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ARTICLE

Two-Stage Investment Decision-Making Research for Power Grid Projects Considering Uncertainty of Regional Development Stages: Multi-Attribute Decision-Making and Robust Optimization

Yi Sui*, Zhibin Song, Zhuopeng Shi, Yiliang Hao and Yawei Zhao

State Grid Shanxi Electric Power Company Economic and Technological Research Institute, Taiyuan, China

*Corresponding Author: Yi Sui. Email: 18935118977@163.com

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ABSTRACT: As the core hub of energy production and consumption, the scientificity of power grid investment allocation directly affects renewable energy integration and power supply reliability. However, regional development stages exhibit significant uncertainty due to factors such as policy orientation and economic-technological progress. Existing power grid investment decision-making methods mostly ignore regional development differences, making it difficult to balance regional development equity and investment efficiency. To address this, this paper proposes a two-stage robust optimization model for power grid investment considering the uncertainty of regional development stages. Firstly, a comprehensive evaluation index system covering operational, technical, economic, and social dimensions is constructed, and the DEMATEL-ANP method is adopted to determine index weights and calculate the basic investment allocation scale for each city. Secondly, aiming at maximizing the net present value (NPV) of investment, a robust optimization theory is introduced to establish an adjusted allocation model, which balances the conservatism and economy of the model by adjusting the maximum deviation ratio to achieve dynamic investment adjustment under uncertain scenarios. Finally, five cities in Shanxi Province at different development stages are selected as a case study to verify the model's effectiveness. The results show that the model can balance regional development equity and investment efficiency; the investment allocation among cities presents the characteristics of "steady growth in high-development-level cities, adaptive growth rate in potential cities, and basic guarantee in underdeveloped regions", providing scientific support for precise power grid investment under the new power system.

KEYWORDS: Power grid investment; uncertainty of regional development; DEMATEL-ANP; robust optimization; two-stage decision-making

1 Introduction

The construction of a new power system characterized by high-proportion renewable energy integration is a key path for China to achieve the "dual carbon" goals and high-quality energy development [1,2]. As the core hub connecting regional energy production and consumption within a province, the scientificity of power grid investment allocation directly determines renewable energy integration efficiency, power supply reliability, and the level of regional energy coordinated development. As the basic unit of provincial energy allocation and economic development, the impact of differences in urban development stages on power grid investment decisions has become increasingly prominent [3]. Affected by policy formulation, economic and technological development, regional power grid development exhibits significant randomness and volatility, increasing the uncertainty of regional power grid development stages [4,5]. Therefore, accurately characterizing the uncertainty of regional development stages, rationally allocating power grid investment, and researching precise investment decision-making methods are crucial for achieving efficient power grid investment.

Currently, power grid investment decision-making mainly falls into two categories: multi-attribute decision-making [6–8] and mathematical modeling analysis [9,10]. Multi-attribute decision-making refers to selecting the optimal investment plan through constructing an evaluation index system and conducting comprehensive evaluation. Zhang et al. proposed a comprehensive decision-making method for pumped storage power station investment and construction based on the Delphi method, interval intuitionistic fuzzy theory, grey relational theory, entropy weight method, and prospect theory [11]. Hussain et al. discussed the theory and basic operations of intuitionistic fuzzy sets (IFS) and proposed an investment decision-making model for solar panels [12]. Yüksel et al. constructed a multi-country hydropower investment decision-making evaluation model using spherical fuzzy entropy, and through ranking alternative schemes, it was shown that China is the most suitable country for hydropower energy investment [13]. Ilham et al. introduced the development of a multi-benefit decision-making (MBDM) index for solar photovoltaic (PV) investment planning and applied it to power grid investment decision-making [14].

Mathematical modeling analysis mainly involves constructing an investment decision optimization model with the goal of minimizing investment and construction costs and solving for the optimal scheme. Wang et al. proposed a new investment decision planning method for low-carbon transition of power grids based on deep neural networks, aiming to address multi-dimensional key indicators related to power grid transition and provide reliable power industry layout and investment plans for power system investment decision-making [15]. Yang et al. took 30 provinces in China as research objects, constructed a real options model, and explored the impact of carbon emission trading markets, energy storage subsidies, and their synergistic effects on the optimal investment decisions of household PV-ESS projects [16]. Liu et al. developed a component-based technology learning curve model to predict future costs, integrated real-time operation optimization throughout the life cycle into the real options model, and proposed a new investment decision-making model [17]. Considering the uncertainty of renewable energy generation and decision-makers' different attitudes towards risks, Wang et al. proposed an adaptability evaluation method for power grid planning schemes considering multiple decision-making psychology [18]. To realize the optimal determination of the location and capacity of multiple energy storage methods in the power system, Yang et al. proposed a collaborative optimization planning model for multiple energy storage [19].

Through the above literature analysis, it can be seen that: (1) When applying multi-attribute decision-making to investment decision-making, most studies consider three dimensions: economic, social, and environmental, while rarely considering the technical dimension. However, under the new power system, large-scale renewable energy integration requires advanced technology support. (2) In the process of optimizing power grid investment decision-making, economic benefits are usually the only optimization and evaluation goal, and differences in regional development are rarely considered, resulting in optimization models that cannot guarantee stable investment benefits and investment allocation results that deviate from actual regional needs. In addition, against the background of increasingly complex economic and power grid development influencing factors, formulating power grid investment decisions based on a single method cannot ensure that the optimization results meet the constraints under all investment environments [20,21]. Specifically, cities with low regional power grid development levels often have low power grid investment benefits. If power grid investment decisions are only based on comprehensive benefits, the development imbalance between different regions will be exacerbated. However, considering only regional power grid development levels for investment will lead to excessively low power grid investment benefits. Therefore, it is necessary to balance regional power grid development and investment benefits.

A more critical limitation is that existing research either relies on standalone multi-attribute decision-making or mathematical optimization models. Simple integrated models can only achieve a mechanical combination of the two, which inherently fails to address the dual challenges of regional disparities and uncertainty. Standalone investment optimization models prioritize economic benefits but lack a priori consideration of regional development differences, resulting in optimization outcomes that favor developed areas and neglect developmental equity. Standalone multi-attribute decision-making models excel in characterizing multi-dimensional regional features but cannot handle dynamic uncertainty, leading to poor robustness against risk in their fixed allocation results. Simple integrated models that embed multi-attribute indicators into optimization constraints face the curse of dimensional and logical decoupling, making the solution process overly complex and unable to balance fairness and efficiency effectively.

Based on this, this paper proposes a two-stage integrated model whose layered design aligns with the practical logic of grid investment decision-making. The first stage employs DEMATEL-ANP to determine the baseline investment allocation, addressing regional development disparities and ensuring allocative fairness; the second stage treats this baseline allocation as a rigid constraint and utilizes robust optimization to achieve dynamic adjustments under uncertainty, thereby realizing risk resistance. This layered design avoids the mechanical superimposition of indicators and constraints, overcomes the curse of dimensionality, and achieves an organic unification of "investment assurance" and "uncertainty response." The contribution of this paper is as follows:

(1) Combining multi-attribute decision-making method and mathematical optimization method, a two-stage power grid investment model under the new power system is proposed. In the first stage, the multi-attribute decision-making method is used to determine the basic power grid investment allocation scale for regions at different development levels; on this basis, the second stage uses mathematical optimization theory to construct an adjusted power grid investment allocation model. Thus, the balance between regional power grid development and investment benefits is achieved through two-stage decision-making.
(2) Based on the construction goals of power grid projects under the new power system, a comprehensive evaluation index system for the basic allocation of power grid project investment covering operation, technology, economy, and society is constructed. The DEMATEL-ANP method is used to calculate index weights and measure the basic allocation scale of power grid investment.
(3) Taking the maximization of net present value as the objective function, considering the uncertainty of regional development stages, the robust optimization theory is introduced to construct an adjusted investment decision allocation model for power grid projects, so as to realize the scientific allocation of power grid project investment in different regions.

The structure of the full paper is organized as follows: Section 2 elaborates on the overall concept of the two-stage decision-making framework; Section 3 focuses on the issue of fairness assurance, constructing a baseline allocation model based on DEMATEL-ANP to quantify the basic development needs of regional power grids; Section 4 concentrates on efficiency improvement and risk control, introducing robust optimization to build an investment adjustment model that optimizes investment benefits under uncertain environments; Section 5 conducts an empirical analysis using five cities in Shanxi Province as examples—specifically, Section 5.2 verifies the fairness effect of the baseline allocation model, Section 5.3 validates the robust optimization effect of the adjustment model, and Section 5.4 comprehensively evaluates the superiority of the two-stage framework in balancing multiple objectives through model comparison; Section 6 concludes the full paper.

2 System Description

The overall research framework of this paper is shown in Fig. 1.

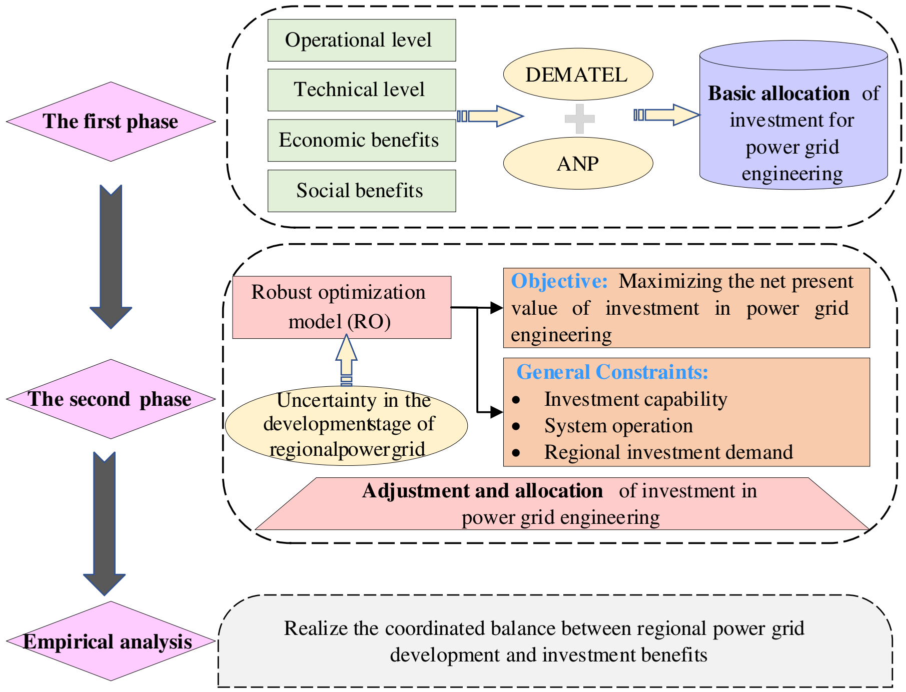

Figure 1: Two-stage optimization model for investment allocation in power grid engineering.

