# Research on Comprehensive Evaluation Model of Research on Cost Determination Technology for Transmission Line Engineering

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**Abstract.** The sustained expansion of China's economic infrastructure has precipitated a corresponding escalation in socioeconomic demand for electrical energy. As critical infrastructure underpinning national power distribution networks, the optimization of capital allocation and construction efficiency parameters emerges as a critical operational imperative for sustaining macroeconomic development trajectories and maintaining grid operators' service continuity. Within this operational context, systematic assessment of investment efficacy and construction optimization metrics in power transmission infrastructure projects assumes substantial practical relevance for advancing technical governance standards, elevating project delivery quality benchmarks, and enhancing capital deployment efficacy within China's energy infrastructure development paradigm.

**Keywords:** Transmission line engineering, cost determination technology, comprehensive evaluation model

## 1 Introduction

The progressive deepening of China's power sector institutional reforms and the comprehensive implementation of market competition mechanisms have intensified cost management pressures on grid operators. This operational environment elevates the strategic importance of developing comprehensive evaluation methodologies for power infrastructure investment efficiency, which serves as a critical driver for optimizing capital utilization effectiveness and enhancing engineering implementation standards within the energy infrastructure development paradigm. [1-2].

The Chinese government has established strategic objectives for achieving carbon neutrality and accelerating renewable energy integration within the power sector. While substantial cost reductions in renewable technology deployment have been realized, systemic challenges persist regarding intermittency management expenditures and the financial implications of large-scale renewable capacity expansion. [3] In developed regions constrained by limited alternative energy options, advanced


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smart grid architectures demonstrate potential for optimizing hybrid energy systems through strategic integration of conventional and renewable sources, thereby mitigating environmental externalities and enhancing operational cost efficiencies. [4] Current investment evaluation frameworks frequently exhibit deficiencies in comprehensive cost-benefit analysis, particularly regarding regional load demand dynamics, capital recovery viability, and lifecycle profitability assessments, which compromises the financial sustainability of grid infrastructure modernization initiatives [5].

The sustained expansion of China's economic infrastructure has precipitated proportional growth in power grid development initiatives, subsequently elevating capital requirements for energy transmission infrastructure. These large-scale projects exhibit characteristic challenges including extended implementation timelines and numerous variables influencing expenditure governance [6]. Recent methodological advancements incorporate fuzzy network DEA frameworks for operational efficiency assessments, particularly in contexts requiring sustainability integration and probabilistic data interpretation [7].

Capital optimization constitutes a critical operational imperative for all stakeholders in infrastructure development projects, including project owners, contractors, and subcontractors. Schedule deviations and budgetary noncompliance frequently serve as primary catalysts for contractual disputes within the construction sector. Multidimensional risk exposure arises from owner-related variables, contractor operational parameters, environmental constraints, and concurrent interdependencies among risk factors. Budgetary overruns generate systemic repercussions extending beyond individual projects to influence macroeconomic stability. Empirical investigations identify substantial risk aggregation effects, with commodity price volatility, quality assurance protocols, and managerial competency emerging as predominant determinants of fiscal performance in construction project execution.[8].

Literature [9] methodologically categorizes cost escalation determinants into five operational clusters: price volatility, quality assurance metrics, design specification variables, implementation efficiency parameters, and professional competency indicators. This taxonomical framework reveals the heterogeneous characteristics of cost overrun mechanisms, enabling precise identification of stakeholder groups with optimal risk mitigation capacities. The classification system facilitates decision-making entities in systematically comprehending cost overflow behavioral patterns and strategically formulating targeted control protocols within project governance frameworks.

This study develops a data envelopment analysis (DEA)-based evaluation architecture for assessing power infrastructure investment efficiency, incorporating multidimensional performance indicators. The methodology is empirically validated through case studies of provincial grid infrastructure initiatives during 2016-2017 operational cycles, establishing a replicable framework for optimizing capital allocation strategies in energy transmission infrastructure development.

## 2 Fundamental Theoretical Framework of DEA

The analytical technique known as Data Envelopment Analysis combines mathematical optimization approaches with operational research concepts and economic productivity theories. This evaluation framework was first established through groundbreaking work by scholars Charnes and Cooper, along with their research team, before becoming widely recognized in academic circles as the standardized DEA approach.

