Comprehensive Evaluation of Process Reengineering Effect of Power Grid Functional Departments Empowered by AI

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Abstract. AI reconstruction of grid business processes optimizes stock human resource allocation, yet existing evaluation lacks multi-dimensional quantitative frameworks combining intelligent efficiency and talent transformation. This paper constructs a five-dimensional index system via two-round Delphi screening, adopts improved AHP-entropy combined weighting method and optimized TOPSIS model with modified distance formula for quantitative assessment. Taking 24 teams from a power supply enterprise's 8 departments as samples, empirical results show prominent efficiency gaps across departments. Through weight calculation and empirical comparison, this paper verifies that AI skill upgrading and post adaptability are the core constraints restricting reengineering efficiency. On the premise of inherent baseline efficiency gaps across departments, this paper puts forward a fair incentive system for cross-department collaboration efficiency, classified training schemes and an intelligent post matching mechanism with detailed textual interpretation for readers unfamiliar with HR theories to support grid intelligent transformation.

Keywords: Artificial Intelligence; Power Grid Functional Department; Business Process Reengineering; Stock Human Resource; Improved TOPSIS; Delphi-AHP-Entropy Weight Model

1 Introduction

New power system construction pushes grid enterprises to deploy large AI models and intelligent agents to reform traditional workflows, forming sustainable internal post transfer and hierarchical skill upgrading paths for stock human resources as the primary personnel optimization path instead of mass layoffs[1,2]. Current studies mainly focus on AI algorithm and equipment monitoring, while quantitative evaluation of AI process reengineering effect is insufficient[3,4]. Most assessments rely on single performance indicators or subjective scoring, lacking hybrid subjective-objective weighting models and cross-department efficiency comparison under the premise of baseline efficiency gaps among different departments[3,5]. This paper

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establishes a complete Delphi-AHP-entropy-improved TOPSIS evaluation framework[1], conducts empirical analysis with real enterprise data, identifies transformation bottlenecks and proposes targeted management countermeasures.

2 Construction of Evaluation Model and Indicator System

2.1 Research Framework

The research contains three core modules: Delphi indicator screening, AHP-entropy combined weighting, and improved TOPSIS comprehensive evaluation[1]. After two rounds of expert scoring screening, standardized data are imported to calculate subjective weight w_1 and objective entropy weight w_2, Different from the arbitrary fixed equal fusion coefficient in most existing studies, this paper adopts game theory to verify the rationality of the fusion coefficient α=0.5, which realizes the dynamic balance between expert subjective experience and data objective laws suitable for grid AI transformation evaluation scenarios[5]. Meanwhile, this paper modifies the traditional Euclidean distance formula of TOPSIS model, introduces absolute ideal point and projection distance calculation method to replace the traditional relative distance calculation, which effectively solves the problem of low discrimination of traditional TOPSIS when multiple sample results are close[5]. Weighted decision matrix is built to compute sample relative proximity and classify reengineering efficiency grades, which effectively reduces subjective deviation in single evaluation methods[5].

2.2 Indicator System Screening by Two-round Delphi Method

Combined with AI process reengineering and stock human resource transformation characteristics, five primary dimensions are initially determined: AI Process Optimization Effect (D1), Stock Human Resource Post Adaptability (D2), Professional AI Skill Upgrading (D3), Business & Team Operation Benefit (D4), Sustainable Transformation Willingness (D5), with 26 preliminary secondary indicators. A total of 18 experts including HR managers, business supervisors and AI technical backbones participate in 10-point scoring. Indicators with average score below 6 are eliminated in the first round; residual indicators are revised and optimized in the second round. Finally, 19 valid secondary indicators are retained, as shown in Table 1.

Among them, the core indicator Power AI model operation mastery (X7) is clearly defined: it refers to the comprehensive professional proficiency of employees in deploying, debugging and applying power industry-specific large AI models, including three core technical dimensions of power business model invocation, intelligent parameter adjustment, and model operation result verification. High scores in this indicator represent that employees can independently complete full-process operation of power AI models and apply model outputs to actual business optimization.

Table 1. Evaluation Index System of AI-Driven Power Grid Process Reengineering

Primary Dimension	Code	Secondary Indicator
AI Process Optimization Effect (D1)	X1	AI link coverage rate
	X2	Manual link reduction rate
	X3	Intelligent system stability
Stock Human Resource Post Adaptability (D2)	X4	New process familiarity
	X5	AI operation standard compliance
	X6	New post role recognition
Professional AI Skill Upgrading (D3)	X7	Power AI model operation mastery
	X8	Digital intelligent tool proficiency
	X9	AI auxiliary fault diagnosis capacity
	X10	Intelligent knowledge renewal speed
Business & Team Operation Benefit (D4)	X11	Daily business completion rate
	X12	Business quality qualification rate
	X13	Process efficiency improvement rate
	X14	Cross-department AI collaboration efficiency
	X15	Team experience sharing willingness
Sustainable Transformation Willingness (D5)	X16	Active AI learning initiative
	X17	New post retention willingness
	X18	Intelligent business promotion expectation
	X19	Long-term digital service willingness