The research of this paper mainly carries out the following steps:

In the first stage, the construction of the basic allocation model. Closely following the construction goals of power grid projects under the new power system, a power grid investment evaluation index system is constructed from four dimensions: operation, technology, economy, and society; the DEMATEL-ANP method [22,23] is adopted to determine the weight of each index; and then the basic power grid investment allocation scale F_n^* suitable for cities at different development levels is measured, which serves as the core benchmark parameter for the constraint system of the second-stage adjusted allocation model, and is the only mathematical input of Stage 1 to Stage 2, forming the primary coupling node of the two-stage framework.

In the second stage, the construction of the adjusted allocation model. Taking the optimization of comprehensive power grid investment benefits as the objective function, considering the uncertainty of regional development stages, the robust optimization theory is introduced to construct an investment adjustment and allocation model. The basic allocation result F_n^* is embedded into the investment capacity constraint in the form of a deviation limit, which is the formalized mathematical coupling form of the two stages. The balance between the conservatism and economy of the model is adjusted through robust optimization parameters to realize the dynamic adjustment of the power grid investment scale of each city under uncertain scenarios.

Finally, combining the above two-stage models, a two-stage power grid investment decision-making scheme of "basic allocation–dynamic adjustment" can be formed, so as to realize the coordinated balance between regional power grid development and investment benefits. Cities at different development stages within a province are selected as case study objects to analyze the optimal direction of power grid investment in cities at different development stages and put forward targeted investment allocation suggestions.

3 Basic Power Grid Investment Allocation Model Based on Multi-Attribute Decision-Making

3.1 Construction of Power Grid Project Investment Evaluation Index System

Combining the construction goals of power grid projects under the new power system, namely "ensuring operation, upgrading technology, improving benefits, and empowering society", starting from the core functions and multi-dimensional value dimensions of the project, a comprehensive power grid project investment evaluation index system covering four dimensions: operation, technology, economy, and social environment is constructed.

Specifically, in the process of index system construction, first, focusing on the core operational attributes of power grid projects, indicators that can directly reflect load utilization efficiency, equipment reliability, and external transmission channel effectiveness are selected to form the operational level dimension [24]; second, closely following the current construction requirements of the new power system, the technical level dimension is established around intelligent coverage, renewable energy adaptation, fault self-healing capability, and grid structure optimization [25]; third, from the perspective of investment decision-making and operational benefits, the economic benefit dimension is constructed through indicators such as internal rate of return, asset load efficiency, and unit power supply cost [26]; finally, combining the "dual carbon" goals and people's livelihood needs, the social and environmental benefit dimension is formed with the core of pollutant emission reduction, renewable energy integration, income support, and employment promotion [27]. Thus, the index system not only focuses on the basic operation and technological innovation attributes of power grid projects but also considers investment returns and green people's livelihood contributions, realizing a comprehensive and multi-dimensional characterization of the impact evaluation of power grid project investment decisions. The specific index system is shown in Table 1. The specific meanings of each indicator are shown in the Appendix A.

Table 1: Power grid project investment impact evaluation index system.

First-Level Indicators	Indicator Serial Number	Second-Level Indicators	Indicator Serial Number
Operational Level	U1	Annual Maximum Load Rate	U11
		Annual Equivalent Average Load Rate	U12
		Transformer Forced Outage Rate	U13
		Utilization Rate of Power Grid External Transmission Capacity	U14
Technical Level	U2	Power Grid Intelligent Coverage Rate	U21
		Renewable Energy Grid Connection Adaptation Rate	U22
		Power Grid Fault Self-healing Response Time	U23
		Power Grid Structure Rationality Index	U24
Economic Benefits	U3	Total Investment Internal Rate of Return	U31
		Registered Capital Net Profit Rate	U32
		Unit New Asset Load Increment	U33
		Unit Power Supply Investment Cost	U34
Social and Environmental Benefits	U4	Total Equivalent Emission Reduction of $SO_2/NO_x/CO_x$ Particulates	U41
		Promoted Renewable Energy Consumption	U42
		Electricity-Supported Per Capita Income of Residents	U43
		Boosted Number of New Jobs	U44

3.2 Index Weighting Method Based on DEMATEL-ANP

Since there is a certain correlation between the four dimensions of operational level, technical level, economic benefits, and social and environmental benefits in the constructed evaluation index system, this paper selects the DEMATEL-ANP combined weighting method to determine the weight of each index. The DEMATEL-ANP combined weighting method first uses the DEMATEL method to qualitatively determine the correlation attributes between first-level indicators, and then uses the ANP method to determine the weight of each second-level indicator. The specific calculation steps are as follows:

(1) Judge the influence relationship between first-level indicators. For the first-level indicator set $U = (U_1, U_2, \ldots, U_\mathrm{n})$ in this paper, if the first-level indicator U_i has a direct impact on U_j, numbers 0–4 can be used to represent no impact, weak impact, medium impact, strong impact, and very strong impact between indicators, respectively. Thus, a direct relationship matrix $A = \left[a_{ij}\right]_{n\times n}$ of mutual influence between first-level indicators can be constructed, where a_{ij} represents the impact degree of the first-level indicator U_i on U_j, $1 \leq i \leq \mathrm{n}$, $1 \leq j \leq n$.

(2) Calculate the comprehensive influence matrix. The standard correlation matrix B is obtained from the direct relationship matrix A:

$$B = \frac{1}{\underset{0\leq i\leq n}{max} \sum_{j=1}^{n} a_{ij}} \times A \tag{1}$$

The comprehensive matrix reflects the causal relationship of first-level indicators in the entire system, and the specific calculation method is as follows:

$$T = \left[t_{ij}\right]_{n\times n} = \lim_{k\to+\infty} \left(B + B^2 + B^3 + \ldots + B^k\right) = B(I - B)^{-1} \tag{2}$$

where I is the identity matrix;

(3) Calculate the centrality and cause degree of indicators. On the basis of obtaining the comprehensive influence matrix T, define the sum of elements in each row of T as the influence degree D, and the sum of elements in each column as the affected degree R of the corresponding indicator. The calculation formulas are as follows:

$$D = \sum_{j=1}^{n} t_{ij}, R = \sum_{i=1}^{n} t_{ij} \tag{3}$$

The influence degree D of an indicator represents the comprehensive impact degree of the indicator on all other indicators, and the affected degree R represents the comprehensive impact degree of the indicator by all other indicators. On this basis, $D + R$ is defined as the centrality of the indicator, representing the importance of the indicator in the entire indicator system. If $D - R > 0$, it indicates that the impact degree of the indicator on other indicators is greater than the impact degree it receives from other indicators, so the indicator is called a cause factor; otherwise, it is considered that the indicator is greatly affected by other indicators and is called a result factor.

(4) Construct the network hierarchical structure of the indicator system. According to the centrality and cause degree of first-level indicators determined by DEMATEL, the influence and affected relationships between control layer indicators and network layer indicators in the indicator system are constructed.

(5) Construct the super matrix of network hierarchical analysis. Assume that the elements of the control layer of ANP are $S_1, S_2, \ldots, S_m$; the elements of the network layer are $U_1, U_2, \ldots, U_n$, where U_j contains elements u_{ji} $(i = 1, 2, \ldots, n_j)$. Taking the element S_s $(s = 1, 2, \ldots, m)$ of the control layer as the criterion and the element U_j in u_{jk} as the sub-criterion, the elements in the element group U_i are compared

according to their impact degree on u_{jk}, that is, a judgment matrix is constructed under the criterion S_s, and the weight vector $w_{i1}^{(jk)}, w_{i2}^{(jk)}, \ldots, w_{in_i}^{(jk)}$ is obtained by using the eigenvalue method. For $k = 1, 2, \ldots, n_j$, repeat the above steps to obtain the matrix:

$$W_{ij} = \begin{bmatrix} w_{i1}^{(j1)} & \cdots & w_{i1}^{(jn_j)} \\ \vdots & \ddots & \vdots \\ w_{in_i}^{(j1)} & \cdots & w_{in_i}^{(jn_j)} \end{bmatrix} \tag{4}$$

where, the column vector of W_{ij} represents the impact degree ranking vector of all elements in U_i on the element u_{jk} in U_j. If u_{jk} is not affected by the element u_{ip} in U_i, then $w_{ip}^{(jk)} = 0$. For each U_i and U_j, repeat the above steps to obtain the super-matrix under the criterion S_s. According to the number of control layer elements, there are m supermatrices, and their general form is:

$$W^{(s)} = \begin{bmatrix} W_{11}^{(s)} & \cdots & W_{1n}^{(s)} \\ \vdots & \ddots & \vdots \\ W_{n1}^{(s)} & \cdots & W_{nn}^{(s)} \end{bmatrix} \tag{5}$$

(6) Construct the weighted super matrix of ANP. Each element of the super matrix $W^{(s)}$ is a matrix, and its submatrix $W_{ij}^{(s)}$ is column-normalized, but $W^{(s)}$ is not column-normalized. Column-normalizing $W^{(s)}$ can obtain the weighted super matrix. The specific method is: taking S_s as the criterion and the element group U_j as the sub-criterion, compare the relative importance of all element groups, and obtain the weight vector $B_j^{(s)} = (b_{j1}^{(s)}, b_{j2}^{(s)}, \ldots, b_{jn}^{(s)})^T$, according to the eigenvalue method. For all $j = 1, 2, \ldots, n$, repeat the above steps to obtain the weighted matrix:

$$B^{(s)} = (B_1^{(s)}, B_2^{(s)}, \ldots, B_n^{(s)})^T = \begin{bmatrix} b_{11}^{(s)} & \cdots & b_{1n}^{(s)} \\ \vdots & \ddots & \vdots \\ b_{n1}^{(s)} & \cdots & b_{nn}^{(s)} \end{bmatrix} \tag{6}$$

Then, the submatrices in the super matrix W are weighted to obtain the column-normalized weighted super matrix under the criterion S_s as follows. Similarly, there should be m weighted super matrices.

$$W^{(Bs)} = \left(W_{ij}^{(Bs)}\right)_{n\times n}, W_{ij}^{(Bs)} = b_{ij}^{(s)} \times W_{ij}^{(s)} \tag{7}$$

(7) Stable processing of the super matrix. To accurately reflect the interdependence between elements, it is necessary to stabilize the super matrix. By calculating the limit relative ranking vector of each super matrix: $\lim\limits_{k\to+\infty} {W^{(s)}}^k$, if the limit converges and is unique, the value of the corresponding row of the original matrix is the stable weight of each evaluation indicator.

