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A Cloud- and Game Model-Based Approach to Project Evaluations of Sustainable Power Supply Investments

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Abstract: In light of electrical energy's increasing role in economic systems worldwide, prioritizing investments in sustainable power supplies has become paramount. This study proposes a model based on cloud theory and game theory to evaluate sustainable power supply investment projects. It establishes a foundation for assessing the merits of power supply investments, which are crucial for continuous electricity provision and economic advancement. By integrating an enhanced analytic hierarchy process and the entropy method, the study develops a dual-weighted evaluative index system. This hybrid approach addresses ambiguities and enhances the weight determination accuracy, which, when applied to the Liaojiawan Transformer Substation, verifies the project's high benefit level, corroborated by empirical data. This innovative methodology offers a strategic framework for future power supply investments.

Keywords: sustainable power supply investment; power supply projects; investment benefit; cloud and game models

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1. Introduction

Given the rapid economic expansion and the resulting surge in demand for electricity across various sectors, the investment in sustainable power supply has become paramount. This growth necessitates not only the expansion of the grid infrastructure but also a detailed examination of the complex environmental factors that influence such developments [1]. Therefore, conducting research on developing a sustainable, scientifically robust methodology for evaluating the benefits [2] of power supply projects is essential. The motivation is to ensure the integrity of construction, operations [3], and management practices [4], addressing the need for comprehensive assessment tools in the face of environmental, economic, and technological complexities.

The research surrounding sustainable power supply investments has evolved, utilizing fuzzy membership functions for enhanced distribution network operations [5]. Despite such progress, challenges like a reliance on expert judgments and the subjectivity in determining weights remain, potentially skewing results [6]. The incorporation of cloud models offers a promising solution, facilitating a balanced blend of qualitative and quantitative data and promising more accurate evaluations. This highlights the importance of advancing research to address biases and improve the decision-making process for sustainable power investments.

Addressing the above-mentioned limitations in current evaluation methods, this study proposed a cloud- and game model-based approach to project evaluations of sustainable power supply investments. By developing an index system grounded in prior research, this method harmonizes subjective and objective assessments. Game theory aids in determining comprehensive indicator weights, while cloud model theory refines investment benefit evaluations. This contribution is expected to enhance decision-making in power supply project management, offering a more balanced and accurate framework for evaluating the impacts of investments.

2. Literature Review

2.1. Cloud Computing and Decision Models

Cloud computing and decision models involve examining how these technologies enhance project evaluations. Wang Y.'s model [7] introduces an innovative blend of cloud models and game theory, addressing uncertainties in project evaluation. Meng X. et al.'s approach [8] uses fuzzy logic to evaluate risks in power supply projects, highlighting the importance of precise risk assessments. Zhu Q. et al.'s work [9] on supply chain management underscores the cloud model's adaptability. Aras A. and Büyüközkan G.'s review [10] on digital transformation offers a broader context for these technologies' impact. Sun M.'s study [11] explores blockchain's role in financial management, suggesting its potential in secure, decentralized project evaluations. Lastly, Hrouga M.'s conceptual framework [12] for collaborative supply chains demonstrates the integral role of Industry 4.0 technologies in modernizing project evaluation and management. Together, these studies illustrate the dynamic potential of combining cloud computing, game theory, and advanced decision models to enhance sustainable power supply investment projects.

Decision models for renewable energy and sustainable practices involve analyzing the integration and optimization of renewable energy sources into power systems. Studies like Gnibga et al.'s study [13] on renewable energy in data centers and the challenges of grid dependency, Wang Z et al.'s [14] exploration of energy sharing through Nash bargaining models, and Li Q et al.'s study [15] on optimal scheduling for integrated energy systems highlight the complexities of incorporating renewable energy efficiently. These research efforts, alongside Hu et al.'s [16] work on joint planning for power supply and storage, Song X et al.'s [17] study on shared energy storage systems, and Wu et al.'s [18] study on operation optimization, showcase innovative methods to improve renewable energy utilization and storage. Collectively, they underline the potential of cloud- and game model-based approaches in navigating the intricate dynamics of sustainable power supply investments, ensuring more efficient and strategic integration of renewable resources.

2.2. Digital Transformation and Evaluation Applications

Digital transformation and game theory applications reveal significant insights. Studies such as He S and Tang Y's work on digital diffusion in enterprises [19] demonstrate this. Additionally, Guo et al.'s exploration of behavioral strategies in green technology [20] and Ning J and Xiong L's analysis of renewable energy enterprises' digital transformation [21] illustrate how game theory can guide strategic decision-making in this evolving landscape. These studies collectively highlight the critical role of digital transformation and game theory in enhancing project evaluations for sustainable power supply investments, offering a deeper understanding of market dynamics and strategic interactions in the digital age.

An advanced understanding of how to evaluate and mitigate the risks in sustainable power projects is important. Zhu M et al.'s approach [22] combines FMEA and fuzzy super-efficiency SBM, offering a nuanced risk assessment method. Similarly, Li X et al. [23] and Xia Y et al. [24] leverage game theory and peer-to-peer market analysis, showcasing innovative strategies for managing investment risks. Radovanović M et al.'s multicriteria decision-making model [25] further exemplifies the complexity of evaluating sustainable investments. These methodologies underscore the critical role of sophisticated risk assessment and investment models in fostering sustainable energy projects.