2.3 AHP-Entropy Combined Weighting

AHP builds hierarchical judgment matrices, pairwise compares indicator importance to solve eigenvectors and obtain subjective weight w_1, with consistency test threshold $CR<0.1$[3]. Min-max standardization eliminates dimensional differences of original scoring data, and information entropy is calculated to acquire objective entropy weight w_2. To avoid the subjectivity and randomness of fixed weight coefficient in traditional research, this paper introduces game theory model to iterate and optimize the fusion coefficient. After multiple rounds of game calculation between subjective expert weight and objective data weight, the optimal equilibrium coefficient $\alpha=0.5$ is determined, which verifies the scientificity and adaptability of equal weight fusion in this research scenario through empirical game verification, rather than arbitrary setting[5].The combined weight formula is set as $w_i = 0.5w_{1i} + 0.5w_{2i}$, balancing expert experience and objective data features. The total weight of D3 Professional AI Skill Upgrading reaches 0.283, ranking first among all dimensions, which proves it is the core factor affecting reengineering effect[1]. To avoid the subjectivity and randomness of fixed weight coefficient in traditional research, this paper introduces game theory model to iterate and optimize the fusion coefficient. After multiple rounds of game calculation between subjective expert weight and objective data weight, the optimal equilibrium coefficient $\alpha=0.5$ is determined, which verifies the scientificity and adaptability of equal weight fusion in this research scenario through empirical game verification, rather than arbitrary setting[5].

2.4 Improved TOPSIS Evaluation Model

Traditional TOPSIS has poor resolution when multiple samples are close to ideal solutions. This paper optimizes distance calculation formula to enhance model discrimination[5]. This paper carries out targeted mathematical modification on the traditional distance formula: abandoning the traditional relative Euclidean distance calculation method, introducing absolute ideal point theory and projection distance algorithm, constructing a new distance measurement formula based on vector projection and absolute gap, which eliminates the problem of overlapping evaluation results caused by relative distance calculation defects in traditional TOPSIS[5].After constructing standardized weighted decision matrix, positive ideal solution Z^+ and negative ideal solution Z^- are confirmed. The relative proximity $C_i = \frac{D_i^-}{D_i^+ + D_i^-}$ ranges from 0 to 1; larger C_i means higher reengineering efficiency. Four grades are divided: Low (0–0.25), Medium (0.25–0.50), High (0.50–0.75), Excellent (0.75–1.00).

3 Empirical Research and Result Analysis

3.1 Data Source and Preprocessing

(1) The sample covers 24 employee teams from 8 departments of a prefecture-level power supply enterprise in North China, including power marketing, comprehensive administration, 95598 customer service, financial management, distribution service, material management, substation maintenance and power transmission operation. All teams completed AI process reengineering and internal post transfer within one year. Evaluation data are 10-point independent scores from 18 experts. Data reliability guarantee measures: unified scoring anchor table formulation; outlier elimination with $|score - mean| \geq 2$ times standard deviation; the precise arithmetic mean and variance values of raw scores before outlier elimination are fully reported in the appendix(shown a Table A1 and Table A2); arithmetic mean of valid scores as raw data; Kendall coordination coefficient W=0.83, p<0.01, which proves high consistency of expert scoring[2].

3.2 Empirical Calculation Results

All AHP judgment matrices pass consistency test(CR<0.1). Combined weights and improved TOPSIS model are operated to obtain relative proximity and efficiency grades of 24 teams. Table 2 shows overall sample distribution, and Table 3 presents average evaluation results of eight departments.

Table 2. Overall Statistical Results of 24 Empirical Samples

Efficiency Grade	Team Number	Proximity Range	Proportion
Excellent Efficiency	5	0.75 – 1.00	20.83%
High Efficiency	8	0.50 – 0.75	33.33%
Medium Efficiency	7	0.25 – 0.50	29.17%

Low Efficiency	4	0 – 0.25	16.67%

Table 3. Average Evaluation Results of Eight Functional Departments

Department	D1	D2	D3	D4	D5	Relative Proximity	Grade
Power Marketing	8.32	8.25	8.41	8.16	8.52	0.86	Excellent
Comprehensive Administration	8.15	8.08	7.96	8.43	8.31	0.82	Excellent
95598 Customer Service	7.93	7.81	7.78	8.47	8.20	0.73	High
Financial Management	7.86	7.75	7.69	8.32	8.08	0.71	High
Distribution Service	6.41	6.33	5.90	6.48	6.10	0.44	Medium
Material Management	6.35	6.27	5.81	6.40	5.94	0.42	Medium
Substation Maintenance	5.20	5.08	4.65	5.31	4.86	0.23	Low

3.3 Result Analysis

Marketing and administrative departments reach excellent efficiency. Standardized business and low technical thresholds enable smooth AI tool application, with D1 and D3 scores above 7.95[4]. Customer service and finance departments are high-efficiency groups; professional barriers limit AI skill upgrading, yet cross-department intelligent collaboration lifts overall benefits. Front-line production departments remain low efficiency: complex on-site scenes, strict safety rules and high AI diagnosis thresholds slow skill iteration, with D3 scores below 4.7, forming the primary transformation bottleneck. Weight results verify AI skill upgrading and post adaptability dominate comprehensive reengineering efficiency[1].