The core of the analytic network process is to solve the super matrix, which needs to be calculated with the help of Super Decision software.

3.3 Calculation of Investment Allocation Coefficient

According to the above analysis, the standardized values of all indicators in the nth region and their indicator weights are linearly weighted to obtain the power grid investment fund allocation weight of the region, that is:

$$F_n = \sum_{j=1}^{J} W_j^{(Bs)} x_{nj} \tag{8}$$

where, x_{nj} is the standardized value of the j-th influencing factor data in the nth region. F_n is the power grid construction investment fund allocation weight of the nth region.

The calculation method of the power grid project construction fund investment allocation result is:

$$F_n^* = \frac{F_n}{\sum_{n=1}^{N} F_n} \times Z' \tag{9}$$

where, F_n^* is the basic power grid project investment allocation result of the nth region. Z' is the total amount of funds to be allocated.

4 Adjusted Power Grid Investment Allocation Model Based on Robust Optimization

Among the various factors affecting regional development stages, factors such as regional electricity load and per capita GDP have significant uncertainty. Therefore, it is necessary to model the uncertainty of regional power grid development. The robust optimization method is adopted to formulate an optimal robust scheme, so that the investment decision can still meet the constraints of the optimization model under the "worst-case" environment of uncertain factors, and the investment decision result under the optimal objective function is obtained.

4.1 Modeling of Regional Development Uncertainty

In grid investment decision-making, the uncertainty surrounding regional development stages primarily stems from the coupled effects of multiple factors such as policy orientation, economic growth, and technological evolution. These factors often exhibit complex correlation structures and asymmetric fluctuation characteristics, and how to appropriately characterize this uncertainty directly impacts the reliability and practicality of the optimization results.

To balance model operability with robustness, this paper employs a box uncertainty set to model the uncertainty of regional development stages, where the fluctuation range of the data can be expressed as:

$$P_{D,n} \in \left(\hat{P}_{D,n} - \Delta P_{D,n}^{max} \hat{P}_{D,n} + \Delta P_{D,n}^{min} \right) \tag{10}$$

where, $P_{D,n}$ is the uncertain variable of the power grid development stage in the nth region introduced after considering uncertainty, and $\hat{P}_{D,n}$ is the power grid development data value of the nth region. $\Delta P_{D,n}^{max}$ and $\Delta P_{D,n}^{min}$ are the maximum and minimum allowable fluctuation deviations of the uncertainty of the power grid development stage in the nth region, respectively, and $\Delta P_{D,n}^{max}$ is a positive number. The uncertainty of the regional power grid development stage is equivalent by using an uncertainty auxiliary vector, then:

$$P_{D,n} = \hat{P}_{D,n} + u_{D,n}^{min} P_{D,n}^{min} - u_{D,n}^{max} P_{D,n}^{max} \tag{11}$$

where $P_{D,n}^{max}$ and $P_{D,n}^{min}$ are the maximum and minimum allowable fluctuation values of the uncertainty of the power grid development stage in the nth region, respectively. $u_{D,n}^{max}$ and $u_{D,n}^{min}$ are the auxiliary variables for the uncertainty of the power grid development stage in the nth region, and their feasible region is $U = [0, 1]$.

In this section, the box uncertainty set is adopted primarily based on the following considerations: (1) The historical fluctuation ranges of regional development indicators are relatively easy to obtain, whereas precise distributional information or correlation structures are often difficult to estimate; (2) The box uncertainty set preserves the linear structure of the optimization problem, avoiding the excessive computational burden associated with introducing more complex uncertainty sets; (3) By adjusting the maximum deviation ratio, the conservativeness of the model can be flexibly controlled to meet the requirements of different decision-making scenarios. Compared with other uncertainty set modeling approaches (such as ellipsoidal sets or polyhedral sets), although the box uncertainty set assumes that the uncertain parameters are independent and fluctuate symmetrically—which involves certain simplifications—its advantages of intuitive modeling, few parameters, and high solution efficiency make it more practical for the multi-region, multi-period investment decision-making scenarios considered in this study.

4.2 Construction of Robust Optimization Model for Adjusted Power Grid Investment Allocation

4.2.1 Objective Function

Considering the present value of annual investment capital inflow, the present value of capital outflow mainly based on power transmission and distribution costs, and the tax paid, the net present value is used to describe the power grid investment benefit. Net present value refers to the algebraic sum of the cash inflow and outflow values of an investment plan during the investment period, discounted to the "0" time point under a given interest rate. The specific expression of the net present value of power grid project investment is:

$$N_{pv} = \sum_{t=1}^{T} \left(V_{in} - V_{out}\right)_t \left(1 + I\right)^{-t} \tag{12}$$

where V_{in} and V_{out} are cash inflow and outflow, respectively. I is the discount rate, which is generally 8% in the power industry. This value is determined based on the recommended range (typically 6%–10%) for the benchmark rate of return in the power industry, as specified in the Interim Measures for Economic Evaluation of Electric Power Construction Projects and the *Interim Provisions for Economic Evaluation of Power Grid Construction Projects*. Considering the evolving trends in financing costs and risk premiums for grid companies in the context of the current electricity market reform, a median value of 8% is adopted as the benchmark discount rate.

$$\begin{cases} V_{out} = \sum\limits_{n=1}^{N} p_{tr} P_n^E \left(1 - R_s\right) \\ V_{in} = \sum\limits_{n=1}^{N} \left[p_{el}\left(1 - r_n^{loss}\right) P_n^E + p_{cap} P_n^{cap}\right] R_{tax} \end{cases} \tag{13}$$

where p_{tr} is the unit cost of power transmission and distribution, P_n^E is the electricity load of the n-th region, and R_s is the income tax rate of the power grid company. p_{el} and p_{cap} are the unit energy price and unit capacity price, respectively. r_n^{loss} is the comprehensive line loss rate. P_n^{cap} is the capacity demand of the nth region. R_{tax} is the tax-exclusive amount ratio.

4.2.2 Constraint Conditions

(1) Investment capacity constraint

The baseline allocation results from the first stage, denoted as F_n^*, comprehensively consider the key factors influencing power grid project investments, reflecting both the fundamental development needs of regions and the orientation towards fairness. Therefore, the decision variables y_n in the second-stage optimization model should maintain an appropriate correlation with F_n^* to prevent regional imbalances caused by an excessive pursuit of economic benefits. This linkage is enforced through the following deviation constraint:

$$\left|\frac{y_n - F_n^*}{F_n^*}\right| \le \Delta_a \tag{14}$$

where, y_n is the total power grid project investment in the n-th region, and Δ_a is the acceptable deviation ratio, set to 10% in this study. This value is determined based on the investment allocation dynamic adjustment management rules of provincial power grid companies, which balances the flexibility of robust optimization adjustment and the rigidity of basic allocation fairness, and is widely used in multi-regional power grid investment constraint setting [23]. The mathematical essence of this constraint is to treat the first-stage allocation result F_n^* as a baseline anchor for the second-stage optimization. That is, the decision variable y_n is confined within an interval centered on F_n^*. This mechanism ensures that the second-stage optimization conducts limited adjustments while respecting the baseline allocation, thereby achieving a synergy between fairness assurance and efficiency optimization.

For the investment allocation of power grid projects in different regions, the investment allocation results of previous years should also be fully considered to avoid the allocation amount to a certain region exceeding the previous allocation amount too much, that is:

$$\frac{y_n - y_n'}{y_n'} \le \alpha \tag{15}$$

where, y_n' is the amount allocated to the nth region in the previous year, and α is the acceptable growth rate of the allocation amount, set to 15% in this study. The value is based on the annual investment growth control target of *Shanxi Electric Power Grid in the 14th Five-Year Plan for Energy Development of Shanxi Province*, and is consistent with the actual investment capacity of provincial power grid companies for urban-level grid project construction.

During the total investment period, the total investment shall not exceed a certain range, that is:

$$\sum_{n=1}^{N} y_n = Z' \tag{16}$$

(2) System operation constraint

The capacity-load ratio reflects the reserve situation of power grid capacity and can effectively reflect the coordination of the power system in each region. An excessively high capacity-load ratio of the power grid means that a large number of power supply equipment are idle, reducing the power grid investment efficiency; an excessively low capacity-load ratio will inhibit power consumption and restrict economic development. Therefore, power grid investment should seek a dynamic balance between power grid capacity reserve and investment cost control, so that the ratio of the increased substation capacity to the load in the power supply area is maintained within a certain range. The economic expression of the capacity-load ratio is used to describe the power grid coordination. The regional power grid capacity-load ratio can be calculated according to the following formula:

$$C_{n,min}^{cap} \le C_{cap,n} = \frac{P_{cap,n}}{P_{load,n}^{max}} \le C_{n,max}^{cap} \tag{17}$$

where, $C_{cap,n}$ is the capacity-load ratio of the n-th region, $P_{cap,n}$ is the main transformer capacity of the nth region, and $P_{load,n}^{max}$ is the annual maximum load of the nth region. $C_{n,max}^{cap}$ and $C_{n,min}^{cap}$ are the upper and lower limits of the capacity-load ratio, respectively.

(3) Regional Investment Demand Constraint

To clarify the development stages and investment demands of various regions during the investment period, relevant development data are collected, and the improved Logistic model is used to divide the regional development stages. According to the definition, the improved Logistic growth curve model can be expressed as:

$$q_t = \frac{c}{\left(1 + e^{a-bs(t+l)}\right)^{1/s}} + o \tag{18}$$

where, $a, b, c > 0$. a is a parameter related to the initial value of the function, b is a growth rate parameter, and c is a parameter related to the saturation value of the function. s is a density constraint parameter, $0 < s < +\infty$. l and o are coordinate correction parameters.