2.3. Evaluation Index System for Investment Effects of Power Supply Projects

The appraisal of investment benefits within power supply projects has been recognized as a multifaceted endeavor, encompassing a multitude of elements across social, economic, technological, resource, and environmental domains. The requisition of a comprehensive and pragmatic index system has been established as a precondition for the successful realization of investment benefit assessments pertaining to power supply projects [26]. It is through such a system that decision-makers [27] may be afforded a thorough and impartial evaluation and comparison of the comprehensive advantages that are inherent to disparate power supply projects [28], thereby facilitating judicious investment decisions and mitigating associated risks.

In an effort to delineate genuine investment yields, a meticulous investigation into this project's principal effects on meeting functional aspects was undertaken, based on the inherent distinguishing features of individual projects. The quantification of investment advantages of power supply projects mandated an integrative approach [29], melding quantitative calculation methodologies with qualitative techniques. The foundational principles governing this integration include uniqueness [30], hierarchy [31], scientificalness [32], and relevance [33], as presented in Table 1. Specifically, the enhancement of the power supply capacity, amelioration of the power supply quality, augmentation of economic benefits, and compliance with social and environmental policies have been defined as first-level indicators [34] of the project's benefits in socio-economic and technological contexts [35]. These first-level indicators have subsequently been categorized into more granular second-level indicators.

Table 1. Evaluation system for investment effects of power supply projects.

Objective Layer	First-Level Indicators	Second-Level Indicators	Indicator Explanation
Comprehensive Benefits	Improved Power Supply Capacity	Optimized Load Ratio (C1)	Optimization of load ratio following project operation
		Increased Transformer Capacity (C2)	Enhancement of transformer capacity subsequent to project implementation
		Substation Load Balance (C3)	Refinement of substation load matching post-construction
		High-Voltage Line Load Uniformity (C4)	Improvement in high-voltage line load uniformity after project execution
	Improved Power Supply Quality	Optimized High-Voltage Power Grid (C5)	Stabilization and optimization of high-voltage power grid within project framework
		Optimized Voltage Quality (C6)	Enhancement of voltage qualification rate through project-driven optimization
		Optimized Current Distribution (C7)	Streamlining and optimization of current distribution
		Compressed High-Voltage Power Supply Diameter (C8)	Expansion and optimization of power supply radius subsequent to project implementation
	Improved Economic Benefits	Reduced Line Loss (C9)	Reduction in and optimization of line loss following project execution
		Operating Cost (C10)	Annual incremental expenditure attributable to project
		Improved Power Supply Effect (C11)	Effects from augmentation of power supply from commissioned projects
	Fulfilled Social and Environmental Policy	Project Technology Improvement (C12)	Long-term impact of commissioned projects
		Economic Benefits (C13)	Economic advantages generated through commissioned projects
		Customer Satisfaction (C14)	Reflection of customer satisfaction pertaining to power supply projects

3. Investment Benefit Evaluation Model Employing Cloud Model and Combination Weighting

Within the domain of power supply investment project evaluations, uncertainties are often encountered. To address this challenge, an investment benefit evaluation model for power supply projects was constructed, leveraging both game theory-based combination weighting and the cloud model, as illustrated in Figure 1.

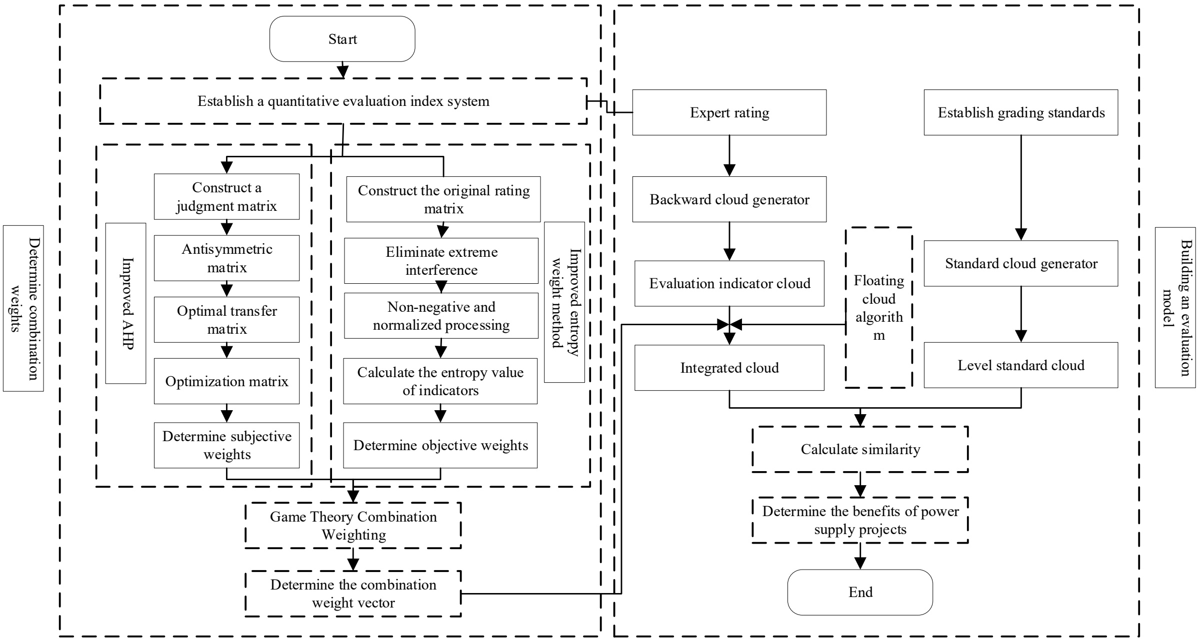

Figure 1. Schemes follow the same formatting.

