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Data Value-Added Service Comprehensive Evaluation Method on the Performance of Power System Big Data

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Abstract: With the development of digital economy, the integration and secure sharing of energy big data have become pivotal in driving innovation across the energy production, distribution, and consumption sectors. For power enterprises, leveraging data to enhance operational efficiency and drive business development will play a crucial role in value added. Firstly, based on the value-added service framework system of grid enterprises, this paper explores the basic technologies for power data applications and designs a technical roadmap for value-added services. Secondly, the proposed methodology incorporates the analytic hierarchy process (AHP) and gray comprehensive evaluation method (GCE) to determine the weights of key factors affecting the value-added services. Empirical research is conducted to validate the feasibility of typical value-added services. Additionally, this paper proposes methods for evaluating the benefits of value-added services and identifies key technologies in data mining and management, customer value discovery, and data asset utilization, providing theoretical support and practical pathways for the digital transformation of power enterprises.

Keywords: value-added; comprehensive evaluation; big data; digital transformation

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1. Introduction

The rapid development of new-generation information technology has accelerated the deep integration of the energy revolution and the digital revolution. In recent years, a new round of technological and industrial revolutions has formed a historic intersection with China's energy revolution. Emerging technologies such as big data, Internet+, the Internet of Things (IoT), artificial intelligence (AI) [1], smart energy, mobile terminals, and virtual reality have provided conditions and support for the development of multi-level, multi-channel, and interactive value-added power services. Technological innovation has greatly propelled the energy revolution, and the integration of these two has had a significant impact on China's energy structure and economic development model. To this end, the Chinese government has proposed to promote the energy technology revolution, drive industrial upgrading, and base itself on the national conditions, closely following the new trends of the international energy technology revolution, with green and low-carbon as the direction, to promote technological innovation, industrial innovation, and business model innovation in a classified manner, and closely integrate with other high-tech fields, cultivating the energy technology and its related industries into a new growth point that drives China's industrial upgrading. Under this background, it is particularly necessary for grid enterprises to develop value-added services.

In recent years, the development of emerging technologies such as big data [2], the Internet of Things, mobile internet, cloud computing, and artificial intelligence has provided a technical foundation for the development and practice of value-added service models. Many domestic enterprises have used these emerging technologies to carry out a series of value-added services, improving customer service levels while enhancing the quality and efficiency of enterprise operation [3]. For example, JD.com has taken many measures to provide users with reliable and inclusive digital financial services, achieving a fully intelligent logistics system through technological innovation [4]. Through an intelligent layout of warehousing and logistics networks [5], JD Logistics provides merchants with integrated supply chain solutions, including warehousing, transportation, distribution, customer service, and after-sales, as well as a full range of logistics products and services such as express, freight, large items, cold chain, cross-border, customer service, and after-sales [6,7]. Based on technical guarantees, JD Real Estate will also track the entire process of offline second-hand house transactions, adding JD platform guarantees for consumers [8]. The Industrial and Commercial Bank of China provides health and medical value-added services for its customers [9,10]. Trip.com meets the era's demand for convenient travel, bringing convenience to travelers while providing diversified value-added services [11].

In addition to technological advancements, several key factors are driving the evolution of value-added services. First, regulatory frameworks and policy incentives play a crucial role in encouraging digital transformation within the energy sector, fostering a competitive environment for innovation. Second, the increasing emphasis on sustainability and carbon neutrality has led enterprises to integrate energy-efficient and environmentally friendly solutions into their service offerings. Third, the growing demand for customer-centric, data-driven services is reshaping traditional business models, requiring companies to develop more personalized and intelligent energy solutions. Fourth, the rise in decentralized energy systems and prosumers is transforming the traditional supply–demand relationship, necessitating new service models that enable peer-to-peer energy trading, real-time monitoring, and optimized energy distribution.

Moreover, the increasing role of energy storage solutions, including battery technologies and virtual power plants, is expanding the scope of value-added services by enabling more flexible energy management. The development of blockchain technology also presents opportunities for transparent, decentralized energy transactions, enhancing trust and efficiency in energy markets. Furthermore, with the advancement of 5G and edge computing, real-time data processing and intelligent decision-making capabilities are improving, allowing for more responsive and adaptive service models.

Foreign enterprises, represented by energy companies, have adopted various value-added service models. For example, Tokyo Electric Power Company (TEPCO) responds to customers' differentiated energy needs through comprehensive energy services.

Taking TEPCO as an example, it formulates differentiated service strategies based on user types [12], dividing users into large customers and residential customers [13]. Alliander, the largest electricity and natural gas network operator in the Netherlands, leads the Dutch distribution network market and is a leading energy and energy internet operator in Europe [14–16]. In response to the global energy transition and the development trend of the energy service market, Alliander not only provides high-quality and reliable energy supply services but also actively explores various value-added services, becoming a practitioner leading the Dutch energy transition in areas such as energy efficiency services, electric vehicle charging stations, energy data management, and the energy internet [17]. OPower analyzes and mines energy data from utility companies and various third-party data through its software, providing users with a set of energy-saving suggestions suitable for their lifestyles [18]. C3 Energy, a U.S. energy internet of things company that provides paid software and compensatory data processing, has grown into a leading enterprise in the energy big data field. Acting as a system maintainer, monitor, and communication platform, C3 Energy integrates a large amount of data using technologies such as big data, smart grid analysis, social networks, machine learning, and cloud computing, providing real-time grid monitoring and instant data analysis for utility or power companies [19,20], while also managing demand response for end-users.

Although there are certain differences in the typical practices of value-added services among these large domestic and foreign enterprises, they all have strong pertinence and operability, achieving good results in practice. It is important to deeply analyze these practices and value-added service cases, find commonalities and patterns, and combine them with the business layout and characteristics of power companies, which will have significant reference significance for doing a good job in data value-added services in the power system.

The contributions of this study are as follows:

(1) Pioneering Research on the Evaluation of Data Value-Added Services: Data value-added services have emerged as a new business in recent years, but there is limited research in this area. This study is pioneering in evaluating data value-added services in the context of the power industry, as this perspective has not been widely explored in existing studies. Therefore, the contribution of this study is highly innovative and fills a significant gap in the literature.
(2) Lack of Research on Data Value-Added Services for Power Industry Data: While existing studies on data value-added services generally focus on broad methods and techniques, there is a notable gap in research that applies these concepts specifically to power industry data. Previous research has concentrated more on general data analysis methods, without addressing the unique characteristics of the power industry. This study fills this gap by providing a theoretical framework and practical approach for data value-added services specific to the power industry.
(3) Consideration of Multi-Dimensional Indicators: This study considers multiple dimensions of indicators, such as economic, management, and social benefits, which are critical for evaluating data value-added services. Most existing studies focus on a single dimension of evaluation, lacking a comprehensive analysis of the combined impact of various factors. By incorporating these multi-dimensional indicators, this study offers a more holistic approach to evaluating data value-added services, providing both theoretical and practical insights.

2. Benefit Evaluation of Value-Added Services in Power Grid Enterprises

2.1. Analysis of the Practical Benefits of Value-Added Services

By analyzing the practical benefits of four typical types of value-added services in power grid enterprises based on comprehensive business data—management value-added services, grid operation value-added services, user-side value-added services, and social value-added services—this study lays the foundation for summarizing and refining the business benefits of value-added services.

(1) Management Value-Added Services. Power grid companies actively develop management value-added services using information management systems and historical data, which helps improve management efficiency and supports the development of grid-related businesses. Currently, the management value-added services provided by power grid companies mainly include decision support for company operations

and efficiency improvement, which can further expand business opportunities and promote the healthy and sustainable development of the company.

(2) Grid Operation Value-Added Services. Power grid enterprises have accumulated a wealth of business data and experience in areas such as power load forecasting, grid equipment condition monitoring, and refined management of distribution network fault repairs. The value-added services provided on this basis mainly support the safe, stable, and efficient operation of the grid from five aspects: meeting equipment management needs; optimizing distribution network planning and operation; improving operation and inspection efficiency; conducting predictive and warning controls; and adapting to the needs of new energy development. With the rapid development of company business, it is necessary to rely on the advantages of comprehensive business data and new technologies such as next-generation artificial intelligence to improve business process efficiency and operational levels through data-driven approaches, further ensuring the quality of grid operation and achieving both social and economic benefits.