Based on this, the regional power grid development stages are divided into initial development stage, rapid development stage, mature development stage, and post-development stage according to the development characteristics. Cities in different development stages have different investment demands. Let the time nodes for dividing each stage be t_1, t_2 and t_3 respectively. The development characteristics of different stages are summarized in Table 2.

Table 2: Characteristics of regional development stages.

Development Stage	Corresponding Period	Development Potential	Development Growth Rate	Development Acceleration
Initial Development Stage	$[0, t_1)$	Large	Small	Positive
Rapid Development Stage	$[t_1, t_2)$	Large	Large	Positive
Mature Development Stage	$[t_2, t_3)$	Small	Large	Negative
Post-Development Stage	$[t_3, \infty)$	Small	Small	Negative

According to the development characteristics of different development stages in Table 2, the investment demands of various regions can be divided, that is, the investment allocation amount of each region, which needs to meet the following constraints:

$$y_{n,t}^{min} \leq y_{n,t} \leq y_{n,t}^{max} \tag{19}$$

where, $y_{n,t}^{max}$ and $y_{n,t}^{min}$ are the maximum and minimum investment demands of the n-th region in the t-th year after calculating the power grid development stages of different regions, respectively.

(4) Net present value constraint

When the net present value $N_{pv} \geq 0$, the investment decision scheme is economically feasible. Therefore, during power grid project investment, the following constraints need to be satisfied:

$$N_{pv,t} \geq 0, t \in [0, T] \tag{20}$$

4.3 Transformation and Solution of Robust Optimization Model

The vector form of the robust optimization model for adjusted power grid investment allocation constructed in the previous section is:

$$\begin{cases} \max\limits_{y} \boldsymbol{C}^T \boldsymbol{y} \\ s.t. \boldsymbol{Ay} \le \boldsymbol{k} \\ \boldsymbol{By} = \boldsymbol{d} \end{cases} \tag{21}$$

where, C is the coefficient column vector corresponding to Eq. (12). y represents the adjusted investment allocation result of the nth region in the t-th year. A and B are the coefficient matrices corresponding to the constraint conditions. k and d are constant column vectors.

According to the cost-benefit calculation method of power grid enterprises, the uncertainty of regional power grid development stages may restrict the cash inflow of enterprises, thereby limiting the economic benefits of power grid investment. To make the final investment allocation result feasible even under the worst-case scenario of uncertainty in regional power grid development stages, the robust optimization model is adopted to find the economically optimal investment decision scheme when the uncertainty of regional power grid development stages changes towards the worst-case scenario. At this time, Eq. (21) can be transformed into a robust optimization model, that is:

$$\begin{cases} \min\limits_{\boldsymbol{u} \in U} \max\limits_{y \in \Omega_{\tilde{u}}} \left(\boldsymbol{C}^T \boldsymbol{y} \right) \\ s.t. \boldsymbol{Ay} \le \boldsymbol{k} \\ \boldsymbol{By} = \boldsymbol{d} \end{cases} \tag{22}$$

where, u is the auxiliary variable for the uncertainty of regional power grid development stages, including $u_{D,n}^{max}$ and $u_{D,n}^{min}$. $\Omega_{\tilde{u}}$ is the feasible region of the adjusted investment allocation result under a certain regional development stage, where the optimal solution $\tilde{u}$ is determined in the outer minimization problem. At this time, in the objective function, the outer minimization problem optimizes the regional power grid development index $P_{D,n}$, aiming to find the worst-case scenario within the uncertain set where the uncertain variables of the current regional development stage minimize the power grid project investment benefit; the inner maximization problem optimizes the investment allocation result and power grid characteristic variables, aiming to find the investment decision scheme that maximizes the investment return under the worst-case scenario.

Through duality theory and strong duality, the min solution problem can be transformed into a max problem, and the two types of max are combined. At this time, the original problem can be transformed into:

$$\begin{cases} \max\limits_{\gamma,\lambda} \boldsymbol{k}^{\mathrm{T}} \boldsymbol{\gamma} + \boldsymbol{d}^{\mathrm{T}} \boldsymbol{\lambda} \\ s.t. \boldsymbol{A}^{\mathrm{T}} \boldsymbol{\gamma} + \boldsymbol{B}^{\mathrm{T}} \boldsymbol{\lambda} \le \boldsymbol{C} \\ \boldsymbol{\gamma} \ge 0 \end{cases} \tag{23}$$

where, γ and λ are the dual variable vectors corresponding to the first and second row constraints in Eq. (21), respectively.

In addition, in the process of characterizing the uncertainty of development stages, assuming that the positive and negative maximum deviation amounts of variables are equal, Eq. (11) can be replaced by Eq. (24) to characterize the uncertainty of development stages.

$$u_{n,t} = \hat{u}_{n,t} + \left(1 + \overline{u}_{n,t}\pi - \underline{u}_{n,t}\pi\right) \tag{24}$$

where, $\overline{u}_{n,t}$ and $\underline{u}_{n,t}$ represent the maximum and minimum deviation values, respectively. $\hat{u}_{n,t}$ is the initial value of the uncertainty of the development stage. The maximum deviation ratio π is initially set to 0.1, which is a moderate uncertainty level selected based on two practical considerations: first, it is the mainstream reference value for robust optimization parameter setting in power system investment research considering regional development uncertainty [18,20]; second, it is consistent with the actual fluctuation range of core development indicators (electricity load, per capita GDP) of cities in Shanxi Province in the past 5 years (8%~12%), ensuring the parameter's fit with the research scenario.

The solution process of the robust optimization model is as follows:

Step 1: Input the initial uncertainty set vector u, set the lower bound $LB = -\infty$, and the upper bound $UB = +\infty$.

Step 2: Solve Eq. (21) according to the initial C_1 to obtain the initial solution y_0 and the objective function z_0, and set $z_0 = UB$.

Step 3: Introduce the uncertain set u to solve Eq. (23), obtain the dual problem objective function $f(x)$ and the latest uncertain set vector u^*, and set $LB = max(LB, f(x))$.

Step 4: Substitute u^* into Eq. (21), update the upper bound UB, and check whether $UB - LB$ converges. If yes, output the results y and z; if not, return to Step 3.

5 Case Study Analysis

5.1 Data Sources and Parameter Settings

To verify the effectiveness of the proposed two-stage investment decision-making model and solution method for power grid projects considering the uncertainty of regional development, five cities in Shanxi Province, China, are selected as practical cases for power grid project investment decision-making analysis. The investment cycle is 5 years, and the initial investment amount is 30 billion RMB. The case modeling and solution are based on the MATLAB R2022b program development and simulation platform, and the YALMIP toolbox is used to call the Gurobi 9.0.2 commercial solver to solve the optimization model.

The historical construction and operational data of urban grid projects used in this paper are primarily derived from statistical data provided by the Economic Research Institute of State Grid Shanxi Electric Power Company, statistical yearbooks of Shanxi Province and its cities, and publicly available information from the Shanxi Provincial Energy Administration and the Power Exchange Center, including data on renewable energy grid-connected capacity, power generation, and the operational status of cross-regional transmission corridors. Additionally, some missing data were supplemented and validated through field re-search and expert interviews to ensure the completeness and reliability of the dataset.

Based on the historical construction and operation data of power grid projects in various cities, the indicators for comprehensive effectiveness evaluation are calculated. Considering the historical data such as power supply and regional GDP of various cities, the power grid development stages of various cities are divided, and the division nodes of power grid development stages are calculated, as shown in Table 3.

Table 3: Comprehensive effectiveness evaluation indicators and development stages of power grid project construction.

Second-Level Indicators	A	B	C	D	E
U11	85.00%	78.00%	65.00%	45.00%	60.00%
U12	72.00%	68.00%	55.00%	38.00%	50.00%

(Continued)

Table 3 (continued)

Second-Level Indicators	A	B	C	D	E
U13	0.01	0.02	0.03	0.05	0.015
U14	60.00%	90.00%	70.00%	50.00%	85.00%
U21	95.00%	88.00%	75.00%	60.00%	82.00%
U22	70.00%	92.00%	80.00%	65.00%	98.00%
U23	0.2	0.3	0.4	0.8	0.25
U24	0.95	0.9	0.85	0.7	0.92
U31	12.00%	10.00%	9.00%	5.00%	8.00%
U32	35.00%	30.00%	22.00%	15.00%	28.00%
U33	25	20	18	10	16
U34	0.03	0.04	0.05	0.08	0.045
U41	1000	1200	800	600	1500
U42	300	650	400	200	800
U43	4500	3800	3200	2800	3500
U44	35,000	30,000	22,000	18,000	28,000

According to the characteristics such as the growth potential, growth rate, and growth acceleration of the development index in each stage in Table 2, the upper and lower limits of investment demand in various cities are divided. Among them, the investment demand development acceleration in the rapid and mature development stages during the investment period is relatively large, while the investment demand growth rate in the post-development stage is relatively stable. Based on the above characteristics, the development value growth rate and growth acceleration in the improved Logistic model are calculated, and the investment demand growth rate range of regions in each development stage is set as shown in Table 4.

Table 4: Development stages and investment demand growth rate ranges.

Development Stage	Investment Demand Growth Rate Range
Initial Development Stage	0.80~1.05
Rapid Development Stage	0.90~1.15
Mature Development Stage	0.90~1.20
Post-Development Stage	0.80~1.05

5.2 Basic Allocation Results in the First Stage

This section aims to verify the effectiveness of the baseline allocation model in ensuring regional fairness. Before applying the raw data to the DEMATEL-ANP model, the original data must be standardized according to Eq. (25).

$$\begin{cases} x_{ij}^* = \dfrac{x_{ij} - m_j}{M_j - m_j} \\ x_{ij}^* = \dfrac{M_j - x_{ij}}{M_j - m_j} \end{cases} \tag{25}$$

where x_{ij}^* is the standardized indicator value, x_{ij} is the original indicator value, $M_j = \max_i \left\{x_{ij}\right\}, m_j = \min_i \left\{x_{ij}\right\}$. For benefit-type (maximizing) indicators, standardization is performed using the first term of Eq. (25); for cost-type (minimizing) indicators, standardization is performed using the second term of Eq. (25). After transformation, the maximum value of the indicator is 1, and the minimum value is 0. This method is not applicable when the indicator values are constant.