To accurately discern the model index's weight, a combination weighting methodology rooted in game theory was employed. This approach was designed to mitigate the influence of human subjectivity while concurrently allowing for a comprehensive consideration of both subjective and objective information. The strength of this method lies in its ability to strike a harmonious balance between the objectivity and subjectivity of data.

For the purpose of precisely and scientifically determining evaluation grades, the cloud model was utilized. It has been recognized as an efficacious solution for navigating the inherent ambiguity and vagueness of evaluation objectives. In this context, the cloud model emerges as an apt strategy for resolving issues related to uncertainty.

Figure 1 outlines a process for assessing power supply investment benefits. It begins with constructing a quantitative evaluation index system, followed by establishing initial settings such as expert ratings and backward cloud generation. The process includes analyzing matrix results, determining subjective and objective weights through various methods including the analytic hierarchy process (AHP) and entropy, and combining them using game theory to form weighted criteria. These criteria feed into a cloud model that evaluates investment benefits. The flowchart indicates that the results are refined through multiple iterations involving the standard cloud generator and sensitivity checks against established standards, concluding with a comprehensive analysis of investment benefits.

3.1. Combination Weighting Based on Game Theory

Game theory, regarded as a robust mathematical framework, has been utilized for the modeling and analysis of complex strategic interactions among various players. Within the specific application to combination weighting in the evaluation of the benefits of power supply project investments, game theory was harnessed to elucidate the optimal means of resource allocation among diverse options.

The fundamental principle underlying combination weighting involves the process by which several distinct factors are subjected to weighted averaging, leading to the identification of the optimal weight that is assignable to each factor. Through the game theory model, the analysis of strategic interactions between players within a game and the subsequent determination of the most effective approach to resource allocation can be achieved. By resolving the Nash equilibrium, the optimal combination of weights to be allocated across different factors was ascertained, with the aim of maximizing the overall expected value of each alternative.

The application of game theory within this context was instrumental in transcending the limitations of relying solely on subjective or objective evaluation methods. In the process of assessing the benefits of power supply project investments, the index weight was recognized as the foundational element, and the deployment of a method encompassing both subjective and objective combination weighting was proven to effectively balance the shortcomings of either approach.

Consequently, an optimized analytical hierarchy process, coupled with an entropy weight method, was proposed for the subjective–objective weighting of indicators. Game theory was employed to ascertain the optimal weight of the indicators, facilitating a more nuanced understanding of the interplay between objective and subjective considerations in evaluating investment benefits.

This section delineates the theoretical underpinnings and methodological advancements in leveraging game theory for combination weighting, particularly in the field of power supply project evaluation. Its relevance to the broader context of strategic decision-making highlights the potential for further exploration and application in other complex, multifaceted domains.

3.2. Improved AHP

The AHP is recognized as a decision-making technique rooted in human subjective cognition. Within this method, the discernment of the relative significance of diverse factors is consigned to human subjective consciousness, confining the analysis to the cognitive processing of these factors in real-world situations. This approach enables a straightforward determination of weights, but consequently, a corresponding lack of objectivity is discerned [11]. In order to closely align the method with empirical reality, the iterative performance of consistency testing and correction within the judgment matrix is often mandated.

Recognizing the need for enhanced objectivity and precision, research has aimed at an optimized analytical hierarchy process. This optimization seeks to rectify the identified shortcomings, providing a more robust framework for decision-making that reconciles the intuitive and quantitative aspects of evaluation. The specific steps to achieve this optimization are delineated as follows [12]:

First step: The judgment matrix E is constructed:

$$E = \left(e_{ij}\right)_{n \times n} \tag{1}$$

In this equation, e_{ij} represents the degree of importance of the i-th factor compared to the j-th factor, and it satisfies $e_{ji} = \frac{1}{e_{ij}}$, $e_{ij} > 0$ and $e_{ii} = 1$.

Second step: Based on $f_{ij} = lge_{ij}$, the antisymmetric matrix F of the judgment matrix E is obtained, characterized by $f_{ij} = -f_{ji}$.

Third step: From the second step, the optimal transmission matrix G of the antisymmetric matrix F is found, making $\sum_{i=1}^{n}\sum_{j=1}^{n}\left(g_{ij} - f_{ij}\right)^2$ minimal.

$$g_{ij} = \frac{1}{n}\sum_{k=1}^{n}\left(f_{ik} - f_{jk}\right) \tag{2}$$

Fourth step: The optimized matrix E^* is constructed, wherein ${e_{ij}}^* = 10^{g_{ij}}$.

Fifth step: The weight vector W is determined.