(3) User-Side Value-Added Services. To adapt to the new environment of the electricity market, power grid companies actively leverage their strengths to develop user-side value-added services, innovating work and service models from two aspects: enhancing customer energy efficiency and improving customer service levels. These efforts aim to optimize customer energy usage patterns, explore potential user needs, and maximize value creation for users and societal benefits, thereby building and strengthening customer advantages in market competition and enhancing corporate economic benefits.

(4) Social Value-Added Services. Power grid enterprises can promote the refinement and intelligence of government management and public services by leveraging their power data resources. Currently, the social value-added services provided by companies mainly include the following three aspects: offering auxiliary services for energy conservation and efficiency; aiding government scientific decision-making; and optimizing public services. Social value-added services are characterized by their public welfare, service orientation, and social nature. By providing auxiliary services for energy conservation and efficiency, they can promote the use of clean energy and contribute to energy conservation and emission reduction. By aiding government decision-making and optimizing public services, they create greater value for the public and stakeholders in the industry chain.

2.2. Research on the Evaluation Index System for the Benefits of Value-Added Power Data Services

From the analysis in the previous section, it is evident that the comprehensive benefits of value-added data services provided by power grid enterprises are primarily reflected in economic benefits, management benefits, and social benefits. These aspects are composed of numerous factors and require the construction of a comprehensive measurement system based on principles of scientificity, systematicness, comprehensiveness, independence, measurability, and comparability. This ensures a comprehensive and scientific measurement of the comprehensive benefits of value-added services. Given the complexity of value-added services, when evaluating their benefits, it is necessary to explore the underlying value characteristics of different types of businesses. Based on the common characteristics of four typical value-added services, factors such as economic benefits, management benefits, and social benefits of power grid enterprises' value-added services should be considered comprehensively. These factors should be gradually decomposed to identify and select measurable indicators and specific indicators that can be practically evaluated, thereby constructing a general-purpose evaluation index system.

2.2.1. Analysis of Management Efficiency Indicators

Management efficiency is also a crucial part of corporate efficiency, as management activities are pervasive in all aspects and stages of a company's production and operation. As a large, diversified business group with trillion-level assets and millions of employees, the company should place even greater emphasis on management and its efficiency. When power enterprises engage in value-added service businesses, management efficiency can be comprehensively measured from two perspectives: operational capability and user satisfaction.

(1) Operational Capability

Operational capability refers to the ability to integrate internal resources of a power grid enterprise to provide value-added services under the constraints of external conditions. The maturity of technology is the most universal and representative constraint, encompassing aspects such as the technical level of scientific and technological achievements, process flow, supporting resources, and the industrial practicality of the technology's life cycle. The maturity of technology can be used to measure the support or limitation of technology for the operation of value-added services in power grid enterprises. The higher the maturity of a particular value-added service's technology, the stronger its operational capability. The maturity of technology can be assessed by inviting experts to score based on the technology maturity evaluation criteria table.

(2) User Satisfaction

Customers are a significant asset for a company, and user satisfaction comprehensively reflects the user's recognition of the company's management. User satisfaction, also known as customer satisfaction or customer satisfaction index, is the abbreviation for the customer satisfaction survey system in the service industry. It is a relative concept, representing the degree of match between customer expectations and customer experiences. In other words, it is the index derived by customers after comparing the perceived effect of a product with their expectations. The user satisfaction of value-added services in power grid enterprises is primarily influenced by the convenience and economic benefits the service brings to users.

2.2.2. Analysis of Social Benefit Indicators

The power industry is a fundamental industry that is closely related to national energy security, economic development, and social stability, playing a pivotal role in economic and social development. While pursuing economic benefits, power grid enterprises should actively fulfill their social responsibilities, be accountable to stakeholders and the environment, and achieve the unity of corporate development with social and environmental considerations. The development of value-added services by power grid enterprises is an effective way to achieve social benefits. The social benefits of value-added services in power grid enterprises mainly include social economic benefits and ecological environmental benefits.

(1) Social Economic Benefits

Social economic benefits refer to the positive impacts that value-added services of power grid enterprises have on the external social economy during the production, operation, and consumption processes. Employment conditions can largely reflect the economic development status of a region. Therefore, it is possible to measure the contribution of value-added services of power grid enterprises to employment stimulation. The development of value-added services in power grid enterprises involves the power industry and various related industries, requiring the participation of all parties and a large number of human resources, which will directly or indirectly provide a significant number of employment opportunities for society. The direct employment effect indicator reflects the direct employment benefits brought by the project, while the indirect employment multiplier indicator reflects the extent to which the project stimulates employment in related industries.

(2) Ecological Environmental Benefits

Ecological environmental benefits are the sum of ecological and environmental benefits, referring to the achievements in reducing and preventing pollution from industrial and agricultural production on human production and living environments or improving environmental quality through the implementation of certain measures. The ecological environmental benefits of value-added services in power grid enterprises are mainly influenced by the energy savings and pollution reduction effects of the service. The better the ecological environmental benefits, the better the social benefits of the value-added service.

Through the analysis, sorting, and summarization of the benefit evaluation indicators of value-added services in power grid enterprises, and by conducting a scientific hierarchical division, a reasonable hierarchical structure has been formed. This structure comprehensively considers indicators from the dimensions of economic benefits, management benefits, and social benefits, constructing an evaluation index system for the benefits of value-added services in power grid enterprises based on full-business data applications, as summarized in Table 1.

Table 1. Evaluation index system.

	First-Level Indicator	Second-Level Indicator	Third-Level Indicator	Qualitative Indicator	Quantitative Indicator	Reference Range
Value-added Service Benefit Evaluation Index System for Power Grid Enterprises Based on Full Business Data	Economic benefits	Profitability	Internal rate of return (%)		√	[0, 20]
			Static Payback Period (Years)		√	[0, 30]
		Development Potential	Market Prospects	√		——
			Macro Policy Support		√	[0, 20]
	Management benefits	Operational capability	Technical maturity	√		——
		User satisfaction	Ease of use		√	[0, 15]
			Economic efficiency in use		√	[0, 15]
	Social Benefits	Social and Economic Benefits	Increased Employment Value	√		——
		Ecological and Environmental Benefits	Energy Conservation	√		——
			Pollution Reduction	√		——

3. Construction of the Quantitative Evaluation and Calculation Model for the Benefits of Value-Added Services in Power Grid Enterprises

3.1. Determination of Indicator Weights

To conduct a comprehensive evaluation of the benefits of value-added services in power grid companies, it is necessary to integrate and analyze each individual indicator using a comprehensive evaluation method. Before performing the comprehensive evaluation, it is essential to distinguish the importance of each indicator. Therefore, this paper first combines the analytic hierarchy process (AHP) to assign weights to each indicator. Additionally, it improves the AHP by incorporating the exponential scale method and group judgment techniques to enhance the objectivity of the weight calculation results.

The traditional AHP has two significant shortcomings: Firstly, it focuses more on the consistency of the judgment matrix but less on its rationality. This is because insufficient attention is paid to the quantity and quality of scale experts, leading to poor reliability of individual experts' judgments. Secondly, Saaty's 1–9 scale has flaws: The AHP principle requires that the comparison judgment value a_{ij} be the ratio of the importance of factor a_i to a_j, but the 1–9 scale provides the difference in importance between a_i and a_j. This causes two issues: (1) it distorts the calculation results of relative weights; (2) it leads to the inconsistency between the matrix consistency and the consistency of judgment thinking, making the matrix consistency index unable to truly reflect the degree of thinking consistency. To address these shortcomings, this paper replaces the 1–9 scale with an exponential scale and introduces group judgment. Specifically, L (where $L > 1$) experts simultaneously (or independently) provide pairwise comparisons of the relative importance of various evaluation indicators (regarding a certain objective), thereby forming L judgment matrices. The process of calculating the ranking weights of each element from these L judgment matrices is then carried out.

The specific steps for determining the weights are as follows (Figure 1):

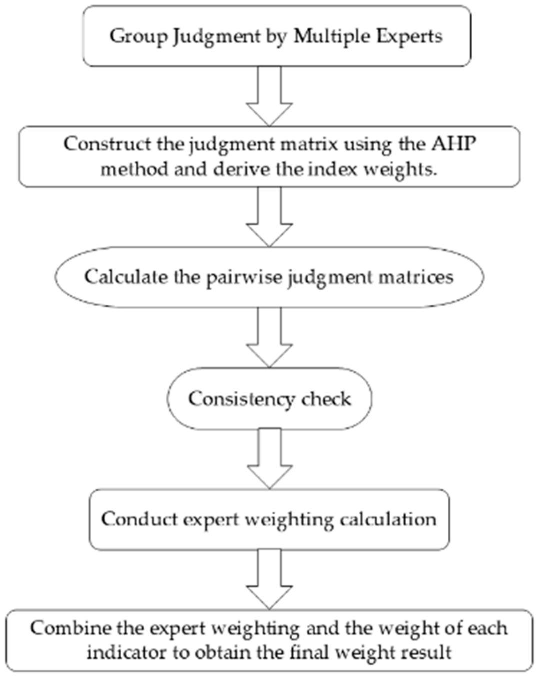

Figure 1. The steps for determining the weights.