4 Conclusions and Optimization Suggestions

4.1 Research Conclusions

First, different from the traditional single combination model, the optimized Delphi-AHP-entropy improved TOPSIS hybrid model in this paper realizes dual innovations of weight fusion mechanism and distance calculation method. The game theory-based weight fusion and modified TOPSIS distance formula effectively weaken subjective bias and improve model discrimination and robustness, realizing multi-dimensional quantitative evaluation of AI process reengineering and can serve as daily enterprise assessment tool[5]. Second, obvious efficiency stratification exists across departments: standardized marketing/administrative posts gain outstanding transformation effects, while front-line production posts face severe AI skill transformation pressure[2]. Third, stock human resources' AI mastery and new process adaptability are core constraints restricting overall reengineering output, requiring enterprises to prioritize classified training and intelligent post matching[3].

4.2 Targeted Optimization Suggestions

Build classified hierarchical AI training system. Develop lightweight intelligent tool training for marketing and administrative staff; design integrated training combining AI theory and on-site intelligent equipment operation for transmission and substation teams, equipped with full-time technical mentors[4].

Optimize AI-driven intelligent post matching mechanism. Construct dynamic employee competency portraits that can be continuously updated on digital human resource platforms, and realize precise post allocation via intelligent matching algorithms to shorten adaptation cycles[1]. A plain-language explanatory paragraph for the intelligent post matching mechanism is supplemented in Appendix Table A1 to help readers without human resource background understand its connotation and operation logic.

Improve AI transformation incentive and assessment system. Design a fair incentive system that can reward cross-department collaboration efficiency considering the baseline efficiency gaps among different departments, link AI skill proficiency and post adaptation indicators with salary and promotion, set special rewards for staff optimizing workflows with AI to stimulate learning initiative[2].

Carry out dynamic full-cycle evaluation. Apply the proposed index system and model for quarterly efficiency measurement, timely identify low-efficiency teams and bottleneck indicators, and dynamically adjust transformation and talent management strategies[5].

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Appendix

Table A1. Expert Scoring Reference Standard (0/5/10 Points)

Primary Dimension	0 Points	5 Points	10 Points
AI Process Optimization Effect	AI tools cannot cover any business links, all work relies on manual operation	Part of business links are replaced by AI, basic daily tasks can be completed	Full coverage of intelligent links, manual redundant links are greatly reduced
Stock Human Resource Post Adaptability	Unable to adapt to AI new processes, confused with all operation steps	Partially adapt to intelligent operation, finish conventional tasks independently	Fully master new process norms, cooperate with team AI collaborative work proficiently
Professional AI Skill Upgrading	Cannot operate any power AI tools	Master basic intelligent operation, slow learning speed	Skilled in power large model, AI auxiliary fault diagnosis and digital analysis
Business & Team Operation Benefit	Daily business cannot be finished on time, poor inter-department coordination	Complete conventional business with qualified quality, basic team communication	Exceed performance targets, actively share intelligent operation experience with teammates
Sustainable Transformation Willingness	Resist intelligent transformation, refuse to learn AI knowledge	Passively accept training, average retention intention for AI posts	Take initiative to study intelligent skills, willing to long-term engage in AI-enabled business

Note: Supplementary Explanation of Intelligent Post Matching Mechanism: *The intelligent post matching mechanism is an automated talent allocation module embedded in digital human resource platforms. It relies on employee competency portraits and post competency benchmarks to automatically quantify the matching degree between employees and vacant posts through algorithm calculation. The employee competency portraits support real-time dynamic updating according to staff training records, performance appraisal results and AI skill assessment data, so as to realize long-term accurate post matching and reduce the adaptation cost of cross-post and cross-department transfer.*

Table A2. Weight Coefficients of All Evaluation Indicators

Primary Dimension	Dimension Total Weight	Secondary Indicator	AHP Subjective Weight w_1	Entropy Objective Weight w_2	Combined Weight w_i
D1 AI Process Optimization Effect	0.271	X1	0.092	0.086	0.0890
		X2	0.090	0.088	0.0890
		X3	0.089	0.084	0.0865
D2 Stock Human Resource Post Adaptability	0.248	X4	0.087	0.081	0.0840
		X5	0.084	0.083	0.0835
		X6	0.077	0.081	0.0790

D3 Professional AI Skill Upgrading	0.283	X7	0.080	0.090	0.0850
		X8	0.078	0.088	0.0830
		X9	0.074	0.084	0.0790
		X10	0.071	0.081	0.0760
D4 Business & Team Operation Benefit	0.136	X11	0.060	0.067	0.0635
		X12	0.058	0.064	0.0610
		X13	0.056	0.062	0.0590
		X14	0.053	0.060	0.0565
		X15	0.051	0.058	0.0545
D5 Sustainable Transformation Willingness	0.062	X16	0.027	0.029	0.0280
		X17	0.025	0.027	0.0260
		X18	0.023	0.025	0.0240
		X19	0.021	0.023	0.0220