The optimized matrix E*is normalized:

$$\bar{e}_{ij}^* = \frac{e_{ij}^*}{\sum_{i=1}^{n} e_{ij}^*} \tag{3}$$

The sum vector is obtained by row addition:

$$W_i' = \sum_{j=1}^{n} \bar{e}_{ij}^* \tag{4}$$

Through normalization of the sum vector, the characteristic vector for the optimized matrix can be acquired, which is the required weight vector:

$$W_i = \frac{w_i'}{\sum_{i=1}^{n} w_i'} \tag{5}$$

Traditional entropy weight methods were used to overlook the inherent importance level of the indicator, sometimes leading to pronounced inconsistencies between the determined indicator weights and the actual empirical results. While the adherence to mathematical principles in these methods was scrupulously maintained, the absence of consideration for the decision-maker's subjectivity, compounded by the undue influence of sporadic data points, has been found to engender substantial fluctuations in the indicator value.

In response to these limitations, a refinement of the information entropy calculation formula was devised. This optimized approach seeks to reconcile the mathematical rigor of traditional methods with a more nuanced appreciation of contextual factors, thereby yielding a more accurate and representative weighting scheme. The specific steps undertaken for this optimization are delineated as follows:

Construction of the original data matrix A':

$$A' = (x_{ij})_{n \times m} (i = 1, 2, \ldots, n, j = 1, 2, \ldots, m) \tag{6}$$

In this equation, m represents the number of evaluation indicators, n represents the number of data samples, and x_{ij} represents the attribute value of the j-th indicator in the i-th sample.

Standardization to eliminate extreme value interference:

The standardization transformation formula is as follows:

$$\bar{x}_{ij}^* = \frac{x_{ij} - \bar{x}_j}{q_j} \tag{7}$$

where $\overline{x_j}$ is the mean of the j-th indicator; q_j is the standard deviation of the j-th indicator.

Non-negative processing of the indicator is performed:

Since the entropy weight method requires positive indicator values, the translation method is applied to make subsequent information entropy calculations meaningful. The formula is as follows:

$$x_{ij}^+ = x_{ij}^* + l \tag{8}$$

In this equation, x_{ij}^+ represents the non-negative processed indicator value; l is the moving distance, determined according to the actual situation.

Normalization processing is carried out:

The formulas are as follows:

$$A = (y_{ij})_{n \times m} (i = 1, 2, \ldots, n, j = 1, 2, \ldots, m) \tag{9}$$

$$y_{ij} = \frac{x_{ij}^+}{\sum_{i=1}^{n} x_{ij}^+} \tag{10}$$

In these equations, y_{ij} is the standardized value of the i-th evaluation score for the j-th indicator.

Calculation of the information entropy for each indicator is carried out as follows:

$$S_j = -k\sum_{i=1}^{n}\left[y_{ij}\ ln(y_{ij})\right] \tag{11}$$

In this equation, $k = \frac{1}{ln\ n}, i = 1, 2, \ldots, n$

The determination of an indicator's weight based on information entropy is achieved as follows:

$$W_j = \frac{1 - S_j}{\sum_{j=1}^{m}(1 - S_j)} \text{ and } \sum_{j=1}^{m} w_j = 1 \tag{12}$$

To mitigate the occurrence of disproportionate entropy weight differences arising from minor variations in the information entropy, the calculation formula for the entropy weight is optimized as follows:

$$w_j = \frac{\sum_{k=1}^{m} S_k + 1 - 2S_j}{\sum_{j=1}^{m}\left(\sum_{k=1}^{m} S_k + 1 - 2S_j\right)} \text{ and } \sum_{j=1}^{m} w_j = 1 \tag{13}$$

3.3. Combination Weighting Theory Method Based on Game Theory

The combination weighting method, characterized by the integration of both subjective and objective weighting techniques, was developed to mitigate the pronounced human bias that is inherent to purely subjective weighting. Concurrently, this approach is also recognized to remedy, to some extent, the absence of a decision-maker's subjective intent that is typically associated with purely objective weighting.

Incorporating principles from game theory, a mathematical field that encompasses the study of competitive and cooperative interactions between entities, the equilibrium concept is utilized in this context. Within the framework of project evaluation, two weights are considered the players in a game, both seeking to reach a Nash equilibrium. Through this method, the optimal weight combination is achieved, thus transcending the inherent constraints of relying solely on either subjective or objective evaluation methods. The specific process for attaining this balance can be delineated as follows:

Weights obtained using the optimized hierarchical analysis method and optimized entropy weight method are denoted as $w_1 = (w_{11}, w_{12}, \ldots, w_1\text{N})$ and $w_2 = (w_{21}, w_{22}, \ldots, w_2\text{N})$. A linear combination of w_1 and w_2 is then used to form the combined weight, as represented by the following formula:

$$w = \beta_1 w_1^T + \beta_2 w_2^T \tag{14}$$

In the equation, β_1 and β_2 are the coefficients of the combination of subjective and objective weights, respectively.

