process (AHP) or entropy weight method.

Based on the above analysis, a robust scheduling model is constructed as shown in (36):

$$\begin{cases} \min a \\ s.t. \quad \max f(P_t^{wind}, P_t^{pv}, d) \geq B_c \\ B_c = (1 + \delta^O) B_0, \delta^O \in (0,1) \\ h(P_t^{wind}, P_t^{pv}, d) = 0 \\ g(P_t^{wind}, P_t^{pv}, d) \leq 0 \\ (11) - (17) \end{cases} \tag{36}$$

Here, B_c represents the set threshold for opportunity benefits; δ^O is the opportunity factor, which reflects the deviation degree of the expected benefit target B_c being higher than B_0, indicating the operator's risk appetite towards revenue targets.

In this scheduling model, α can be regarded as a constant. Since the operator's revenue is positively correlated with charging demand and grid injection power, the optimal solution of the lower-level model will necessarily be achieved at the lower bound of the information gap region. Therefore, the model can be equivalently transformed, as shown in (37). It should be noted that only the parts different from the initial model are presented here to avoid repetition.

$$\begin{cases} \max a \\ s.t.\ \max f(P_t^{wind}, P_t^{pv}, d) \geq B_c \\ P_t^{wind} = (1 - a^w)\widetilde{P}_t^{wind} \\ P_t^{pv} = (1 - a^p)\widetilde{P}_t^{pv} \end{cases} \quad (37)$$

Due to the existence of nonlinear terms in the collaborative scheduling model based on IGDT, the big-M method can be adopted to introduce auxiliary constraints for equivalent linearization of the product terms of continuous variables and Boolean variables. This process further transforms the initial mixed-integer nonlinear optimization problem into a mixed-integer linear optimization model, which can be solved by mature commercial software such as CPLEX 12.9.0 or Gurobi 11.0.1.

5. Case Study

5.1. Introduction of the Test System

To verify the effectiveness of the proposed method in this paper, an improved IEEE-33 node test system is used for case verification. The structure of the test system is shown in Figure 3 below [28,29]. The area contains three large charging stations that can accommodate the charging needs of up to 200 EVs. There are two photovoltaic power stations at nodes 24 and 32, and a wind farm is connected at node 14. Detailed wind power and photovoltaic output data are shown in Figure 4 below. In the IGDT method, uncertainty is characterized primarily by the range of error between predicted and actual values, which is depicted through deviation coefficients. This error range reflects the volatility and uncertainty of renewable energy output. Unlike stochastic optimization and robust optimization, IGDT employs a non-probabilistic approach to deal with uncertainty. It does not require knowledge of the specific probability distribution of uncertain factors but instead obtains a set of robust optimization solutions by controlling deviation coefficients to maximize the range of variation in uncertain quantities. By optimizing the error range of uncertain quantities, the IGDT method is able to find a set of solutions that perform well under uncertain conditions. This ensures the robustness of the scheduling strategy, i.e., its ability to withstand fluctuations in renewable energy output to a certain extent. System operators only need to provide renewable energy resources under the current conditions and formulate dispatch strategies based on the model presented in this article. Through the use of Internet of Things (IoT) technology, the dispatch decisions can be sent to users, which significantly reduces the complexity of the dispatch decision-making process and avoids additional investments.

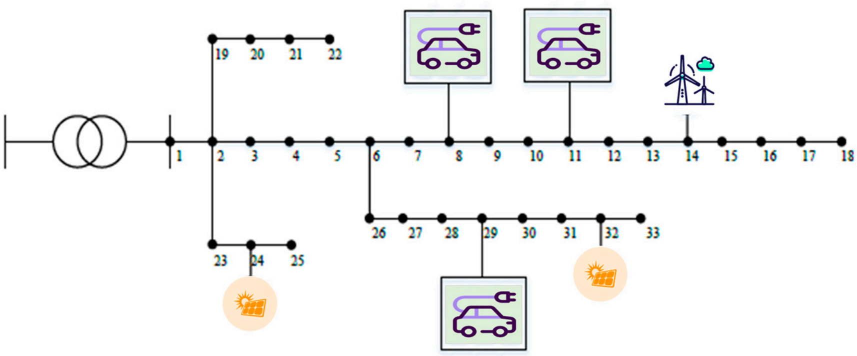

Figure 3. Topology of the modified IEEE-33 testing system.