(1) Group Judgment by Multiple Experts

Suppose there are m experts participating in the evaluation for a certain decision-making problem, and n indicators are available for selection. Under a certain criterion, each expert conducts pairwise comparisons of these n indicators to obtain the judgment matrix $A_k = \left(a(k)_{n \times n_{ij}}\right)$, $a_{ij}{}^{(k)} > 0$, $a_{ij}{}^{(k)} = 1/a_{ij}{}^{(k)}$, where $i, j = 1, 2, \ldots, n$ and $k = 1, 2, \ldots, m$. Here, k represents the k-th expert, n represents the number of indicators, and a_{ij} is the relative importance of indicator i to indicator j under the exponential scale. The description of the indicator scale is shown in Table 2.

Table 2. Exponential scale and 1–9 scale.

Distinction	Equally Important	Slightly Important	Significantly Important	Strongly Important	Extremely Important
1–9 Scale	1	3	5	7	9
Exponential Scale a0, a8	a0	a2	a4	a6	a8

Among them, the value of a is based on Saaty's 1–9 scale. Assuming that factor A is extremely more important than factor B, with the degree of importance ratio being m, then from $a^n = m$ we can derive the parameter $a = \sqrt[n]{m}$. Generally, considering that the degrees of importance in pairwise comparisons should be within the same order of magnitude for easier comparison, most scholars believe that 9 is the limit for the ratio of importance. Therefore, taking (i.e., the degree of importance is divided into 9 levels) and $m = 9$, then $a = \sqrt[8]{9} = \sqrt[3]{3} \approx 1.3160$.

(2) Construct the judgment matrix using the AHP method and derive the index weights.

(1) Calculate the pairwise judgment matrices, obtain the maximum eigenvalue and its corresponding eigenvector, normalize the vector so that the sum of all the data equals 1, resulting in the eigenvector $W_k = \left(w_1{}^{(k)}, w_2{}^{(k)}, w_3{}^{(k)}, \ldots, w_n{}^{(k)}\right)^T$, which represents the relative weight of the factors at the same level for the factors at the upper level, i.e., the single-level ranking. When multiple experts are involved, their individual judgments need to be aggregated into a single set of pairwise comparisons. This can be performed by: Averaging the individual ratings: Each expert's pairwise comparison matrix is averaged to create a single collective matrix. This ensures that the judgments of all experts are taken into account. Weighting expert opinions: If some experts are considered more reliable or experienced than others, their opinions can be weighted accordingly when aggregating the results.

(2) Consistency check. The results of single-level ranking do not represent the final results and need to be tested for consistency. The steps for the consistency check are as follows:

Calculate the consistency index (CI):

$$CI = \frac{\lambda_{\max} - n}{n - 1}, \tag{1}$$

where $\lambda_{\max}$ is the maximum eigenvalue, which is obtained by performing an eigenvalue decomposition on the judgment matrix. In AHP, the closer λ max is to the matrix's order n, the better the consistency of the matrix. A higher λ max value indicates a worse consistency of the judgment matrix. And n is the order of the matrix, which represents the number of elements (or criteria) in the hierarchical structure being compared. For example, if you are comparing 3 elements in a system, then $n = 3$. $CI = 0$ indicates perfect consistency; CI close to 0 indicates satisfactory consistency; the larger the CI, the more serious the inconsistency.

Calculate the average random consistency index (RI):

The RI is obtained by calculating the eigenvalues of pairwise judgment matrices multiple times and taking their average. Different orders of matrices correspond to different RI values, as shown in Table 3.

Table 3. Order of the judgment matrix and corresponding average random consistency index values.

Order	2	3	4	5	6	7	8	9	10
RI	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Calculate the consistency ratio (CR):

$$CR = \frac{CI}{RI} \tag{2}$$

where CR (consistency ratio) is a measure used to assess the overall consistency of the judgment matrix in the analytic hierarchy process (AHP). It is the ratio of the consistency index (CI) to the random consistency index (RI). A lower CR value (typically less than 0.1) indicates that the matrix has good consistency, while a higher CR value suggests poor consistency and that the judgment matrix may need to be revised. CI is a value used to assess how consistent the comparisons are within the judgment matrix. RI is a constant value that depends on the size (n) of the judgment matrix and represents the expected consistency index for a randomly generated matrix. It serves as a benchmark to compare the consistency of the actual judgment matrix. The values of RI are pre-calculated for different matrix sizes and can be found in AHP tables. For example, for a matrix of order 3 (n = 3), the RI value is 0.58.

Generally, the consistency test is passed only when $CR < 0.1$. At this point, the corresponding values in the normalized eigenvector can be used to represent the relative weights. Otherwise, the pairwise judgment matrix must be reconstructed from the beginning and recalculated until it passes the consistency test.

(3) Conduct expert weighting calculation

The final weights should integrate the opinions of all experts in the expert group. Simply averaging the weight vectors with $\frac{1}{n}$ is insufficient; actual judgment capabilities of each expert need to be weighted. To obtain the weights of each expert, their consistency with the judgment matrix can be used as a measure. The higher the consistency of the judgment matrix Ak given by expert k, the stronger the expert's judgment capability. During the consistency test, the smaller the CRk value, the higher the consistency level. According to Formula (3), the smaller the CIk, the higher the consistency level of Ak, and the larger the expert weight should be. Therefore, we define:

$$\lambda_k = \frac{\frac{1}{CI^k}}{\sum\limits_{i=1}^{n} \frac{1}{CI^i}} \tag{3}$$

In the above formula, λ_k represents the weight of expert k, and n represents the number of experts.

Thus, the expert weight vector U is obtained as $U = (\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5)^T$.

(4) Combine the expert weighting and the weight of each indicator to obtain the final weight result

$$w_i = \sum_{k=1}^{m} \lambda_k \times w_i^{(k)},\ i = 1, 2, 3, \ldots, n \tag{4}$$

The final weight vector is $W = (w_1, w_2, w_3, \ldots, w_n)^T$.

3.2. Construction of Comprehensive Evaluation Model

After analyzing and comparing the commonly used principal component analysis, fuzzy comprehensive evaluation methods, and multi-index comprehensive evaluation methods based on neural networks, the gray comprehensive evaluation method offers significant advantages in handling incomplete or uncertain data while being computationally simple and exhibiting strong dynamic adaptability. For the value-added service benefit evaluation of power grid enterprises, where data may not always be complete or accurate, the gray comprehensive evaluation method demonstrates strong suitability for addressing such challenges. and considering the characteristics of value-added service benefit evaluation in power grid enterprises, the value-added service benefit evaluation of power grid enterprises is influenced by dynamic factors such as changes in market demand and policy adjustments. The gray comprehensive evaluation method has strong adaptability to dynamics, allowing the evaluation model to be adjusted according to changes in the external environment. The preliminary research method was initially determined to be the gray comprehensive evaluation method. This means constructing a value-added service benefit evaluation model based on the gray comprehensive evaluation method.

One of the theoretical pillars of the gray comprehensive evaluation method is the whitening weight function, which is designed based on known information. It reflects the subjective judgment of the "preference" level of a gray number or gray class for different values within its range, depicting the degree to which each data point belongs to the gray number or gray class. This is particularly suitable for the research object in this paper. Therefore, the final selection is the comprehensive evaluation method based on the gray system whitening weight function. This method can better handle qualitative indicators by integrating multiple expert scores, thereby leveraging more expert experience and avoiding subjectivity from a single expert, making the evaluation results more objective. However, for quantitative indicators, if the scoring method is still used, it would subjectify the objectively true indicators. Therefore, different methods are needed to handle quantitative indicators. This paper improves the original model to allow both qualitative and quantitative indicators to be input into the model simultaneously. The specific steps are as follows:

(1) Evaluation Factor Set and Index Weight Set

Let $U = u_1, u_2, \ldots, u_p$ be the set of p types of factors constituting the evaluation factor set, with the overall evaluation goal being U. Under the i-th type of factor, n_i evaluation indices v_{ij} (where $j = 1, 2, \ldots, n_i$) are set. Since different evaluation indices have varying impacts on the overall evaluation goal U, the analytic hierarchy process (AHP) is applied to determine the weights of each index. Let the weight vector of the p factors relative to U be $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_p)$, and the weight vector of the p evaluation indices v_{ij} under the i-th type of factor U_i relative to U_i be $\omega_i = (\omega_{i1}, \omega_{i2}, \ldots, \omega_{ip})$.