According to the principles of game theory, the Nash equilibrium point is found, minimizing the difference between the combined weight and the subjective and objective weights. The target function and constraints are

$$\begin{gathered} min(\ \|\ \|\ \|\ w - w_1^T\ \|_2 + \|\ w - w_2^T\ \|_2) \\ = min(\|\ \beta_1 w_1^T + \beta_2 w_2^T - w_1^T\ \|_2 + \|\ \beta_1 w_1^T + \beta_2 w_2^T - w_2^T\ \|_2) \\ s.t. \sum_{k=1}^{2} \beta_k = 1 \end{gathered} \tag{15}$$

By solving this model, the optimal combination weights for subjective and objective factors can be obtained. To solve the minimum value in the constraint, a Lagrange function is constructed:

$$L(\beta_1, \beta_2, \lambda)\ = \|\ \beta_1 w_1^T + \beta_2 w_2^T - w_1^T\ \|_2 + \|\ \beta_1 w_1^T + \beta_2 w_2^T - w_2^T\ \|_2 + \frac{\lambda}{2}\left(\sum_{k=1}^{2} \beta_k - 1\right) \tag{16}$$

Based on the differential principle, the optimal first-order derivative that is a necessary condition for Equation (16) is

$$\begin{cases} \beta_1 w_1 w_1^T + \beta_2 w_1 w_2^T = w_1 w_1^T \\ \beta_1 w_2 w_1^T + \beta_2 w_2 w_2^T = w_2 w_2^T \end{cases} \tag{17}$$

The corresponding linear equation set is

$$\begin{bmatrix} w_1 w_1^T & w_1 w_2^T \\ w_2 w_1^T & w_2 w_2^T \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} = \begin{bmatrix} w_1 w_1^T \\ w_2 w_2^T \end{bmatrix} \tag{18}$$

From Equation (18), the combination coefficients β_1 and β_2 are derived, and then normalized:

$$\beta_i^* = \frac{\beta_i}{\sum_{i=1}^{2} \beta_i} \tag{19}$$

The final combined weight is

$$w^* = \beta_1^* w_1^T + \beta_2^* w_2^T \tag{20}$$

3.4. Method for Evaluating Benefits of Power Supply Project Investments Based on Cloud Model

The evaluation of investment benefits of power supply projects is acknowledged as a multifaceted task, imbued with inherent ambiguity and randomness. A pervasive challenge lies in the conversion of these complex qualitative characteristics into representative quantitative numerical values. Based on foundational concepts derived from traditional fuzzy set theory and probability theory, the cloud model was introduced as a promising model for the transition between qualitative constructs and quantitative expressions.

In recent scholarly discourse, the emergence of comprehensive benefit evaluations utilizing the cloud model has been observed. This novel method, capable of effecting a logical transformation between qualitative paradigms and quantitative data in alignment with initial data characteristics, facilitates the rational quantification of qualitative indicators. The resultant comprehensive evaluations, characterized by their intuitiveness and clarity, have been demonstrated to significantly mitigate the inherent ambiguity of the assessment of a project's overall performance. Consequently, a path towards more objective and realistic evaluation results has been discerned.

3.5. Basic Theory

In cloud model theory, the specific form of a "cloud" is determined by its characteristic values, namely, the expected value Ex, entropy En, and hyper-entropy He. A universe of discourse U is assumed to exist, and within it, an arbitrary quantitative value is marked as x. The distribution of x in U, termed a "cloud," corresponds to a particular qualitative concept V in the domain U. Therefore, x, relative to V, has a stable random number $\mu(x)$, i.e., membership, with a value in the 0–1 range, and satisfying the following condition:

$$\mu(x) = e\frac{(x - Ex)^2}{2(En')^2} \tag{21}$$

3.6. Determination of Evaluation Standard Cloud

According to the previously established index system for evaluating the benefits of power supply project investments, various indicators such as an improved load ratio and newly added transformer capacity are set to four levels: poor, average, good, and excellent. The corresponding grades are 0~25, 25~50, 50~75, and 75~100. The upper and lower limits of each evaluation level are designated as p_i^{max} and p_i^{min}, and the cloud's digital characteristic values corresponding to each evaluation level are then calculated using the following specific formula:

$$\begin{cases} E_{Xi} = \left(p_i^{max} + p_i^{min}\right)/2 \\ E_{Ni} = \left(p_i^{max} - p_i^{min}\right)/2\sqrt{2ln2} \\ H_{Ei} = k \end{cases} \tag{22}$$

In the equation, E_{xi}, E_{ni}, and H_{Ei} represent the i-th evaluation level's expected value, entropy, and hyper-entropy, respectively. A constant H_{Ei} can be set as $k = E_{ni}/10$.

3.7. Determination of Evaluation Factor Cloud and Comprehensive Cloud

Based on the range of upper and lower limits of the evaluation level in the evaluation index system, experts are invited to score the performance of each indicator of the evaluation object according to the evaluation level's score range. The score value is set as z, the number of evaluation indicators as m, and the number of experts as I. The calculation formula for the digital characteristic cloud value of the j-th indicator is as follows:

$$\begin{cases} E_{xj} = \frac{1}{I}\sum\limits_{i=1}^{I} z_{ij} \\ E_{nj} = \sqrt{\frac{\pi}{2}}\frac{1}{I}\sum\limits_{i=1}^{I}\left|z_{ij} - E_{xj}\right| \\ H_{ej} = \sqrt{\left|S_j^2 - E_{nj}^2\right|} \end{cases} \tag{23}$$

In the formula, $S_j^2 = \frac{1}{I-1}\sum_{i=1}^{I}\left(z_{ij} - E_{xj}\right)^2$ represents the variance of the expert scores for the j-th indicator.