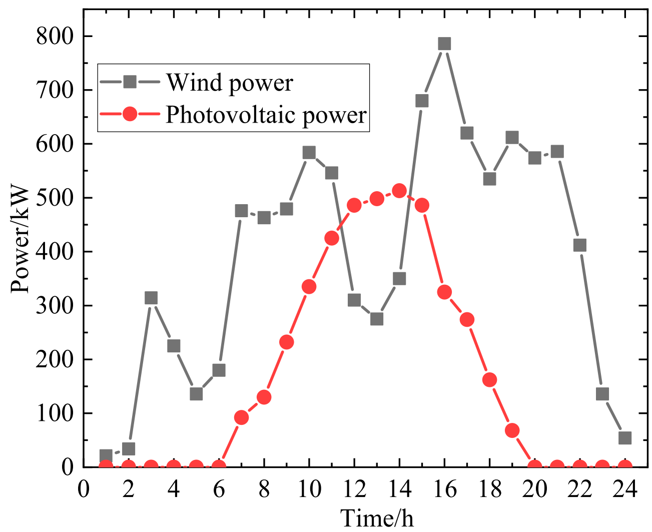

Figure 4. Wind and photovoltaic output data.

5.2. Impact Analysis of Electric Vehicle Charging

Currently, due to the absence of relevant charging policies and fixed electricity pricing mechanisms, a large number of EVs are randomly connected to the distribution network. Irregular management has led to an increase in the demand for load on the distribution network side. The impact of unordered charging of EVs on the microgrid is illustrated in Figure 5. The proposed method can effectively reduce the peak load and alleviate the pressure on the power supply of the power grid. By combining the basic electricity load with the additional load generated by the random charging of EVs within the distribution network, which is simulated using the Monte Carlo method, we can obtain a load curve that includes the random charging of all EVs in the distribution network area. As can be seen from the figure, the peak charging load period of EVs is basically the same as the peak period of the basic electricity load, significantly raising the original load peak in the distribution network, resulting in a noticeable increase in electricity consumption and a substantial exacerbation of the peak-to-valley difference in electricity load.

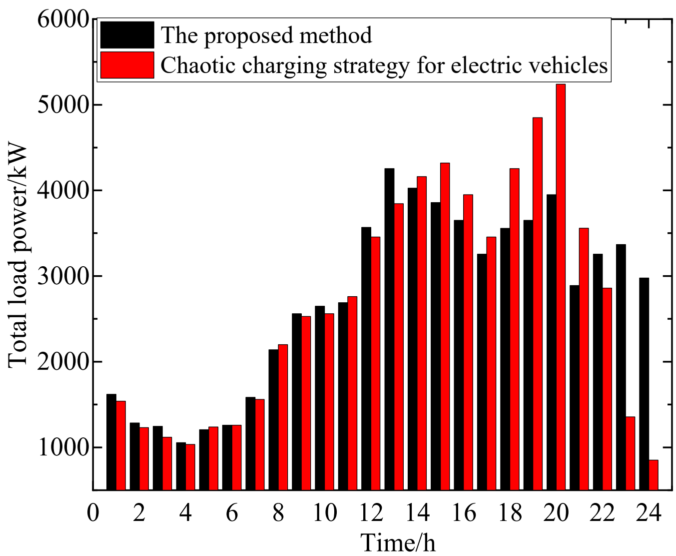

Figure 5. Total load power under different charging strategies.