(2) Calculation of Gray Evaluation Weights

As mentioned above, the methods for handling qualitative and quantitative indicators differ:

(1) Qualitative Indicator Processing

① Calculation of the Sample Matrix for Evaluation Indicators

Suppose m experts are invited to evaluate the observed values of n economic benefit indicators for a certain evaluation object. The score given by the k-th$(k = 1, 2, \ldots, m)$ expert for the i-th indicator is denoted as ${b_i}^k (k = 1, 2, \ldots, m)$, and the resulting evaluation indicator sample matrix B is formed accordingly.

$$B = \begin{pmatrix} {b_1}^1 & {b_1}^2 & \cdots & {b_1}^m \\ {b_2}^1 & {b_2}^2 & \cdots & {b_2}^m \\ \cdots & \cdots & \cdots & \cdots \\ {b_n}^1 & {b_n}^1 & \cdots & {b_n}^m \end{pmatrix} = \left({b_i}^k\right)_{n \times m} \quad (5)$$

Generally, b_i^k is taken from the range $[0, 10]$ or $[0, 100]$.

② Determining the gray classes and their whitening weight functions

The $n \times m$ scores given by m experts, which are the whitening values, are used to determine the gray classes to which each indicator belongs. To do this, it is necessary to first set the number of gray classes, the value ranges for each gray class, and the whitening weight functions for each gray class.

Assume that a total of M gray classes are defined, and the value range $[b_1, b_{M+1}]$ of indicator i is divided into M gray classes: $[b_1, b_2], \ldots, [b_k, b_{k+1}], \ldots, [b_M, b_{M+1}]$.

Let the N-type whitening weight function for index i be denoted as $f_i^N(x)$. Commonly used whitening weight functions include upper limit measure whitening weight functions, moderate measure whitening weight functions, and lower limit measure whitening weight functions.

The gray number is denoted as $\otimes \in \left[b_i^N(1), b_i^N(2), -, -\right]$, which is referred to as the upper limit measure whitening weight function. The expression for the whitening weight function $f_i^N(x)$ is as follows:

$$f_i^N(x) = \begin{cases} 0, x < b_i^N(1) \\ \frac{x - b_i^N(1)}{b_i^N(2) - b_i^N(2)}, x \in \left[b_i^N(1), b_i^N(2)\right] \\ 1, x > b_i^N(2) \end{cases} \tag{6}$$

Among them, $b_i^N(\bullet)$ represents the threshold for gray class N, and x is the observed value of the i-th indicator.

The gray number is $\otimes \in \left[b_i^N(1), b_i^N(2), -, b_i^N(4)\right]$, referred to as the moderate measure whitening weight function with its whitening weight function $f_i^N(x)$.

$$f_i^N(x) = \begin{cases} 0, x \notin \left[b_i^N(1), b_i^N(4)\right] \\ \frac{x - b_i^N(1)}{b_i^N(2) - b_i^N(1)}, x \in \left[b_i^N(1), b_i^N(2)\right] \\ \frac{b_i^N(4) - x}{b_i^N(4) - b_i^N(2)}, x \in \left[b_i^N(2), b_i^N(4)\right] \end{cases} \tag{7}$$

The gray number is $\otimes \in \left[-, -, b_i^N(3), b_i^N(4)\right]$, which is called the lower limit measure whitening weight function, and its whitening weight function $f_i^N(x)$ is

$$f_i^N(x) = \begin{cases} 0, x \notin \left[0, b_i^N(4)\right] \\ 1, x \in \left[0, b_i^N(3)\right] \\ \frac{b_i^N(4) - x}{b_i^N(4) - b_i^N(3)}, x \in \left[b_i^N(3), b_i^N(4)\right] \end{cases} \tag{8}$$

③ Calculate the gray evaluation coefficient and gray evaluation weight

For indicator i, the gray evaluation system for the nth gray class is $x_{i,N}$:

$$x_{i,n} = \sum_{k=1}^{m} f_N\left({b_i}^k\right) \tag{9}$$

The total gray evaluation coefficient for each evaluation gray category is x_i:

$$x_i = \sum_{N=1}^{M} x_{i,n} \tag{10}$$

The gray evaluation weight belonging to the nth gray class is denoted as $r_{i,N}$:

$$r_{i,n} = \frac{x_{i,n}}{x_i} \tag{11}$$

The gray class weight vector of the ith indicator is $R_{i,N}$:

$$R_{i,N} = (r_{i,1}, r_{i,2}, \ldots, r_{i,N}) \tag{12}$$

(2) Quantitative Indicator Processing

① Determine the Extremum Interval and Rating Classification of Each Indicator

Firstly, it is necessary to fully consider the characteristics of each indicator and determine the extremum interval for each quantitative indicator. Assuming a total of N gray classes are divided, the value range $[c_1, c_{N+1}]$ of indicator i is divided into N gray classes: $[c_1, c_2], \ldots, [c_k, c_{k+1}] \ldots, [c_N, c_{N+1}]$.

② Calculate the Gray Evaluation Weights

Let x be the observed value of indicator i, determine the center of the gray class, and denote the center of the k-th gray class M_k as $\frac{c_k+c_{k+1}}{2}$. The relative distance from the observed value x to the center M_k of the k-th gray class is expressed as:

$$D_k(x) = \frac{|x - M_k|}{\frac{1}{2}|c_k - c_{k+1}|} \tag{13}$$

The gray evaluation weights of quantitative indicators are primarily determined by the relative distances from each observed value to the centers of each gray category. Given that quantitative indicators are more objective, the results of gray category evaluation should be relatively concentrated, so only the nearest three gray categories are considered. The gray evaluation weight of indicator i belonging to the nth gray category is denoted as $r_{i,n}$:

When $x \leq M_1$, we have:

$$r_{i,n} = \begin{cases} 1, n = 1 \\ 0, others \end{cases} \tag{14}$$

$r_{i,n}$ represents a value associated with two indices i and n, which correspond to specific elements in a set or matrix.

$x \leq M_1$ suggests that x is a variable that is being compared to a threshold value M_1. When x is less than or equal to M_1, the condition applies, which impacts the value of $r_{i,n}$.

$r_{i,n} = 0$, others: For all other values of n, $r_{i,n}$ is set to 0. This implies that $r_{i,n}$ is a binary indicator that selects a specific scenario (when n = 1) and assigns a value of 1, while all other scenarios result in a value of 0.

When $M_1 < x \leq c_2$, we have:

$$r_{i,n} = \begin{cases} \frac{D_2(x)}{D_1(x)+D_2(x)}, n = 1 \\ \frac{D_1(x)}{D_1(x)+D_2(x)}, n = 2 \\ 0, others \end{cases} \tag{15}$$

For $M_1 < x < c_2$, $r_{i,n}$ is calculated based on the weighted ratio between $D_1(x)$ and $D_2(x)$.

When n = 1, $r_{i,n}$ represents the proportion of $D_2(x)$ relative to the total sum of $D_1(x)$ and $D_2(x)$.

When n = 2, $r_{i,n}$ represents the proportion of $D_1(x)$ relative to the total sum of $D_1(x)$ and $D_2(x)$.

For other values of n, the weight is set to 0.

When $c_2 < c_k < x < c_{k+1} < c_N$, we have:

$$r_{i,n} = \begin{cases} \frac{1}{2} \times \frac{\sum_{j=k-1}^{k+1} D_j(x) - D_{k-1}(x)}{\sum_{j=k-1}^{k+1} D_j(x)}, n = k-1 \\ \frac{1}{2} \times \frac{\sum_{j=k-1}^{k+1} D_j(x) - D_k(x)}{\sum_{j=k-1}^{k+1} D_j(x)}, n = k \\ \frac{1}{2} \times \frac{\sum_{j=k-1}^{k+1} D_j(x) - D_{k+1}(x)}{\sum_{j=k-1}^{k+1} D_j(x)}, n = k+1 \\ 0, others \end{cases} \tag{16}$$

For $c_2 < c_k < x < c_{k+1} < c_N$,the value of $r_{i,n}$ is determined by a weighted ratio involving the sum of values $D_j(x)$ over the range $j = k-1$ to $j = k+1$.