The comprehensive cloud is obtained based on the specific indicator's corresponding evaluation factor cloud and its weight, with greater weighted indicators having a more substantial impact on the comprehensive cloud's shape. The calculation formula for the comprehensive cloud is as follows:

$$\begin{cases} E_X = \frac{E_{x1}w_1 + E_{x2}w_2 + \cdots + E_{xn}w_n}{w_1 + w_2 + \cdots w_n} \\ E_N = \frac{E_{n1}{w_1}^2 + E_{n2}{w_2}^2 + \cdots + E_{nn}{w_n}^2}{{w_1}^2 + {w_2}^2 + \cdots {w_n}^2} \\ H_E = \frac{H_{e1}{w_1}^2 + H_{e2}{w_2}^2 + \cdots + H_{en}{w_n}^2}{{w_1}^2 + {w_2}^2 + \cdots {w_n}^2} \end{cases} \tag{24}$$

In the equation, $w_1, w_2, \ldots, w_n$ represents the combination weight value of the indicator.

To better determine the result, two evaluation clouds, V_1 and V_2, are set, with corresponding digital characteristic cloud values of $V_1(E_{x1}, E_{n1}, H_{e1})$ and $V_2(E_{x2}, E_{n2}, H_{e2})$. The similarity $V(V_1, V_2)$ of these two clouds can be obtained using Equation (25):

$$V = (V_1, V_2) = \frac{1}{2} + \frac{1}{2\mu} - \mu \tag{25}$$

The calculation formulas for μ and β are shown in Equations (26) and (27):

$$\mu = \int_{-\infty}^{\beta} \frac{1}{\sqrt{2\pi}} exp(\frac{t^2}{2}) dt \tag{26}$$

$$\beta = \frac{|Ex_2 - Ex_1|}{\sqrt{En_1^2 + He_1^2} + \sqrt{En_2^2 + He_2^2}} \tag{27}$$

Finally, the evaluation level is judged based on the similarity between the evaluation object's comprehensive cloud and the clouds of the different evaluation levels set. Based on the principle of maximum similarity, the final evaluation result level can be determined.

4. Evaluation of Investment Benefits of Power Supply Projects

4.1. Calculation of Combined Weights

For the case study, an analysis was carried out on the Hengyang Liaojiawan Transformer Substation Project, completed in 2016 in Hunan Province. The evaluation involved collaboration with five State Grid field experts who assessed various indicators and their significance using a percentage scale. The outcome of their assessments is detailed in Table 2, providing a structured basis for decision-making regarding the project's performance and outcomes.

Table 2. Experts' scoring of benefits.

Expert														
Expert 1	85	87	92	83	87	82	79	86	90	78	81	87	88	88
Expert 2	80	92	83	81	92	97	87	82	87	87	84	85	93	85
Expert 3	72	55	90	87	82	80	82	75	92	81	65	70	86	87
Expert 4	90	86	72	89	95	70	70	65	85	69	79	91	88	80
Expert 5	89	90	86	85	90	85	75	80	89	85	80	89	89	83

Initially, the experts were asked to perform pairwise comparisons of the evaluation indicators, from which subjective weights of the indicators were ascertained based on the improved AHP. Taking the first-level indicators in Table 1 as an example, the judgment matrix constructed in this paper is as follows: The subjective weight of the first-level index can be calculated according to Formulas (1)–(5). Similarly, the weight of each second-level index can be obtained. Then, multiply the first-level weight and second-level weight to obtain the weight of the indicator, as shown in Table 3.

$$E = \begin{bmatrix} 1 & 3 & 4 & 2 \\ 1/3 & 1 & 2 & 1/2 \\ 1/4 & 1/2 & 1 & 1/3 \\ 1/2 & 2 & 3 & 1 \end{bmatrix} \tag{28}$$

Table 3. Indicator weights and cloud model characteristic parameters.

Serial Number	**Indicator Name**	**Subjective Weight**	**Objective Weight**	**Combined Weight**	**Indicator Cloud**
1	Improvement in Load Ratio	0.2558	0.0713	0.2421	(83.2,7.219,1.61)
2	Increase in Transformer Capacity	0.0687	0.0946	0.0706	(82.0,13.536,7.09)
3	Balance of Substation Load	0.1122	0.0765	0.1095	(84.6,7.119,3.34)
4	Balance of High-Voltage Line Load	0.0301	0.0608	0.0324	(85.0,3.008,0.98)
5	Improvement in High-Voltage Power Grid	0.0793	0.0674	0.0784	(89.2,4.712,1.58)
6	Enhancement of Voltage Quality	0.0213	0.0601	0.0242	(82.8,8.222,5.21)
7	Optimization of Power Flow Distribution	0.0098	0.0622	0.0137	(78.6,6.116,2.21)
8	Reduction in High-Voltage Power Supply Radius	0.0499	0.0736	0.0517	(77.6,7.620,2.69)
9	Reduction in Line Loss	0.0305	0.0629	0.0329	(88.6,2.607,0.717)
10	Operational Cost	0.0216	0.0733	0.0254	(80.0,6.517,2.74)
11	Increase in Power Supply Benefits	0.0432	0.0890	0.0466	(77.8,6.417,3.68)
12	Advancement in Project Technology	0.0406	0.0881	0.0441	(84.4,7.219,4.21)
13	Impact on Economic Development	0.1572	0.0531	0.1495	(88.8,2.206,1.35)
14	Customer Satisfaction	0.0799	0.0671	0.0789	(84.6,3.108,0.80)

Following the expert evaluations on a scale from 0 to 100 to determine the importance of each indicator, these assessments are summarized in Table 2. The Improved Entropy Weight Method was then used to calculate the objective weights, detailed in Table 3. Utilizing game theory, we integrated subjective and objective weights to establish a unified comprehensive weight for each indicator, with these consolidated results also displayed in Table 3. This process ensures a balanced and precise assessment of each factor's significance.