The relevant peak-to-valley load data in Figure 5 are presented in Table 1. As can be seen from the figure, the integration of EVs into the distribution network has a significant impact on raising the peak load. To accurately measure the influence of EV charging loads on the distribution network, the peak-to-valley difference rate is introduced as a reference value. The data in the table clearly indicate that, compared to the method proposed in this paper, when a large number of EVs randomly charge in the distribution network, both peak and valley loads increase. The peak-to-valley difference rises from the original 3207.3 kW to 4288.4 kW, and the peak-to-valley difference rate increases from 0.75 to 0.82. The increase in the peak-to-valley difference rate suggests fluctuations in the distribution network, with power generation equipment operating at low loads or even shutting down during the valley load period. This reduces the utilization rate of equipment, increases the difficulty of peak shaving and frequency modulation in the distribution network, leads to resource waste, and also increases the construction and operating costs of the power system.

Table 1. Distribution network load indicators under different scenarios.

Mode	Peak Load/kW	Valley Load/kW	Peak-to-Valley Difference/kW	Peak-to-Valley Difference Rate
The proposed method	4256.4	1049.1	3207.3	0.75
Chaotic charging strategy for electric vehicles	5240.5	952.1	4288.4	0.82

5.3. Feasibility Verification of the IGDT Optimization Model

This section focuses on analyzing the impact of different weighting coefficients on various indicators of the distribution network. Since the IGDT optimization method adopted in this study requires simulating the uncertainty of power generation from renewable energy units by adding uncertain parameters to a deterministic model, we first ignore the uncertainty of power generation on the supply side and solve for the optimal values of operating costs and load demand fluctuations in this deterministic model. These optimal values serve as the baseline for the objective function in the subsequent IGDT optimization model. Assuming that the prediction errors follow a normal distribution, 5000 scenarios are randomly generated using the Monte Carlo method. Combined with the K-means clustering reduction method, all scenarios are clustered and reduced, resulting in a final selection of 10 scenarios. The relevant calculation results are presented in Table 2 below.

Table 2. Comparison of results from different optimization methods.

IGDT Optimization Model		Traditional Robust Optimization Method	
Deviation Coefficient/%	Scheduling Cost/¥	Deviation Coefficient/%	Scheduling Cost/¥
1.79	45,224.8	1.24	38,796.87
2.48	49,524.1	1.28	45,324.6
4.26	51,268.9	2.45	46,643.8
5.18	52,215.4	3.26	58,965.5
7.36	53,985.4	4.15	52,174.3
9.32	56,478.2	4.93	58,639.4
10.52	57,413.9	5.36	59,874.1
11.68	58,749.9	10.85	62,543.1
12.48	59,713.2	11.43	64,587.2
14.03	61,532.6	13.69	68,413.5

The larger the deviation coefficient, the stronger the robustness of the model is demonstrated. Therefore, when the scheduling costs are similar, the IGDT optimization model exhibits stronger robustness and better adapts to the severe uncertainty caused by fluctuations in power generation. Compared to the IGDT optimization model, the random optimization model shows a more pronounced trend of increasing scheduling costs as the deviation coefficient increases, indicating that the IGDT optimization method offers better economic performance when the deviation coefficients are approximately the same. In summary, the IGDT optimization method outperforms both traditional robust optimization and random optimization in terms of both economy and robustness, further validating the superiority of this model. Overall, the IGDT approach handles uncertainty by defining intervals for uncertain quantities rather than probability distributions, allowing decision making even when probabilistic information about uncertainty is incomplete or difficult to obtain. In contrast, traditional robust optimization methods often require explicit upper and lower bounds for uncertain factors or knowledge of their probability distribution models. Additionally, IGDT offers two strategies to address uncertainty: the risk-averse strategy and the opportunity-seeking strategy. The risk-averse strategy aims to ensure that system objectives are not below a set worst-case target, while the opportunity-seeking strategy attempts to exceed a positive target value when possible. This flexibility enables IGDT to accommodate different decision-makers' risk preferences and objectives. Furthermore, the IGDT method optimizes the error of uncertain quantities while satisfying pre-set objectives, clarifying the potential impact of these uncertainties on the system. This approach makes optimization objectives more explicit and intuitive, aiding decision makers in understanding decision outcomes. Typically, the IGDT method does not require extensive probabilistic calculations or sampling like some traditional robust optimization methods, resulting in higher computational efficiency in certain scenarios.