When $n = k-1$,$r_{i,n}$ is a proportion of the sum excluding $D_{k-1}(x)$, calculated as half of that ratio.

When $n = k$, $r_{i,n}$ is a proportion of the sum excluding $D_k(x)$, calculated as half of that ratio.

When $n = k+1$, $r_{i,n}$ is a proportion of the sum excluding $D_{k+1}(x)$, calculated as half of that ratio.

For all other values of n, $r_{i,n}$ is set to 0.

When $c_N \le x < M_N$,we have:

$$r_{i,n} = \begin{cases} \frac{D_N(x)}{D_{N-1}(x)+D_N(x)}, n = N-1 \\ \frac{D_{N-1}(x)}{D_{N-1}(x)+D_N(x)}, n = N \\ 0, others \end{cases} \tag{17}$$

For $c_N \le x < M_N$, the value of $r_{i,n}$ is determined by the relationship between $D_N(x)$ and $D_{N-1}(x)$.

For $n = N-1$, the weight $r_{i,n}$ is the ratio of $D_N(x)$ to the sum of $D_{N-1}(x) + D_N(x)$.

For $n = N$, the weight $r_{i,n}$ is the ratio of $D_{N-1}(x)$ to the sum of $D_{N-1}(x) + D_N(x)$.

If n takes any other value, the weight $r_{i,n}$ is set to 0.

When $x \ge M_N$,we have:

$$r_{i,n} = \begin{cases} 1, n = N \\ 0, others \end{cases} \tag{18}$$

When $x \ge M_N$, the value of $r_{i,n}$ is determined solely by n.

For n = N, $r_{i,n}$ equals 1.

For any other n, $r_{i,n}$ equals 0.

The gray weight vector for index i is denoted as $R_{i,N}$:

$$R_{i,N} = (r_{i,1}, r_{i,2}, \ldots, r_{i,N}) \tag{19}$$

(3) Comprehensive Gray Evaluation

By organizing the gray class weight vectors of qualitative and quantitative indicators together and left-multiplying by the indicator weight vector, we can obtain the comprehensive clustering matrix for the N-th gray class of a certain evaluation object as:

$$R_N = W \times (R_{1,N} R_{2,N}, \ldots, R_{n,N}) \tag{20}$$

where $R_{i,N} = (i = 1, 2, \ldots, n)$ represents the gray class weight vector of the i-th indicator.

By determining $\max\{R_N\} = R_{N^*}$,for $1 \le N \le M$, it can be judged that the evaluation object belongs to gray class N^*.

4. Empirical Measurement and Analysis of the Evaluation of Value-Added Services in Power Grid Enterprises

Based on the classification of value-added services in enterprise management, power grid operation, the user side, and socialization, this paper selects four typical cases of value-added services: customer electricity contract compliance monitoring, intelligent operation and maintenance, energy management contracting, and government decision support. By collecting the necessary data based on the established evaluation index system, the paper applies the constructed evaluation model for the value-added services of power grid enterprises to conduct empirical or simulation measurements on the evaluation of value-added services in power grid enterprises based on the application of comprehensive business data. The evaluation results are analyzed, and corresponding decision-making suggestions are proposed.

4.1. Introduction to Customer Electricity Contract Compliance Monitoring

The customer electricity contract compliance monitoring business mainly includes two aspects: preventing electricity fee risks through customer electricity contract compliance monitoring and preventing through customer electricity contract compliance monitoring. The implementation method of customer electricity contract compliance monitoring to prevent is that the company conducts in-depth mining and effective utilization of massive data, such as existing user electricity information, extracts abnormal data related to and its prevention and investigation, and uses technologies such as distributed storage, distributed computing, and massive data mining to analyze behaviors, thereby enhancing the effectiveness and timeliness of preventing and investigating. By integrating real-time monitoring systems using modern smart meters and IoT technologies, customer electricity contract compliance monitoring can significantly improve the accuracy and timeliness of detecting irregularities, ensuring that non-compliance issues are addressed promptly, thus effectively reducing electricity fee risks. For power grid companies, the customer electricity contract compliance monitoring business to prevent improves the efficiency of investigating and reduces electricity fee losses; for users, it helps them standardize their electricity usage behavior and develop good electricity usage habits, further reducing compliance issues. By leveraging artificial intelligence and machine learning algorithms to continuously analyze vast amounts of data, it not only improves anomaly detection accuracy but also predicts potential risks by identifying usage patterns. This optimizes the compliance monitoring process, reducing human intervention and increasing efficiency.

Furthermore, power companies can reduce non-compliance behavior by enhancing user education and awareness. By proactively educating users about the importance of adhering to their electricity contracts and promoting energy-saving practices, power companies can effectively help users form standardized electricity usage habits, further reducing the risk of non-compliance and promoting long-term sustainable usage behavior. Incorporating blockchain technology can further enhance the transparency and security of the customer electricity contract compliance monitoring system. With a decentralized ledger system, both power companies and users can maintain a clear and immutable record of contract terms, electricity consumption, and deviations, reducing the risk of disputes and ensuring the integrity of the compliance monitoring process.

This paper analyzes the results of the comparison of the relationships between the indicators at various levels of customer electricity contract compliance monitoring by five experts, constructs the judgment matrices for the criterion layer, economic benefit index layer, management benefit index layer, and social benefit index layer, and calculates the index weights based on the improved Analytic Hierarchy Process. Power companies can introduce incentive mechanisms for users who consistently comply with their electricity contracts, such as offering discounts, rewards, or participation in eco-friendly initiatives. This not only reduces monitoring costs but also encourages users to adopt long-term compliant electricity usage behaviors, thereby ensuring the long-term effectiveness of the compliance monitoring system.

In addition to preventing electricity fee risks and improving compliance monitoring efficiency, customer electricity contract compliance monitoring can contribute to broader sustainability goals. By minimizing electricity waste and encouraging energy efficiency, compliance monitoring helps reduce carbon emissions and promotes green, low-carbon electricity usage, aligning with global and national climate action goals. Based on Formulas (1) and (2), the specific results shown in Table 4 can be obtained.

Table 4. Summary table of index weights for customer electricity contract compliance monitoring.

Target Layer	Criteria Layer	Indicator Layer	Indicator Weight
Comprehensive Benefits of Customer Electricity Performance Monitoring	Economic Benefits	Internal Rate of Return	0.0595
		Static Investment Recovery Period	0.0303
		Market Prospects	0.1007
		Macro Policy Support	0.1296
	Management Benefits	Technical Maturity	0.1037
		User Convenience	0.2442
		Economic Efficiency	0.1879
	Social Benefits	Incremental Employment	0.0559
		Energy Savings	0.0555
		Pollution Reduction	0.0327

The comprehensive benefits of customer electricity performance monitoring services were evaluated using an improved gray whitening weight function model, with the evaluation results shown in Table 5.

Table 5. Comprehensive benefit evaluation results of customer electricity performance monitoring.

	Excellent	Good	Average	Poor	Evaluation Results
Economic benefits	0.1814	0.2977	0.2380	0.2829	Good
Management benefits	0.3045	0.4666	0.1754	0.0536	Good
Social benefits	0.0000	0.1988	0.5840	0.2171	Average
Comprehensive benefits	0.1930	0.3455	0.2916	0.1699	Average

In terms of economic benefits, the highest value is in the "Good" category, indicating that customers generally perceive a positive impact of the electricity performance monitoring system on economic benefits. Although the values for "Excellent" and "Average" are relatively low, they still show some economic benefits, particularly in cost savings, operational efficiency, and energy optimization.

In terms of management benefits, the value for the "Good" category is 0.4666, which is the highest, suggesting that customers generally consider the management effects of the electricity performance monitoring system to be the most prominent. The relatively low values for "Poor" and "Average" indicate that customers broadly recognize the significance of management benefits, especially in terms of monitoring ease, operational efficiency, and decision support.

In terms of social benefits, the highest value is in the "Average" category, at 0.5840, indicating that the recognition of social benefits is more balanced among customers, but it does not stand out as strongly as the economic and management benefits. Social benefits may include environmental impact, energy conservation, or community welfare, but based on the table, customers' perception of these aspects is more moderate. Particularly, the "Excellent" value is 0, which suggests that the system's impact on social benefits has not been fully recognized or emphasized.

In terms of comprehensive benefits, which represent the overall evaluation of all benefit categories, the highest value is in the "Good" category (0.3455). However, the final evaluation result is "Average", meaning that although individual benefit categories received positive evaluations, the overall outcome has not reached a very high standard. The proportions of "Good" and "Average" are relatively close, indicating that customer perceptions of the overall benefits are somewhat dispersed, and they may not fully recognize the system's all-around benefits.