On the basis of standardizing the raw data, first, the DEMATEL method is used to analyze the interrelationship between first-level indicators. For the four first-level indicators proposed in this paper, the direct influence matrix given by expert judgment is:

$$X = \begin{bmatrix} 0 & 2 & 3 & 1 \\ 3 & 0 & 3 & 2 \\ 1 & 2 & 0 & 2 \\ 1 & 2 & 2 & 0 \end{bmatrix} \tag{26}$$

The comprehensive influence matrix is calculated as:

$$T = \begin{bmatrix} 0.505 & 0.792 & 1.022 & 0.642 \\ 0.911 & 0.743 & 1.208 & 0.851 \\ 0.554 & 0.713 & 0.640 & 0.657 \\ 0.554 & 0.713 & 0.840 & 0.457 \end{bmatrix} \tag{27}$$

The centrality $(D + R)$ and cause degree $(D - R)$ of each first-level indicator are shown in Table 5.

Table 5: Centrality and cause degree of first-level indicators.

First-Level Indicators	$\boldsymbol{D + R}$	$\boldsymbol{D - R}$
U_1	5.485	0.436
U_2	6.673	0.752
U_3	6.273	−1.145
U_4	5.172	−0.044

It can be seen from the comprehensive matrix T and Table 5 that there are influence relationships between the four first-level indicators in the evaluation index system constructed in this paper. The operational level and technical level are cause factors, and their impact on other indicators is greater than the impact they receive from other indicators. The mutual influence between the four first-level indicators can be represented by Fig. 2.

On the basis of the mutual influence relationship of first-level indicators, according to the meaning of second-level indicators, the network hierarchical structure of the power grid project investment impact index system can be obtained, as shown in Fig. 3.

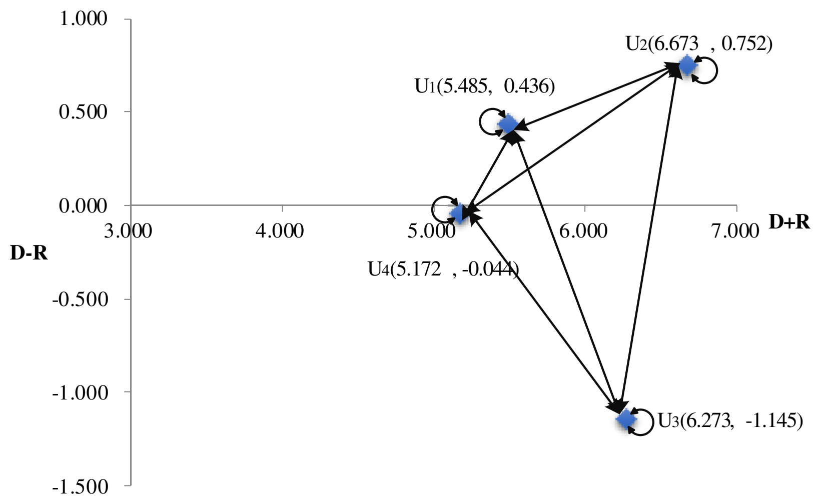

Figure 2: Correlation between first-level indicators.

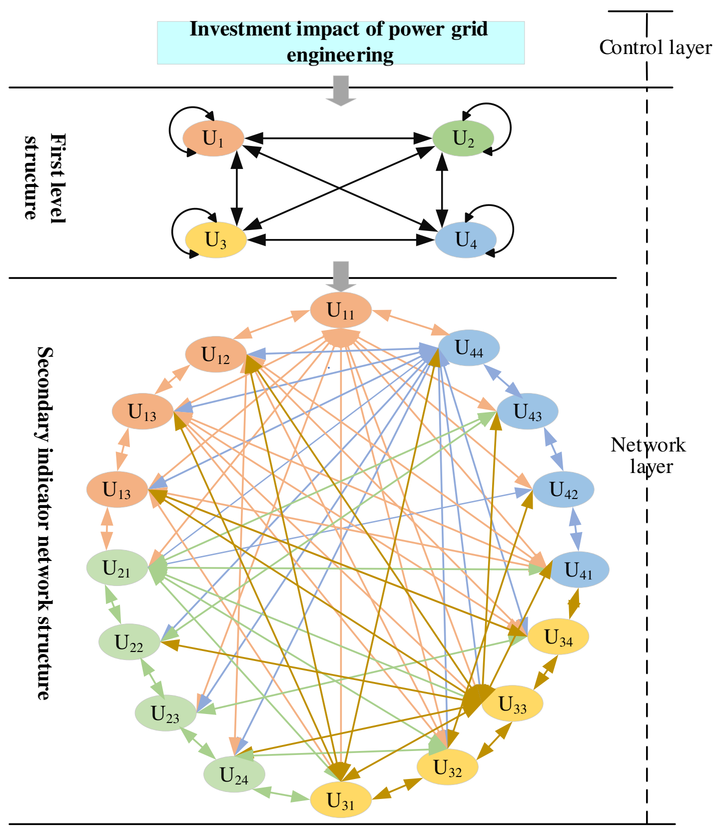

Figure 3: Network hierarchical structure of the indicator system.

According to the ANP network hierarchical structure of the indicator system, the weight coefficients w_{ij} of all second-level indicators are calculated using Super Decision software, as shown in Table 6.

Table 6: ANP weight results of second-level indicators.

Indicators U_{ij}	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**
Weight w_{ij}	0.035	0.030	0.050	0.035
Indicators U_{ij}	U_{11}	U_{12}	U_{13}	U_{14}
Weight w_{ij}	0.080	0.120	0.070	0.080
Indicators U_{ij}	U_{11}	U_{12}	U_{13}	U_{14}
Weight w_{ij}	0.100	0.080	0.060	0.060
Indicators U_{ij}	U_{11}	U_{12}	U_{13}	U_{14}
Weight w_{ij}	0.070	0.050	0.040	0.040

It can be seen from the weight calculation results that among the 16 second-level indicators, the indicators with larger weight values are successively Renewable Energy Grid Connection Adaptation Rate, Total Investment Internal Rate of Return, Power Grid Intelligent Coverage Rate, Registered Capital Net Profit Rate, Power Grid Structure Rationality Index, and Total Equivalent Emission Reduction of $SO_2/NO_x/CO_x$ Particulates. This reflects the emphasis on the technical level and economic benefits of power grid project construction. On this basis, the basic power grid project investment allocation results of the five cities during the investment cycle can be calculated according to Eqs. (8) and (9), as shown in Table 7.

Table 7: Basic power grid project investment allocation results (10^4 RMB).

Year	**A**	**B**	**C**	**D**	**E**
2026	649,210.8	678,094.1	589,208.9	513,191.1	570,295.1
2027	662,195.0	691,656.0	600,993.1	523,455.0	581,701.0
2028	675,179.2	705,217.8	612,777.2	533,718.8	593,106.9
2029	688,163.5	718,779.7	624,561.4	543,982.6	604,512.8
2030	701,147.7	732,341.6	636,345.6	554,246.4	615,918.7

5.3 Adjust the Allocation Results in the Second Stage

Based on the DEMATEL-ANP basic allocation results, this section further validates the effectiveness of adjusting the allocation model in optimizing investment efficiency and controlling risks.

5.3.1 Adjusted Power Grid Investment Allocation Results

Based on the basic power grid investment allocation, the above robust optimization model is solved in this section to obtain the adjusted power grid investment allocation results, as shown in the Fig. 4.

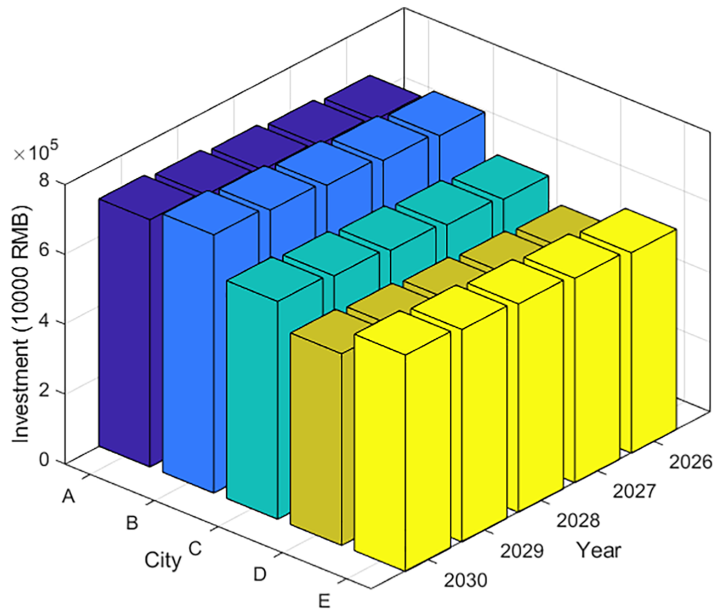

Figure 4: Adjusted power grid investment allocation results (π = 0.1).

It can be seen from the figure that due to the annual increase in the upper limit of investment, the investment allocation of various cities shows an overall upward trend, but the increase range varies. Among them, the investment amount of City A and City B is always at a high level. The main reason is that City A and City B are relatively developed in industry and economy. Maintaining a relatively perfect power grid operation requires increasing investment, maintaining a high investment level and gradually increasing the investment amount, which is in line with the urban economic, social, and power grid development needs. During the investment cycle, City A has the largest allocated fund scale, 6.557 billion yuan, with an annual increase of about 1%. In addition, from the specific indicators, both City A and City B have high annual maximum load rates and total investment internal rates of return. Therefore, investing in power grid projects in City A and City B is not only necessary but also can ensure high returns.

For City D and City E, their development level and annual maximum load rate are relatively low, and their investment amount is low in the allocation results, which matches their development status. However, they are in a period of rapid development during the investment period, so the relatively fast growth rate of investment amount is also consistent with their investment demand. Considering that such regions have great development potential and investment demand, the current results meet the expected power grid development needs and can ensure low investment risk.