To further demonstrate the advantages of the proposed method, this article compares it with traditional robust optimization algorithms and scenario-based stochastic optimization algorithms in terms of both computational time and conservatism. The relevant calculation results are shown in Table 3 below. Specifically, the robust optimization method uses a box model to characterize uncertainty, while the scenario-based stochastic optimization algorithm employs the K-means clustering method to generate 10 typical scenarios.

Table 3. Comparison of performance among different calculation methods.

Model	Total Operation Cost/¥	Total Computation Time/s
The proposed model	53624.6	36.5
The model proposed in [30]	55328.4	32.6
The model proposed in [31]	54742.1	410.7

Through observing Table 1, it can be found that the robust optimization method typically considers the system's performance under the worst-case scenario and seeks the optimal solution under such conditions. This approach often requires more computational resources to traverse all possible combinations of uncertain factors, especially when using a box model to characterize uncertainty. However, due to the low computational complexity of the box model, the robust optimization method generally has a shorter calculation time. While its results are conservative, meaning the optimized solution may not have the best objective function value among all feasible solutions, the solution remains feasible when environmental conditions change, potentially increasing the system's operating cost to a certain extent.

The scenario-based stochastic optimization algorithm simulates uncertainty by generating a series of typical scenarios and performs optimization based on these scenarios. Although this method reduces the computational burden, the process of scenario generation and screening also requires some time. When using the K-means clustering method to generate 10 typical scenarios, the complexity of the clustering process can affect the overall calculation time. While this approach can simulate uncertainty and optimize based on typical scenarios, approximations and simplifications during scenario generation and screening may lead to optimized results deviating from the actual optimal solution, thereby increasing the overall system operating cost.

In contrast, the proposed method in this article does not require determining the probability distribution of uncertain quantities. Instead, it directly optimizes the error of uncertain quantities. This approach can effectively handle the error of uncertainty and determine its impact on the system while satisfying predefined objectives. Therefore, its calculation time is relatively short, second only to the robust optimization method.

6. Conclusions

This paper delves into the impact of electric vehicle charging behavior on the grid load curve in the context of renewable energy power systems, particularly focusing on the multiple uncertainties faced by grid scheduling decisions when electric vehicles and distributed generation sources are integrated on a large scale. Given the economic shortcomings of traditional robust scheduling strategies, this paper proposes an innovative robust and economic scheduling strategy for campus power grids, which is based on the IGDT. Empirical research is conducted using the improved IEEE-33 node test system, and comparisons with existing methods yield the following conclusions:

(1) The random charging of a large number of EVs connected to the distribution network is bound to cause an increase in the peak load of the power grid, adversely affecting its operation. Under the scheduling strategy proposed in this paper, the peak-to-valley difference is reduced from the original 4288.4 kW to 3207.3 kW, and the peak-to-valley difference rate decreases from 0.82 to 0.75.

(2) Compared to other optimization methods, the IGDT optimization model adopted in this study better adapts to Knightian uncertainty scenarios and more effectively reconciles the trade-off between operational stability and scheduling economy.

(3) In future research, there are still several issues that need to be addressed. Although the uncertainties of electric vehicles and renewable energy outputs have been taken into consideration in this paper, the uncertainties in real-world scenarios are far more complex. For instance, system equipment failures and variations in load demand may also have an impact on the scheduling of power systems, yet the paper has not covered all possible sources of uncertainty. Last but not least, although the paper proposes a robust economic dispatch strategy based on information gap decision theory (IGDT), it lacks verification in actual power systems. Real-world systems may encounter various complex scenarios, such as differences in grid structures across regions, load characteristics, and the penetration rate of renewable energy, which can all influence the effectiveness of the proposed dispatch strategy.

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