According to the principle of maximum membership, it can be concluded that the economic benefits of the customer power contract monitoring business are good, the management benefits are good, the social benefits are medium, and the comprehensive evaluation result is average. This means that the value-added service of customer power contract monitoring has relatively good comprehensive benefits, and it is recommended to develop and promote it.

4.2. Smart Operation and Maintenance

Smart operation and maintenance, supported by modern information technologies such as "Big Data, Cloud Computing, the Internet of Things, and Mobile Internet", aims to ensure the safe operation of grid equipment and improve the efficiency and effectiveness of operation and maintenance. It possesses self- and environmental perception, proactive prediction and early warning, auxiliary diagnosis and decision-making, and centralized control functions, forming an organic whole of technologies, equipment, and platforms that achieve automated operation and maintenance business and management. Its main features include panoramic equipment status, automated data analysis, centralized production command, and lean operation and maintenance management.

To further enhance these capabilities, artificial intelligence (AI) and machine learning can be incorporated into smart operation and maintenance systems. By analyzing historical data and continuously learning from operational patterns, AI can improve predictive maintenance, optimize schedules, and detect early signs of failure, significantly reducing downtime and increasing system reliability. Machine learning algorithms can identify patterns in grid performance and predict future equipment needs, helping maintenance teams prioritize tasks and allocate resources more effectively. Based on intelligent devices with the characteristics of "integration, standardization, and modularization", it is possible to achieve comprehensive knowledge and control of equipment status, with interchangeable capabilities among similar devices and modules, significantly reducing the difficulty of operation and maintenance. The perception system of equipment status and operation and maintenance resources based on the Internet of Things can realize the interconnection of information for grid equipment and operation and maintenance resources (people, vehicles, equipment), providing strong support for comprehensive equipment status control and optimal resource allocation. A collaborative ecosystem that includes grid operators, maintenance teams, technology providers, and even end users can foster continuous improvement. By enabling real-time feedback and data sharing, the system can learn from each stakeholder's experiences and best practices, leading to ongoing innovation and more efficient management of grid resources.

This article analyzes the results of a comparison of the relationships between various levels of indicators for smart operation and maintenance by five experts. It constructs the judgment matrices for the criterion layer, economic benefit indicator layer, management benefit indicator layer, and social benefit indicator layer. Based on Formulas (1) and (2), the data in the table can be obtained. Based on the improved analytic hierarchy process, it calculates the weights of the indicators, with the specific results shown in Table 6.

Table 6. Summary of indicator weights for smart operation and maintenance.

Target Layer	Criteria Layer	Indicator Layer	Indicator Weight
Comprehensive Benefits of Customer Electricity Performance Monitoring	Economic Benefits	Internal Rate of Return	0.0647
		Static Investment Recovery Period	0.0642
		Market Prospects	0.1017
		Macro Policy Support	0.0955
	Management Benefits	Technical Maturity	0.2062
		User Convenience	0.1374
		Economic Efficiency	0.0961
	Social Benefits	Incremental Employment	0.0508
		Energy Savings	0.1171
		Pollution Reduction	0.0665

The comprehensive benefits of smart operation and inspection services are evaluated using the improved gray whitening weight function model, with the evaluation results shown in Table 7.

Table 7. Comprehensive benefits evaluation results of smart operation and inspection.

	Excellent	Good	Average	Poor	Evaluation Results
Economic benefits	0.3844	0.2118	0.1597	0.2441	Excellent
Management benefits	0.4621	0.3849	0.1020	0.0510	Excellent
Social benefits	0.0000	0.0151	0.7103	0.2746	Average
Comprehensive benefits	0.3285	0.2418	0.2634	0.1663	Excellent

In terms of economic benefits, the highest value is 0.3844, assigned to “Excellent”, indicating that the smart operation and inspection system is viewed as having a significant positive impact on economic benefits. The relatively lower values for “Good” and “Average” show that while not everyone perceives the system as exceptionally beneficial, most still recognize its contribution, especially in cost savings, efficiency, and optimization.

In terms of management benefits, the highest value is 0.4621 for “Excellent”, which shows that customers overwhelmingly perceive the smart operation and inspection system as being highly effective in terms of management. This could involve improvements in monitoring, decision-making, resource allocation, or management tools. The relatively low values for “Poor” and “Average” suggest that customers consistently see management benefits as one of the standout features of the system.

In terms of social benefits, the highest value is 0.7103 for “Average”, indicating that social benefits, while still recognized, are not perceived as strongly as economic and management benefits. The low value for “Excellent” (0.0000) and the presence of a significant proportion of “Poor” evaluations suggest that customers have a relatively weak perception of the social impact of the smart operation and inspection system. Social benefits could encompass environmental impacts, community welfare, or social responsibility, but these aspects are not as strongly appreciated or highlighted in this evaluation.

In terms of comprehensive benefits, the highest value is 0.3285 for “Excellent”, indicating that the overall perception of the system’s comprehensive benefits is very positive. The fact that “Excellent” outpaces “Good” and “Average” suggests that customers broadly recognize the system’s wide-ranging advantages across multiple dimensions, including economic, management, and potentially even social aspects, though the latter is less pronounced.

According to the principle of maximum membership, it can be concluded that the economic benefits of intelligent operation and inspection services are excellent, the management benefits are excellent, the social benefits are medium, and the comprehensive evaluation result is excellent. This means that the implementation of intelligent operation and inspection as a value-added service has good overall benefits, and it is recommended to develop and promote it.

Therefore, in practical applications, it is recommended to strengthen collaboration with equipment suppliers and technology partners to promote technological updates and to enhance personnel training so that they can better apply smart tools for daily maintenance. In addition to this, the following aspects should be considered for further improvement:

(1) Enhancing Collaboration with Equipment Suppliers and Technology Partners:

Strength: Collaboration with equipment suppliers and technology partners offers access to cutting-edge technologies and solutions that can accelerate the evolution of smart operation and maintenance systems. By working closely with these partners, grid companies can stay up-to-date with the latest developments in automation, IoT integration, and data analytics, ensuring that their systems are constantly evolving and improving.

Weakness: The reliance on external suppliers for technology updates and equipment maintenance can lead to delays or mismatches between system needs and supplier capabilities. There may also be compatibility issues with legacy systems.

Improvement: To overcome this, power companies should foster long-term relationships with multiple suppliers, encouraging knowledge sharing and joint R&D efforts. Regular feedback loops and collaboration on system updates can ensure smoother transitions and faster adoption of new technologies. Additionally, developing internal capabilities for integrating and customizing solutions can help reduce reliance on external vendors.

(2) Personnel Training and Skill Enhancement:

Strength: The ability to use smart tools effectively is crucial for improving the operational efficiency of smart operation and maintenance systems. Comprehensive training programs empower staff to manage new technologies and make data-driven decisions, reducing human errors and improving overall system reliability.

Weakness: One major challenge is the gap between the skills of the current workforce and the complex nature of advanced smart operation and maintenance tools. The adoption of new technologies may outpace the training programs, leaving staff inadequately prepared for the technological shift.

Improvement: To address this, organizations should implement continuous professional development programs that are tailored to specific roles. Incorporating hands-on workshops, simulations, and certification courses will ensure that personnel are consistently up-to-date with the latest advancements. Cross-departmental knowledge sharing and peer learning should also be encouraged to foster a culture of collaboration and improvement.

(3) Optimizing Data Analytics for Predictive Maintenance:

Strength: One of the main advantages of smart operation and maintenance systems is the ability to collect and analyze massive amounts of data in real-time. Advanced data analytics can predict equipment failure, improve maintenance schedules, and reduce downtime.

Weakness: Despite its potential, many smart operation and maintenance systems are still underutilizing the full capacity of data analytics. Poor data quality, incomplete datasets, or misconfigured algorithms can lead to inaccurate predictions and suboptimal maintenance scheduling.

Improvement: To strengthen this aspect, grid companies should invest in improving data quality by integrating data from more sources and ensuring that it is accurate, consistent, and timely. Enhanced AI and machine learning algorithms can further improve predictive accuracy. Additionally, continuous refinement of data processing workflows and regular algorithm evaluations can help optimize maintenance predictions.