Compared with the first stage, City D has the lowest basic allocation (relatively backward development stage), and it slightly decreases after adjustment (a decrease of 1%), but the growth rate matches its own rapid development stage (annual investment demand growth rate of 0.9–1.15), avoiding risks caused by excessive investment while ensuring basic construction needs. City E has the highest renewable energy grid connection adaptation rate (98%), and it is slightly adjusted after adjustment (basically unchanged), balancing social and environmental benefits with investment economy, which is in line with the construction goal of "empowering society".

5.3.2 Analysis of the Impact of Regional Development Uncertainty

The value of the maximum deviation ratio π will have an impact on the power grid project investment results. With the increase of this value, it indicates that the uncertainty of the regional power grid development stage is greater. In view of this, this section further analyzes the impact of the maximum deviation ratio π. When π = 0.2, the robust interval width increases. This value corresponds to a fluctuation range of ±20% of the benchmark value, simulating scenarios where uncertainty is significantly amplified due to extreme policy changes, major technological breakthroughs, or external shocks (e.g., macroeconomic fluctuations, energy policy adjustments). In accordance with the requirement to "reserve 10%–20% flexibility margin" proposed in the "14th Five-Year Plan for Electric Power Development," and considering the structural volatility characteristics of Shanxi Province as a resource-based region undergoing transformation, the 20% fluctuation interval serves as a typical stress-test scenario to ex-amine the model's conservativeness and adaptability under extreme uncertainty. At this time, the robust optimization model for power grid project investment is solved, and the adjusted investment allocation results of various cities during the investment period are obtained, as shown in Fig. 5.

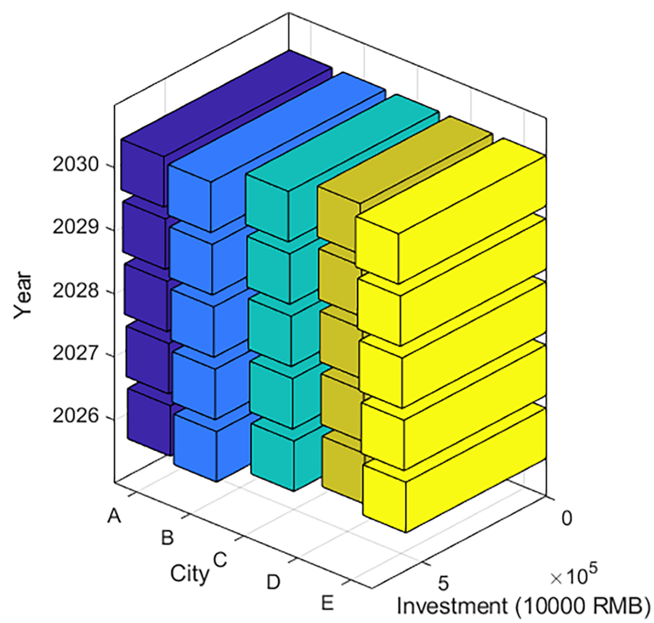

Figure 5: Adjusted power grid investment allocation results (π = 0.2).

Comparing Figs. 4 and 5, it can be seen that increasing the deviation parameter makes the investment allocation results of various cities tend to be flat over time, and the investment results are more conservative. At this time, not only the change trends of investment amounts among different cities are similar, but also the change ranges of investment amounts in each city are flatter. Taking City C as an example, according to the development stage division results, due to its large investment demand during the investment period, the deviation ratio π increases, and the investment allocation result of City D is still at a high level, but the investment change rate from 2026 to 2030 changes from 8.0% to 3.61%. The deviation between the adjusted amount and the basic allocation result of all cities is ≤3%, and the deviation range is smaller than that when π = 0.1, reflecting the enhanced ability to resist uncertainty. It can be seen that increasing the robust interval width can reduce the change range of investment allocation results, reduce economy, but enhance the ability to resist uncertainty, and the investment results tend to be conservative.

Therefore, increasing the robust interval width can not only ensure lower investment risk but also ensure that the annual investment capacity is within the constraints of the regional power grid development stage, so that the investment decision results can meet various constraints when the uncertainty of the development stage is large.

5.3.3 Analysis of the Anchoring Effect of Stage 1 Allocation Results as Constraints in Stage 2

As shown in Eq. (14), the first-stage allocation result F_n^* directly serves as a baseline constraint for the second-stage optimization. To intuitively demonstrate this anchoring effect, the relative deviation is defined as $d_n = (y_n - F_n^*)/F_n^*$, and the distribution characteristics of d_n for each city over the investment period are calculated. When $\pi = 0.1$, the statistical results of d_n for each city are presented in Table 8.

Table 8: Relative deviation between investment allocation and basic allocation in various cities (Average from 2026–2030).

City	Mean of F_n^* (10^8)	Mean of y_n (10^8)	d_n	Maximum Positive Deviation	Maximum Negative Deviation
A	67.12	65.56	−2.32%	−1.85%	−2.78%
B	68.55	68.47	−0.12%	0.35%	−0.62%
C	59.21	59.21	0.00%	0.41%	−0.38%
D	51.32	50.85	−0.92%	−0.54%	−1.23%
E	57.03	55.91	−1.96%	−1.67%	−2.31%

As shown in Table 9, the investment allocation results for each city are strictly controlled within the deviation range of $\Delta_a = 5\%$, with the absolute deviation for most cities being less than 2.5%. This indicates that the second-stage optimization fully respects the fairness orientation of the baseline allocation. Among them, the allocation results for Cities B and C are highly consistent with the baseline allocation (deviation close to 0), while Cities A and E exhibit slight negative deviations, reflecting the model's marginal adjustment towards more efficient regions while remaining within the constraints.

Table 9: Investment returns under different deviation ratios.

Maximum Deviation Ratio π	Total Investment Net Profit (10^8 RMB)	Decline Compared with Deterministic Optimization ($\pi = 0$)	Model Conservatism
0	20.40	–	Lowest (only pursuing economy, ignoring uncertainty)
0.05	19.87	2.67%	Low (slightly considering stability, low uncertainty tolerance)
0.10	19.68	3.66%	Medium (balancing economy and stability)

(Continued)

Table 9 (continued)

Maximum Deviation Ratio π	Total Investment Net Profit (10^8 RMB)	Decline Compared with Deterministic Optimization ($\pi = 0$)	Model Conservatism
0.15	19.38	5.26%	High (focusing on stability, appropriately sacrificing economy)
0.20	19.15	6.53%	Highest (prioritizing stability, strongest ability to resist uncertainty)

5.4 Comparative Analysis of Models

5.4.1 Comparative Analysis of Investment Benefits

When simulating scenarios with large uncertainty of regional power grid development stages and studying the impact of robust interval width on investment decision results, the maximum deviation parameter can be appropriately increased. The robust optimization model first finds the worst-case scenario of uncertainty in regional development stages, and then optimizes the investment allocation, so that the investment allocation results meet all constraints under the worst-case scenario within the robust interval. To more intuitively compare the robust optimization and deterministic optimization results under different robust intervals and verify the conservatism of robust optimization, the robust interval width is adjusted and the net profit of investment allocation decisions corresponding to different interval widths is calculated. The results are shown in Table 9. Among them, $\pi = 0$ corresponds to the maximum deviation value of uncertain variables being 0, which is deterministic optimization.

It can be seen from Table 8 that compared with the deterministic optimization results, the net profit of investment allocation decisions of robust optimization is lower when considering the uncertainty of development stages. With the continuous increase of the maximum deviation value π, the net profit of investment decisions gradually decreases, and the conservatism of the optimization model increases. When $\pi = 0.2$, the total investment profit of the optimization model decreases by 6.53% to ensure lower investment risk. With the increase of the robust interval width, the uncertainty of the development stage in the robust optimization model further increases, and the model obtains a more stable and conservative investment decision result by sacrificing part of the economic benefits. In the actual investment decision-making process, the robustness of the model should be adjusted to seek a balance between economy and stability in the investment decision results, so that the investment results meet the decision-makers' needs.

In summary, the results further confirm that adjusting the deviation parameter can control the robustness of the model's uncertainty set. In actual investment decision-making, investors can adjust the deviation parameter according to the acceptance degree of the uncertainty of the development stage and the adaptability to the risk of various constraint violations to obtain decision schemes under different scenarios.

5.4.2 Comparative Analysis of Different Models

This section aims to comprehensively evaluate the overall performance of the two-stage framework. To fully validate the advantages of the proposed two-stage investment decision-making framework in balancing regional fairness and investment efficiency, as well as enhancing robustness, three benchmark models are designed for comparative analysis with our model. All models are based on the same total investment amount (30 billion RMB), investment period (2026–2030), and regional development uncertainty parameters (using a box uncertainty set with a maximum deviation ratio of $\pi = 0.1$), with the 2026 allocation results taken as an example for horizontal comparison.

Model M0 (Deterministic Optimization): This model does not consider regional development uncertainty and takes maximizing net present value as its single objective.

Model M1 (Single-Stage Robust Optimization): This model introduces a box uncertainty set to describe regional development uncertainty ($\pi = 0.1$) based on M0, with the objective function being to maximize the net present value under the worst-case scenario (i.e., the inner-outer layer optimization of Eq. (22)). However, it still does not include constraints related to the baseline allocation.

Model M2 (Baseline Allocation Only): This model only applies the first-stage DEMATEL-ANP method to calculate the baseline allocation for each city (Table 7), without performing the second-stage robust optimization adjustment.

Model M3 (The Proposed Two-Stage Model): This model adopts the complete framework proposed in this paper, that is, it introduces the robust optimization adjustment ($\pi = 0.1$) based on M2, while simultaneously satisfying the constraints of Eqs. (14) and (15).

To comprehensively evaluate the performance of each model, a quantitative comparison is conducted based on the following four indicators. Total NPV reflects the economic benefits of the investment and is calculated using nominal values (without considering uncertainty). Worst-case NPV assesses the model's risk resistance capability by setting the uncertainty variables to their worst-case values (i.e., the boundaries of the π fluctuation interval) and re-evaluating the NPV under each scenario. The Regional Investment Fairness Index (FI) is measured by the coefficient of variation (standard deviation/mean) of the investment allocation amounts across cities, where a smaller coefficient of variation indicates a more balanced inter-regional allocation. Deviation from Base Allocation (DBA) is measured by the Mean Absolute Percentage Error (MAPE) between each city's allocation amount and the baseline allocation from Model M2, reflecting the degree to which the model adheres to the baseline allocation results. The calculation results for each model are presented in Table 10 (taking the year 2026 as an example).