A subsequent analysis of the weight, clearly portrayed in Figure 2, allowed for several discernible conclusions: (1) A pronounced divergence was detected between the subjective and objective weights for the majority of indicators, with an evident inclination toward the indicators C_1, C_3, and C_{13} in the objective weight. Concomitant with this, the subjective weights demonstrated a relatively condensed distribution, thereby failing to emphasize the core indicators. (2) The employment of game theory for the amalgamation of indicator weights was observed to foster a mutual supplementation, rendering the weight results more congruent with the underlying empirical context.

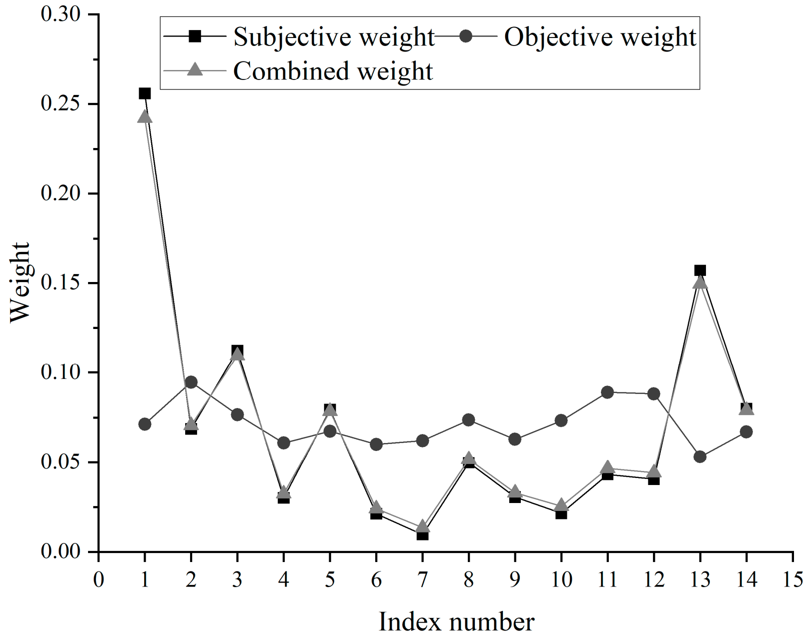

Figure 2. Distribution of indicator weights.

4.2. Establishment of the Evaluation Standard Cloud

The evaluation of the investment benefits of power supply projects was categorized into four distinct grades: poor, average, good, and excellent. The determination of scoring intervals for each grade was conducted, and the computation of the standard cloud model parameters was performed utilizing Equation (22), as delineated in Table 4.

Table 4. Standard cloud model for benefit evaluation.

Evaluation Standard	Scoring Interval	Cloud Model Feature Parameters
Poor	[0, 25]	(12.5,10.617,1.06)
Average	(25, 50]	(37.5,10.617,1.06)
Good	(50, 75]	(62.5,10.617,1.06)
Excellent	(75, 100]	(87.5,10.617,1.06)

Subsequent to the acquisition of the cloud model's characteristic parameters for the evaluation grades, the MATLAB 9.10 software was harnessed, in accordance with the principles of the forward cloud generator, to construct the corresponding cloud images for the evaluation grades. Specifically, the colors red, blue, purple, and green were used to symbolize the grades poor, average, good, and excellent, respectively. This systematic categorization culminated in the creation of the evaluation's standard cloud, a visual representation illustrated in Figure 3. The arrangement, shown from left to right, corresponds to the aforementioned color-coded grades.

This section demonstrates how the cloud model enhances the evaluation process, offering a nuanced and visually engaging way to understand investment benefits. By aligning with forward cloud generator principles, it maintains consistency with recognized methods, effectively combining theoretical insights with practical, quantitative data visualization.

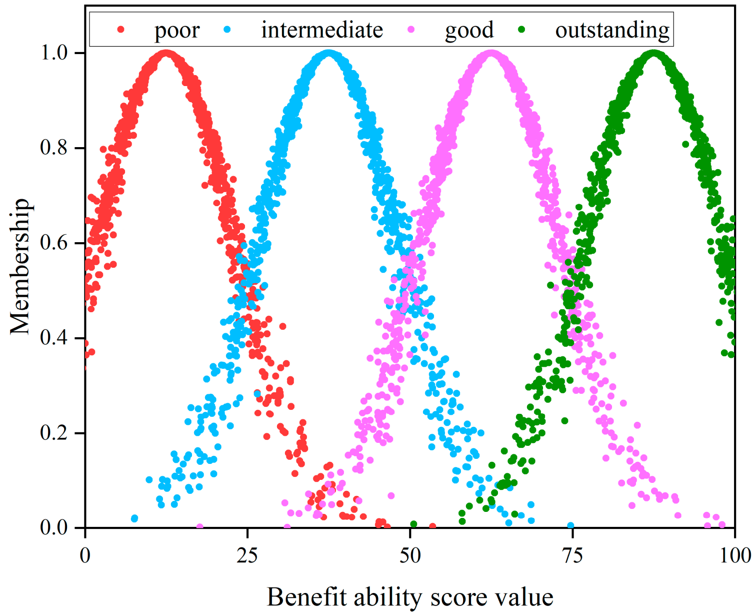

Figure 3. Standard cloud image.