4.3. Energy Performance Contracting

Energy performance contracting (EPC) is a market-based energy efficiency mechanism that emerged in Western developed countries following the global energy crisis in the mid-1970s. Its potential in developing regions is equally significant, as these regions face similar energy challenges, including rising consumption and a high dependence on fossil fuels. The growing importance of sustainability has led to the expansion of EPC models beyond just energy savings to incorporate environmental and social benefits as well. One novel perspective on EPC is its potential to integrate renewable energy sources within the contracting framework. As renewable energy generation becomes more cost-competitive and accessible, ESCOs could incorporate renewable energy solutions into EPC contracts, improving the environmental impact of energy-saving projects. This could include integrating solar panels, wind energy systems, or energy storage technologies, all of which contribute to enhancing energy reliability while reducing reliance on traditional, non-renewable energy sources. In this model, energy service companies (ESCOs) and energy-consuming entities enter into a contractual agreement to set energy efficiency targets for specific projects. The ESCOs provide necessary services to achieve these targets, and the energy-consuming entities pay for these services using the savings generated from energy efficiency improvements. Essentially, EPC is a business model where the cost of energy efficiency project upgrades is borne by the savings generated from reduced energy consumption. This is equivalent to customers using future energy savings to maintain or upgrade their businesses and equipment, thereby reducing operational costs. Alternatively, ESCOs can guarantee energy savings and manage energy expenses for clients, providing energy-saving services.

Another evolving aspect is the use of real-time data analytics and artificial intelligence (AI) to optimize energy management within EPC contracts. Power grid enterprises, leveraging their massive data advantage, can employ advanced machine learning algorithms to predict and optimize energy consumption patterns, providing real-time feedback and predictive maintenance to customers. This can lead to more accurate energy savings forecasts and a higher level of confidence for both parties in the contract, improving the performance and long-term sustainability of energy efficiency projects. Power grid enterprises, located in the intermediate link of generation, transmission, transformation, and distribution, have a large number of power enterprise users. Over the long-term process of production and operation, they have accumulated massive amounts of business data. Among these, energy consumption data, electricity usage data, and energy efficiency data are the foundation for comprehensive energy audits and the determination of energy-saving technical solutions in EPC. Therefore, compared to general ESCOs, power grid enterprises have a significant data advantage when it comes to implementing EPC.

This paper analyzes the results of comparisons made by five experts regarding the relationships between various levels of indicators in EPC. It constructs judgment matrices for the criterion layer, economic benefit indicator layer, management benefit indicator layer, and social benefit indicator layer. Based on an improved analytic hierarchy process (AHP), it calculates the weights of these indicators. Based on Formulas (1) and (2), the specific results shown in Table 8 can be obtained.

Table 8. Summary of EPC indicator weights.

Target Layer	Criteria Layer	Indicator Layer	Indicator Weight
Comprehensive Benefits of Customer Electricity Performance Monitoring	Economic Benefits	Internal Rate of Return	0.1420
		Static Investment Recovery Period	0.0871
		Market Prospects	0.1950
		Macro Policy Support	0.1723
	Management Benefits	Technical Maturity	0.0455
		User Convenience	0.0466
		Economic Efficiency	0.0754
	Social Benefits	Incremental Employment	0.0579
		Energy Savings	0.1144
		Pollution Reduction	0.0639

Using the improved gray whitening weight function model, the comprehensive benefits of energy performance contracting business are evaluated, and the evaluation results are shown in Table 9.

Table 9. Comprehensive benefits evaluation results of energy performance contracting.

	Excellent	Good	Average	Poor	Evaluation Results
Economic benefits	0.6638	0.1887	0.1093	0.0381	Excellent
Management benefits	0.0667	0.4438	0.3872	0.1024	Good
Social benefits	0.4037	0.3511	0.2113	0.0339	Excellent
Comprehensive benefits	0.5024	0.2698	0.1799	0.0479	Excellent

In terms of economic benefits, the highest value (0.6638) is for the Excellent category, indicating that the energy performance contracting system is strongly perceived as having a significant positive impact on economic benefits. This high rating reflects the customers' recognition of cost savings, energy efficiency improvements, and return on investment achieved through EPC. The relatively low values for "Good", "Average", and "Poor" suggest that most customers view the economic outcomes of the system favorably. Energy performance contracting likely leads to significant savings in energy consumption and operational costs, contributing to its strong economic perception.

In terms of management benefits, the highest value for management benefits is 0.4438, which is in the Good category. This suggests that customers perceive the EPC system as moderately effective in improving management processes, including enhanced monitoring, control, and operational efficiency. However, the relatively low value for "Excellent" (0.0667) implies that while management benefits are appreciated, they are not as widely recognized or as impactful as economic or social benefits. The "Average" value of 0.3872 shows that many customers feel that while management improvements exist, they may not be as pronounced or impactful as the economic or social outcomes.

In terms of social benefits, the highest value (0.4037) is in the Excellent category, indicating that social benefits, such as environmental impact, sustainability, and community welfare, are also highly regarded in the context of energy performance contracting. This shows that customers not only recognize the economic and management advantages but also appreciate the positive contribution to social goals. The relatively high percentage of "Good" and "Excellent" values suggests that EPC systems are seen as beneficial in promoting energy conservation and reducing carbon footprints. The very low "Poor" value (0.0339) further indicates that the social impact of EPC systems is widely perceived as a positive outcome.

In terms of comprehensive benefits, the highest value (0.5024) is for the Excellent category, indicating that the overall evaluation of EPC systems is highly favorable. The strong recognition in the "Excellent" category suggests that the combined impact of economic, management, and social benefits results in a highly positive perception of the EPC system as a whole. The relatively low "Poor" value (0.0479) shows that there is little negative perception about the system's comprehensive benefits, with most customers seeing the system as providing substantial value across multiple dimensions. The "Good" and "Average" categories are still present but to a lesser degree, which shows that while the system is mostly positively regarded, there are some who perceive it less favorably.

According to the principle of maximum membership, the following conclusions can be drawn: the economic benefits of the contract energy management business are excellent, the management benefits are good, the social benefits are excellent, and the comprehensive evaluation result is excellent. This indicates that the implementation of contract energy management as a value-added service has good overall benefits, and it is recommended to develop and promote this service.

4.4. Government Decision Support

Developing socialized value-added services for scientific government decision-making is a service provided by power grid companies based on the analysis of economic development trends across various industries using power big data, offering scientific references for government economic decision-making.

Power big data primarily originates from the generation, transmission, transformation, distribution, consumption, and dispatching of electricity in the power production and energy use processes. It is characterized by large volume, diverse categories, and high speed. Currently, China's power system has established the world's largest professional Internet of Things (IoT) related to national and people's livelihoods and is constructing the largest big data and cloud computing platform in China. Additionally, the State Grid Corporation is establishing and improving various systems such as the electricity consumption information collection system, power quality detection system, dispatching automation system, distribution automation system, marketing application system, customer service system, load control system, load monitoring system, production management system, and fault repair system. These systems generate a vast amount of structured and unstructured data, including user profile data, user electricity consumption collection data, distributed power source data, charging pile data, user service information data, grid geographic topology data, grid electrical topology data, primary equipment ledger data, dispatching automation data, distribution automation data, operation data of public and dedicated transformers, distribution network maintenance and fault information, power supply reliability data, equipment image data, equipment geographic spatial information, and historical monitoring data of equipment operation, among others. Furthermore, big data from outside the power industry, such as geographic information data, meteorological data, socio-economic data, and communication internet data, complements and enhances power big data. This is crucial for fully mining the effective information within various datasets, optimizing the structure of power energy, improving the operational level of the power grid and related industries, providing a scientific basis for government decision-making, and enhancing government management.

In addition to improving operational efficiency, the integration of power big data with artificial intelligence (AI) and machine learning (ML) can further revolutionize government decision-making support. By applying AI and ML algorithms, it is possible to predict energy demand fluctuations, analyze economic trends, and optimize grid performance in real time.

This predictive capacity could help government bodies to prepare for future energy needs more effectively, allowing for better long-term planning and resource allocation.

Moreover, the incorporation of advanced data visualization tools can enhance the accessibility and comprehensibility of complex power big data for decision-makers. Interactive dashboards and geospatial visualizations can enable government officials to quickly interpret critical data and make informed decisions based on a comprehensive understanding of the energy landscape.

Another emerging trend is the integration of decentralized energy sources, such as distributed solar or wind power, into the power grid's data system. This would provide more granular insights into energy generation and consumption at the local level, allowing for more flexible, responsive policymaking. With more localized data, the government can fine-tune policies for energy production, distribution, and consumption, fostering more sustainable energy practices at the regional level.