Table 10: Comparison of investment decision results of different models.

Model	Investment Allocation Quota for Each City (10^8 RMB)					NPV	Worst-Case NPV	FI	DBA
	A	B	C	D	E				
MO	70.12	72.89	58.42	48.75	49.82	21.36	18.24	0.185	8.70%
M1	68.45	71.23	59.16	50.34	50.82	20.87	19.13	0.166	6.20%
M2	64.92	67.81	58.92	51.32	57.03	19.52	19.52	0.102	0%
M3	65.56	68.47	59.21	50.85	55.91	19.68	19.68	0.113	2.30%

Note: The Worst-case NPV for M2 is equal to its nominal NPV, as it does not involve uncertainty adjustments; for M3, the NPV remains unchanged under the worst-case scenario through robust optimization adjustments (as guaranteed by the model).

As can be seen from Table 10, Model M0 achieves the highest nominal NPV (2.136 billion RMB), but this comes at the cost of ignoring uncertainty. Model M1, through robust optimization, sees its nominal NPV decrease to 2.087 billion RMB (a decrease of 2.3%), but its worst-case NPV increases from 1.824 billion RMB to 1.913 billion RMB (an increase of 4.9%), demonstrating the risk-averse effect of robust optimization.

Model M2 has a nominal NPV of 1.952 billion RMB, lower than M0 and M1, as it does not perform economic optimization. Model M3 achieves a nominal NPV of 1.968 billion RMB, slightly higher than M2 (+0.8%). At the same time, its worst-case NPV is consistent with the nominal value, significantly exceeding the worst-case values of M0 and M1. This indicates that, while ensuring baseline fairness, the proposed model effectively improves investment economic efficiency and completely hedges against uncertainty risks.

The coefficient of variation for regional investment in M0 is the largest (0.185), indicating that deterministic optimization over-concentrates resources in high-yield cities A and B, exacerbating regional development imbalance. The coefficient of variation for M1 decreases to 0.166 but remains higher than those of M2 and M3. M2 has the smallest coefficient of variation (0.102), reflecting the fairness-assuring role of the baseline allocation. The coefficient of variation for M3 is 0.113, slightly higher than M2 but still significantly lower than M0 and M1, indicating that the second-stage adjustment does not significantly sacrifice fairness while improving economic efficiency.

The deviation (DBA) for M3 is 2.3%, considerably lower than that of M0 (8.7%) and M1 (6.2%), demonstrating that the proposed model fully respects the baseline allocation results from the first stage during the optimization process, ensuring the coherence and policy interpretability of the investment decisions.

Fig. 6 intuitively illustrates the relative positions of each model within the three-dimensional space of "Economy-Fairness-Robustness". It can be observed that M0 pursues economic efficiency but at the expense of fairness and robustness. M1 shows improvement in robustness but still lacks adequate fairness. M2 ensures fairness, yet its economic efficiency remains relatively low. Only M3 achieves a favorable balance among all three dimensions, thereby validating the effectiveness of the two-stage framework proposed in this paper.

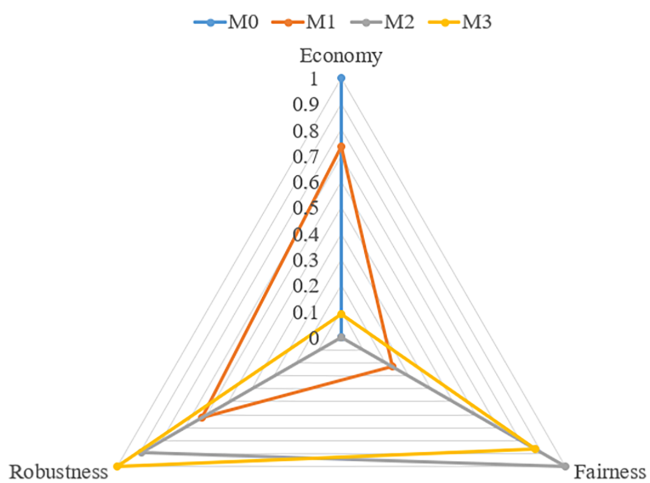

Figure 6: Radar chart comparing different models in terms of economy, fairness, and robustness dimensions.

In summary, the two-stage model proposed in this paper, by organically combining the fairness orientation of DE-MATEL-ANP with the risk-averse capability of robust optimization, significantly enhances the risk resistance of investment decisions (with worst-case NPV 7.9% higher than that of M0) while maintaining a high level of regional fairness (coefficient of variation of only 0.113), at the cost of a minimal sacrifice in economic efficiency (0.8% improvement compared to M2, and 7.9% decrease compared to M0). This result indicates that, although the proposed model does not achieve the optimum in economic performance, it achieves a reasonable trade-off among the three dimensions by exchanging a slight economic loss for substantial gains in fairness and robustness. This fully demonstrates the superiority of the two-stage framework in coordinating multiple objectives.

6 Conclusions

This paper systematically investigates three core issues: first, how to ensure fairness in inter-regional investment allocation, which is addressed by constructing a baseline allocation model based on DEMATEL-ANP; second, how to optimize investment benefits and control risks under uncertain environments, which is resolved by introducing robust optimization to build an adjustment allocation model; and third, how to validate the effectiveness of the two-stage framework in balancing fairness and efficiency, which is verified through case analysis and model comparison using five cities in Shanxi Province. The main research conclusions are as follows:

(1) Regarding the fairness assurance issue: The influencing factors of power grid project investment are analyzed, and the DEMATEL-ANP combined weighting method is used to evaluate the contribution of each influencing factor, thereby constructing a basic allocation model considering regional demand characteristics, providing a solid foundation for subsequent power grid project investment allocation.
(2) Regarding the efficiency optimization and risk control issue: The robust optimization model for adjusted power grid investment allocation considering the uncertainty of regional development stages can optimize the investment allocation decision, and the obtained decision scheme is in line with the regional power grid development needs and investment capacity.
(3) Regarding the framework effectiveness validation: Compared with deterministic optimization, the calculation results of the robust optimization model are conservative, and the benefits of power grid project investment decisions are reduced, but the ability to cope with uncertain interference is stronger, and the faced investment risk is lower. In addition, the increase of the robust interval width can enhance the conservatism of the investment decision scheme. Compared with deterministic optimization, when the robust interval π rises to 0.2, the total investment profit decreases by 6.53%. In actual investment decision-making, investors can adjust the deviation parameter according to the investment risk-bearing capacity of each region to obtain decision schemes under different scenarios.

It should be noted that this paper employs a box uncertainty set for uncertainty characterization. The independence assumption of the box set overlooks the inherent correlations among various factors influencing regional development (e.g., the strong positive correlation between GDP growth and electricity load), which may lead to robust solutions that are either overly conservative or insufficiently covered when addressing joint extreme scenarios. In future research, polyhedral budget sets or data-driven distributionally robust optimization methods could be introduced to characterize the uncertainty structure more precisely while maintaining computational feasibility. Furthermore, the impact of policy instruments such as carbon trading markets and green certificate trading on grid investment returns should be further considered, incorporating policy uncertainty into the robust optimization framework.

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Appendix A Definition and Calculation Method of Main Indicators

(1) Operational Level Dimension

1) Annual Maximum Load Rate (AMLR): It is a core indicator to measure the utilization degree of load-bearing capacity of the power grid system within a certain period. It not only reflects the matching degree between the actual operating load of the system and the rated bearing capacity but also reflects the load utilization efficiency and safety redundancy level. It is a key basis for evaluating the operating status of the power grid and optimizing resource allocation in the new power system.

$$AMLR = \frac{L_{max}}{C_r} \times 100\% \tag{A1}$$

where, L_{max} is the maximum load actually borne by the power grid system within the statistical period. C_r is the maximum safe bearing load of the power grid system.

2) Annual Equivalent Average Load Rate (AEALR): It is a key indicator to evaluate the annual operating efficiency and capacity allocation rationality of power grid projects. By integrating the actual power transmitted by the power grid project throughout the year and the rated bearing capacity, it avoids the one-sidedness of a single peak indicator and can objectively reflect the planning scientificity, investment benefit level, and load-bearing balance of power grid project construction.

$$AEALR = \frac{P_{trans}}{C_r} \times h \times 100\% \tag{A2}$$

where, P_{trans} is the total electric energy actually transmitted by the power grid project within the statistical year, and h is the annual statistical utilization hours.

3) Transformer Forced Outage Rate (FOR): It is a key indicator to measure the reliable operation level and construction, operation, and maintenance quality of power grid projects (core equipment such as main transformers in substations). By calculating the proportion of unplanned outage time or times to the total operation benchmark, it intuitively reflects the sudden outage risk of transformers caused by equipment selection defects, poor construction and installation quality, inadequate operation and maintenance, etc.

$$FOR = \frac{FOR_h}{Total_h} \times 100\% \tag{A3}$$

where, FOR_h is the unplanned outage time caused by faults or abnormalities, including the first type (immediate outage) and the second type (outage required within 6 h) of unplanned outage time. $Total_h$ is the total time within the statistical period.

4) Utilization Rate of Power Grid External Transmission Capacity (URPG): It is a core benefit indicator to quantitatively evaluate the construction effect of external transmission power grid projects such as cross-regional transmission channels and inter-provincial tie lines. Its core

characterizes the matching degree between the actual transmission efficiency of the external transmission channel and the designed rated capacity.

$$URPG = \frac{P_{tr}}{P_r \times h_{tr}} \times 100\% \tag{A4}$$

where, P_{tr} is the actual power transmitted by the power grid external transmission channel, P_r is the designed rated capacity of the power grid external transmission channel, and h_{tr} is the statistical period hours.