4.3. Calculation of Individual and Synthetic Clouds

In the pursuit of validating the model's accuracy, the extraction of the cloud's digital feature values corresponding to each indicator was meticulously carried out. This process was initiated by employing Formula (23) to the score data corresponding to each indicator, as outlined in Table 2. The derived results are subsequently displayed in the fifth column of Table 3.

This integral stage involved the synthesis of the cloud's individual digital features. In conjunction with the previously determined combined weights of the indicators, the overall digital feature values of the cloud were derived, specifically denoted as 84.28, 6.12, and 2.03, utilizing Formula (24). A subsequent step involved the utilization, where a setting of 1000 evenly distributed cloud droplets was implemented to construct the comprehensive benefit evaluation cloud image. This visualization is elucidated in Figure 4.

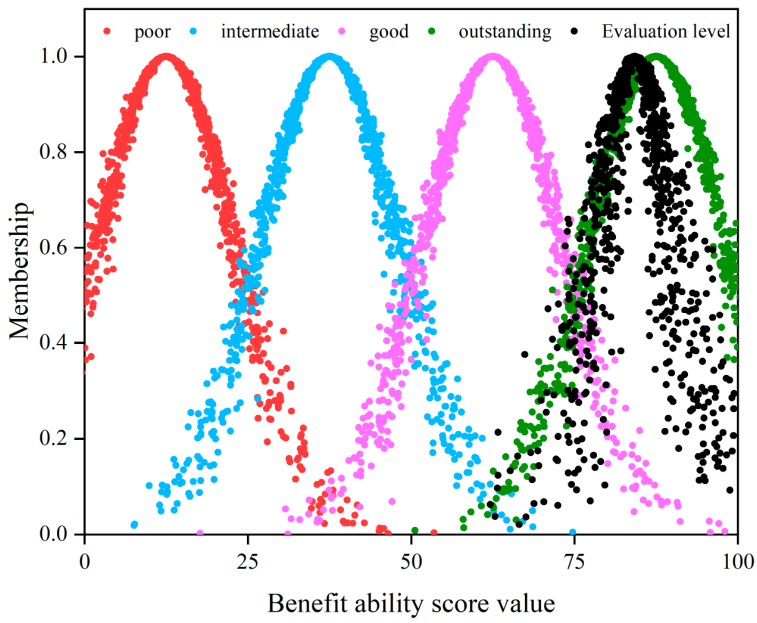

Figure 4. Synthetic cloud image.

The examination of the synthetic cloud image, illustrated in Figure 4, allows for the observation that the cloud droplets representing the power supply project's comprehensive model predominantly reside within the grades of excellent and good. An intuitive assessment was further refined through the enumeration of cloud droplet numbers in each respective region, with the detailed tallies encapsulated in Table 5. A discernible pattern emerged, revealing that the preponderance of cloud droplets were confined to the "excellent" grade, closely followed by the "good" grade. Thus, it was inferred that the benefit grade of the power supply project under scrutiny could be characterized as excellent.

Table 5. Number of cloud droplets in each grade and similarity results.

Evaluation Standard	Scoring Interval	Number of Cloud Droplets	Similarity
Poor	[0, 25]	0	0.0000
Average	(25, 50]	0	0.0047
Good	(50, 75]	66	0.1582
Excellent	(75, 100]	917	0.7956

To fortify the validity of the evaluation grade, the employment of Equation (25) was deemed necessary. This equation facilitated the calculation of the similarity between the synthetic cloud and each standard cloud, with the results documented in Table 5. By invoking the principle of maximum similarity, the investment effect's evaluation grade for the power supply project was unequivocally determined to be excellent. Such a conclusion not only aligned with the model's findings but also corroborated the actual engineering conditions, thus serving as a testament to the model's accuracy.

The approach delineated herein represents a systematic and quantifiable method for evaluating the investment benefits of power supply projects. The synthesis of digital cloud features allows for a nuanced and robust analysis, reflecting both the individual and composite considerations that are inherent to such projects. By combining theoretical constructs with empirical validation, this section underscores the practical applicability and methodological integrity of the model.

5. Conclusions

This research develops a model leveraging game theory and the cloud model for analyzing the investment benefits of power supply projects, leading to several key findings: Firstly, a comprehensive evaluation system with 14 detailed indicators for measuring investment benefits is established, providing a well-rounded overview of a project's viability. Secondly, the model combines subjective and objective indicator weights using advanced analytical methods, improving the weight accuracy by balancing subjective biases with data characteristics. Thirdly, the cloud model's adoption addresses evaluation challenges like ambiguity, demonstrated by experimental results that are consistent with real-world outcomes. Finally, these methodologies offer valuable insights for similar project evaluations, allowing for customizable approaches to fit specific project needs.

This research introduces a dynamic and flexible framework for assessing the benefits of investments in power supply projects, effectively merging theoretical advancements with practical implementations. In future work, the comparison of various methodologies, as well as sensitivity analysis, is a related topic for future works. Its effectiveness has been proven through comparisons with real-time data, highlighting the model's accuracy and its adaptability for use in the dynamic field of power supply investment analysis.

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