The role of cybersecurity also becomes paramount as power big data grows in volume and sensitivity. Protecting these data from breaches or malicious attacks is essential not only for the smooth operation of the power grid but also for safeguarding national security and the trust of the general public. Power grid enterprises and government agencies must ensure that the infrastructure for handling big data is secure and resilient to prevent potential risks.

Lastly, the evolution of smart grids, supported by the real-time monitoring capabilities of power big data, is opening up new avenues for government decision-making in areas such as demand response, energy storage, and grid resilience. These technologies enable dynamic adjustments to energy supply and demand, helping governments address energy shortages, peak loads, and other challenges in a more agile manner.

This article analyzes the comparison results of the relationships between various levels of indicators for government decision support by five experts, constructs the criterion layer, economic benefit indicator layer, management benefit indicator layer, and social benefit indicator layer judgment matrices, and calculates the indicator weights based on the improved analytic hierarchy process (AHP). Based on Formulas (1) and (2), the specific results shown in Table 10 can be obtained.

Table 10. Summary of government decision support indicator weights.

Target Layer	Criteria Layer	Indicator Layer	Indicator Weight
Comprehensive Benefits of Customer Electricity Performance Monitoring	Economic Benefits	Internal Rate of Return	0.0464
		Static Investment Recovery Period	0.0371
		Market Prospects	0.0626
		Macro Policy Support	0.0889
	Management Benefits	Technical Maturity	0.0674
		User Convenience	0.1471
		Economic Efficiency	0.1271
	Social Benefits	Incremental Employment	0.1716
		Energy Savings	0.1466
		Pollution Reduction	0.1052

The comprehensive benefits of government decision support services were evaluated using an improved gray whitening weight function model, with the evaluation results shown in Table 11.

Table 11. Evaluation results of comprehensive benefits for government decision support.

	Excellent	Good	Average	Poor	Evaluation Results
Economic benefits	0.2223	0.3549	0.2624	0.1603	Good
Management benefits	0.1855	0.3370	0.1130	0.3645	Poor
Social benefits	0.0491	0.1143	0.5935	0.2431	Average
Comprehensive benefits	0.1364	0.2469	0.3516	0.2651	Average

In terms of economic benefits, the highest value is in the Good category (0.3549), indicating that the economic impact of the government decision support system is largely seen as positive, though not outstanding. The moderate values for "Excellent" (0.2223) and "Average" (0.2624) show that customers perceive some benefits, such as cost reduction, efficiency improvements, and better allocation of resources, but the overall economic impact might not be seen as transformative. The relatively low value for "Poor" (0.1603) suggests that there is some degree of positive recognition, but not every customer sees the system as delivering high economic value.

In terms of management benefits, the highest value for management benefits is in the Good category (0.3370), but the significant percentage of evaluations in the Poor category (0.3645) indicates that the system is widely perceived as lacking effectiveness in improving management processes. The relatively low value for "Excellent" (0.1855) shows that while the system may offer some management improvements, these are not widely recognized or perceived as significantly impactful. The Poor evaluation suggests that many customers feel that the system has not contributed enough to enhancing management efficiency, decision-making, or overall governance.

In terms of social benefits, the highest value is in the Average category (0.5935), meaning that the social benefits are seen as moderate or balanced. While a portion of the evaluation is positive ("Good" at 0.1143), the largest share of respondents view the social impact as being Average, indicating that while some customers recognize the potential societal advantages (such as improved public services, community welfare, or social justice), these benefits are not as pronounced as the economic or management outcomes. The Poor evaluation (0.2431) indicates that some respondents feel that the system has a limited or negative impact on social issues.

In terms of comprehensive benefits, the highest value is in the Average category (0.3516), suggesting that the overall evaluation of the government decision support system is moderately positive but not exceptional. This reflects a mixed perception, where the combined economic, management, and social benefits are seen as moderate. The Good and Excellent evaluations (0.2469 and 0.1364, respectively) show that some customers recognize value in the system, but it does not stand out as delivering high overall impact across all areas. The Poor evaluation (0.2651) further emphasizes that a significant number of respondents feel the system's overall benefits are below expectations.

According to the principle of maximum membership (shown in Table 12), it can be concluded that the economic benefits of government decision support services are good, the management benefits are poor, the social benefits are medium, and the comprehensive evaluation result is medium. This means that the benefits of providing government decision support as a value-added service are moderate.

Based on the table, the following conclusions can be drawn:

Energy performance contracting performs excellently in both economic and social benefits, and its comprehensive benefits are also strong. This suggests that the scheme not only brings significant economic gains but also generates positive social impact, making it a highly recommended option.

Smart operation and inspection excels in economic and management benefits and performs excellently in comprehensive benefits. Although its social benefits are average, it is still a promising scheme overall, especially in terms of improving management efficiency and economic performance.

Table 12. Empirical measurement of the evaluation of value-added services in power grid enterprises.

	Economic Benefits	Management Benefits	Social Benefits	Comprehensive Benefits
Customer Electricity Performance Monitoring	Good	Good	Average	Average
Smart Operation and Inspection	Excellent	Excellent	Average	Excellent
Energy Performance Contracting	Excellent	Good	Excellent	Excellent
Government Decision Support	Good	Poor	Average	Average

Customer Electricity Performance Monitoring performs well in economic and management benefits but has average social and comprehensive benefits. This indicates that the scheme may be more focused on improving the operational efficiency of the power system, with limited impact on social benefits.

Government Decision Support shows good economic benefits but struggles with management benefits, which are poor. While it performs well in economic terms, its comprehensive benefits are relatively low, suggesting that the scheme may face challenges in management and execution and would require further improvement to enhance its overall effectiveness.

Many studies have shown that customer electricity performance monitoring can effectively improve the reliability and energy efficiency of power systems. However, because it mainly focuses on technical operations, social benefits and comprehensive benefits are often overlooked. Systems like smart operation and inspection play a significant role in improving economic and management benefits. Energy performance contracting (EPC) has broad research support for improving energy efficiency and reducing costs, especially in terms of social benefits, as EPC can significantly lower energy consumption and reduce greenhouse gas emissions, thereby enhancing social benefits. Its economic benefits are typically outstanding. Research on government decision support systems often focuses on improving decision-making efficiency and government management transparency. However, many studies also mention that, although the economic benefits may be good, the improvement in management benefits and social benefits is relatively limited, especially since the effectiveness in management is often influenced by political and administrative environments.

5. Conclusions

This study focuses on the construction of an innovative framework for value-added services in power grid companies, centering on user demand orientation. It delves into customer needs from the customer's perspective, supported by data and technology synergy, to drive mutual value creation and achieve safety and advancement. Through the basic analysis of comprehensive business data in power grid companies and the demand analysis of segmented users in power grid enterprises, it identifies four application directions for innovative value-added services: value-added services for grid operation, enterprise management value-added services, user-side value-added services, and social value-added services. The study scientifically categorizes the benefits and constructs a general evaluation index system, considering the differences in the benefits of various types of value-added services. It selects and improves analysis methods to objectively assign weights to each indicator. After comparing the strengths, weaknesses, and applicability of different comprehensive evaluation methods, it selects and specifically improves the evaluation method to achieve simultaneous input of qualitative and quantitative indicators, completing the model construction. Typical businesses from the four categories of value-added services are selected for quantitative data collection and empirical measurement.

Therefore, practitioners should focus on user demand, deeply understanding the needs of segmented users within power grid companies, especially in terms of personalized value-added services. It is recommended to drive service innovation through the synergy of big data and technology while utilizing intelligent methods to enhance grid operation's safety and stability, thus improving user experience and reinforcing user demand-oriented service innovation. Power grid companies should strengthen intelligent monitoring and fault prediction services to improve grid operation's efficiency and safety. Additionally, in terms of enterprise management, it is recommended that practitioners introduce advanced management tools and information systems to optimize resource management, improve management efficiency, and help companies achieve smart and information-driven management.

Future research could focus on the application and adaptability of value-added services in different regions, comparing the effectiveness and applicability of value-added services in various market environments, further validating the generalizability of the framework, and analyzing the long-term benefits of value-added services. At the same time, the role of cross-industry collaboration and resource sharing in value-added services deserves further attention, particularly in sectors like energy, transportation, and finance, exploring how different industries can create synergies through shared value-added services. Finally, the impact of value-added services on environmental sustainability, social responsibility, and their connection to long-term corporate strategies is an important area for future research. By exploring these aspects, the overall influence and long-term value of value-added services can be significantly enhanced, promoting their widespread application and development globally.

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