(2) Technical Level Dimension

1) Power Grid Intelligent Coverage Rate (ICPG): It represents the proportion of power grid facilities with intelligent functions (such as intelligent perception, automatic control, digital operation and maintenance, etc.) to all power grid facilities. This indicator directly reflects the application effect of intelligent technologies in power grid project construction.

$$ICPG = \left(\frac{N_{int}}{N_{total}} + \frac{L_{int}}{L_{total}}\right)/2 \times 100\% \tag{A5}$$

where, N_{int} is the number of core power grid equipment (units) that have been intelligently transformed within the evaluation scope, including intelligent transformers, intelligent switches, smart meters, digital substations, etc., and N_{total} is the total number of core power grid equipment (units) within the evaluation scope. $\mathrm{L}_{\mathrm{int}}$ is the length of transmission lines/distribution areas within the evaluation scope that have achieved intelligent operation and maintenance and digital monitoring, and $\mathrm{L}_{\mathrm{total}}$ is the total length of transmission lines or the total coverage length of distribution areas within the evaluation scope.

2) Renewable Energy Grid Connection Adaptation Rate (RGAR): It is a core source-grid coordination indicator to quantitatively evaluate the support capacity of power grid project construction for the grid connection acceptance and coordinated operation of renewable energy (wind power, photovoltaic, etc.). It characterizes the matching degree between the actual accepted and connected renewable energy capacity (or power) of the power grid project and the maximum adaptive renewable energy capacity (or power) that the project can carry according to the planning and design.

$$RGAR = \frac{E_{grid-connected}}{E_{adaptable}} \times 100\% \tag{A6}$$

where, $E_{grid-connected}$ is the total renewable energy generation connected to the grid and consumed through the power grid project, and $E_{adaptable}$ is the maximum renewable energy consumption that the power grid project can adapt to.

3) Power Grid Fault Self-healing Response Time (SHPF): It represents the cumulative time of the entire process in which the power grid can automatically complete fault identification, location, isolation, and power supply restoration in non-faulty areas through its own intelligent system (such as intelligent dispatching, distributed control, fault location and isolation technology, etc.) without manual intervention after a fault occurs.

$$SHPF = \frac{\sum_{i=1}^{n}\left(T_{det,i} + T_{iso,i} + T_{res,i}\right)}{n} \tag{A7}$$

where, n is the total number of power grid faults that occurred during the evaluation period, met the self-healing conditions, and successfully achieved self-healing (times), excluding manual intervention faults and major faults beyond the self-healing capacity. $T_{det,i}$ is the time from the occurrence of the i-th fault to the completion of fault identification by the power grid intelligent system, $T_{iso,i}$ is the time from the completion of identification of the i-th fault to the automatic isolation of the fault area by the system to avoid fault expansion, and $T_{res,i}$ is the time from the completion of isolation of the i-th fault to the automatic restoration of normal power supply in the non-faulty area by the system.

4) Power Grid Structure Rationality Index (GSRI): It is a core planning indicator to quantitatively evaluate the comprehensive effects of power grid project construction in terms of grid topology optimization, supply-demand adaptation, safety redundancy, and resource allocation efficiency. It characterizes the adaptation degree of the power grid structure to load distribution, power supply layout, safe operation constraints, and renewable energy grid connection demand through the weighted integration of multi-dimensional sub-indicators.

$$GSRI = \sum_{k=1}^{m} \omega_k \times S_k \tag{A8}$$

where, m is the number of selected sub-indicators, ω_k is the weight of the kth sub-indicator, and S_k is the standardized value of the k-th sub-indicator, with a value range of $[0, 1]$.

To ensure that sub-indicators of different dimensions can be added, the extreme value standardization method is used to standardize each sub-indicator, as follows:

For positive indicators:

$$S_k = \frac{x_k - x_{k,min}}{x_{k,max} - x_{k,min}} \tag{A9}$$

For negative indicators:

$$S_k = \frac{x_{k,max} - x_k}{x_{k,max} - x_{k,min}} \tag{A10}$$

where, $x_{k,max}$ and $x_{k,min}$ are the optimal and worst values of the k-th sub-indicator, respectively. In the calculation of the power grid structure rationality index, four key sub-dimensions can be considered: grid connectivity x_1, zonal load balance x_2, $N-1$ pass rate x_3, and tie line redundancy coefficient x_4.

$$\begin{cases} x_1 = \dfrac{2L}{N(N-1)} \\ x_2 = 1 - \dfrac{max\left|P_2 - \overline{P}\right|}{\overline{P}} \\ x_3 = \dfrac{L_{N-1}}{L} \times 100\% \\ x_4 = \dfrac{\sum \left(C_{link,z} - P_{trans,z}\right)}{\sum P_{trans,z}} \end{cases} \tag{A11}$$

where, L is the number of power grid branches, and N is the number of nodes. P_2 is the zonal load, and $\overline{P}$ is the average zonal load. L_{N-1} is the number of branches that meet the $N-1$ safety constraint. $C_{link,z}$ is the rated capacity of the zonal tie line, and $P_{trans,z}$ is the actual transmission power of the zonal tie line.

(3) Economic Benefits Dimension

1) Total Investment Internal Rate of Return (IRR): It is a core economic benefit indicator to quantitatively evaluate the full-life cycle financial profitability and investment feasibility of power grid project construction. It characterizes the discount rate at which the present value sum of the net cash flows generated by the total investment of the power grid project during the full life cycle is equal to zero.

$$NPV = \sum_{t=0}^{n} \frac{CF_t}{(1 + IRR)^t} = 0 \tag{A12}$$

where, NPV is the net present value, which represents the present value difference of the project's cash flow discounted at the discount rate. CF_t is the net cash flow in the t-th year, that is, cash inflow minus cash outflow.

2) Registered Capital Net Profit Rate (ROE): It is a core economic benefit indicator to quantitatively evaluate the financial benefits and capital operation efficiency of power grid project construction. It characterizes the ability of the power grid project to create net profit using the net assets owned by the owners.

$$ROE = \frac{N_{proj}}{\overline{N_{proj}}} \times 100\% = \frac{N_{proj}}{(N_{beg} + N_{end}) \times 0.5} \times 100\% \tag{A13}$$

where, N_{proj} is the net profit of the power grid project. $\overline{N_{proj}}$ is the weighted average net assets of the power grid project. N_{beg} and N_{end} are the net asset amounts corresponding to the power grid project at the beginning and end of the period, respectively.

3) Unit New Asset Load Increment (IUNL): It is a core economic benefit indicator to quantitatively evaluate the investment efficiency and asset load-bearing benefits of power grid project construction. It characterizes the regional load increment level corresponding to each unit of new power grid assets during the construction cycle of the power grid project.

$$IUNL = \frac{\Delta P_{load}}{\Delta A_{asset}} \tag{A14}$$

where, ΔP_{load} is the new maximum load in the power supply range of the power grid project after it is put into operation. ΔA_{asset} is the total amount of new assets formed by the construction of the power grid project, i.e., the original value of fixed assets converted after the completion and commissioning of the project (including all construction costs such as equipment purchase, civil engineering construction, and installation and commissioning).

4) Unit Power Supply Investment Cost (ICPG): It is a core economic benefit indicator to evaluate the investment economy and resource allocation efficiency of power grid project construction. It characterizes the total construction investment scale corresponding to each unit of planned power supply of the power grid project.

$$ICPG = \frac{I_{total}}{E_{life}} \tag{A15}$$

where, I_{total} is the total construction investment of the power grid project. E_{life} is the planned total power supply of the power grid project during its design life cycle.

(4) Social and Environmental Benefits Dimension

1) Total Equivalent Emission Reduction of $SO_2/NO_x/CO_x$ Particulates (TEER): It is a core environmental benefit indicator to quantitatively evaluate the environmental coordination benefits and green low-carbon transition effects of power grid project construction. It characterizes the cumulative emission reduction of sulfur dioxide (SO_2), nitrogen oxides (NO_x), and carbon dioxide (CO_2) pollutants indirectly achieved through power grid project construction.

$$\begin{cases} TEER = \sum_{p=1}^{n} E_p = E_{SO_2} + E_{NO_x} + E_{CO_2} \\ E_p = E_{sub} * (F_{base} - F_{new}) + \Delta E_{grid} * F_{base} \end{cases} \tag{A16}$$

where, E_p is the emission reduction of the p-th type of pollutant (p Operational Level Dimensio-Operational Level DimensioOperational Level Dimensio 1 corresponds to SO_2, p = 2 corresponds to NO_x, and p = 3 corresponds to CO_2). E_{sub} is the renewable energy generation that replaces fossil energy with the support of the power grid project. F_{base} and F_{new} are the baseline emission factor and the pollutant emission factor of renewable energy generation, respectively. Among them, renewable energy power generation such as wind power and photovoltaic power has no pollutant emissions during the power generation process, so the value is 0; if it includes biomass power generation, the value is based on the actual emission intensity. ΔE_{grid} is the reduction in transmission loss achieved by the power grid project through grid structure optimization and intelligent regulation. n is the number of pollutant types included in the accounting.

2) Promoted Renewable Energy Consumption (PREC): It refers to the new effective renewable energy consumption electric energy increased through power grid project construction (such as grid structure optimization and upgrading, cross-regional transmission channel construction, intelligent dispatching system improvement, and grid connection adaptation capacity enhancement).

3) Electricity-Supported Per Capita Income of Residents (ESIR): It is a core correlation indicator to quantitatively evaluate the social and people's livelihood benefits of power grid project construction. It characterizes the growth in per capita disposable income of regional residents indirectly driven by the new power supply capacity of the power grid project.

$$ESIR = \frac{I_{pc}}{E_a} E_b \tag{A17}$$

where, I_{pc} is the per capita income of residents in the power grid service area. E_a is the total social electricity consumption in the power grid service area. E_b is the new power supply of the power grid project.

4) Boosted Number of New Jobs (BNNJ): It is a core social indicator to quantitatively evaluate the social contribution and people's livelihood empowerment effects of power grid project construction. It characterizes the total number of new jobs created by the investment in power grid project construction through directly driving project construction, indirectly pulling upstream and downstream supporting industries in the industrial chain, and long-term supporting operation and maintenance services.

$$BNNJ = BNNJ_1 + BNNJ_2 = I_{total} \times \frac{J_z}{I_r} + \frac{J_z}{P_{qs}} \times E_b \tag{A18}$$

where, $BNNJ_1$ and $BNNJ_2$ are the number of jobs driven by the power grid project during the construction period and operation period, respectively. J_z is the number of new jobs in the area served by the power grid project. I_r is the total fixed asset investment in the area. $\frac{J_z}{I_r}$ is the number of jobs driven by unit investment. P_{qs} is the total social electricity consumption in the area.

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