As a frontier analytical approach, DEA employs mathematical programming techniques to assess productive efficiency without requiring predefined functional forms or distributional assumptions, designed to assess the technical efficacy of homogeneous decision-making units with multi-dimensional input-output configurations. The methodological framework operationalizes this by designating each evaluative entity as an independent DMU, subsequently constructing analytical cohorts through DMU aggregation. Through systematic ratio analysis of input-output indicators, the model dynamically assigns variable weights to each metric, thereby delineating the efficient production frontier. Individual DMU efficiency status is determined through spatial proximity measurements relative to this frontier, concurrently identifying optimization pathways and magnitude requirements for suboptimal units. This approach eliminates prerequisite parameter estimation constraints, offering inherent advantages in minimizing subjective bias, operational simplification, and error mitigation. Contemporary applications span operational efficiency assessment, resource optimization allocation, and capital effectiveness analysis across diverse industrial sectors.

There are many kinds of DEA $C^2R$ models, among which the theory of models is relatively perfect $n$. The objects $m$ participating $X$ in the $s$ evaluation are $Y$ the $DWU_j$ decision unit, $x_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T$ so $y_j = (y_{1j}, y_{2j}, \ldots, y_{sj})^T$ there $j = 1, 2, L, n$ are total objects, each object has a type input () and type output (), input and output,

$$
\begin{cases}
\max \dfrac{u^T y_0}{v^T x_0} \\
s.t. \dfrac{u^T y_j}{v^T x_j} \le 1 \\
u \ge 0, v \ge 0
\end{cases}
$$

Where, $v = (v_1, v_2, \cdots, v_m)^T$ represents $u = (u_1, u_2, \cdots, u_s)^T$ the $m$ weight $s$ coefficient of the species input and the species output, respectively.

$$\begin{cases} \min[\theta - \hat{e}^T S^- + \hat{e}^T S^+] \\ s.t. \sum_{j=1}^{n} x_j \lambda + S^- = \theta x_0 \\ \sum_{j=1}^{n} y_j \lambda_j - S^+ = y_0 \\ \lambda_j \ge 0, j = 1, 2, \cdots n, \theta \in E_1^+, S^- \ge 0 \end{cases}$$

Among $\hat{e}^T = (1,1,L,1)^T$ them, $\theta_0 = 1$ if $S^- = 0$ satisfied $S^+ = 0$ , $DWU_{j0}$ the DEA is called valid.

Let the optimal solution $\theta^0$ of $\lambda^0$ the $S^{0+}$ $S^{0-}$ model $\theta^0 = 1$ be $S^{0+} = 0$ $S^{0-} = 0$ ,,,, if, and, DMU is $\theta^0 = 1$ DEA; $S^{0-} \neq 0$ if $S^{0+} \neq 0$ , DMU is weak DEA; if, DMU $\theta^0 < 1$ is non-DEA valid.

## 3 Development of Power Grid Investment Performance Metrics Framework

Through systematic investigation of regional power infrastructure investment patterns and integration of domestic and international research findings with expert consultations, an indicator selection framework was established under principles of universal applicability and data accessibility. The finalized metrics encompass capital structure parameters such as total assets and fixed asset valuation, operational efficiency indices including capacity-load ratio, macroeconomic alignment indicators represented by GDP growth rate, and technical performance measures exemplified by line loss rate. Economic output quantification adopts unit asset electricity supply increment as the primary efficiency metric, with detailed operational parameters documented in Table 1.

**Table 1.** Development of Power Grid Investment Performance Metrics Framework.

| **Indicator category** | **Evaluation index** |
|---|---|
| Input indicators | Total assets |
| | Investment in fixed assets |
| | Capacity to load ratio |
| | Line loss rate |
| Output indicators | GDP growth rate |
| | Unit investment increases power |
| | supply |

## 4 Study and Performance Evaluation

In order to confirm the advancement of DEA method, this paper first calculates the results based on the traditional comprehensive evaluation method. In this paper, the output indexes of different units in 2016 were selected for normalization. Using the maximum value normalization method, the values of all indicators are calculated as within the interval of [0,1], and the two indicators are given reasonable weights. The output benefit evaluation results after a weighted average are shown in the Table 2.

**Table 2.** Weighted Average of GDP Growth Rate and Electricity Efficiency per Unit of Investment.

| **company** | **GDP growth rate (normalized)** | **Increase of electricity per unit of investment (normalized)** | **weighted average** |
|---|---|---|---|
| Company H | 1.000 | 0.679 | 0.8395 |
| Company J | 0.367 | 0.699 | 0.5330 |
| Company N | 0.317 | 1.000 | 0.6585 |
| Company Q | 0.000 | 0.000 | 0.0000 |
| Company W | 0.230 | 0.379 | 0.3045 |
| Company K | 0.210 | 0.804 | 0.5070 |
| Company M | 1.000 | 1.000 | 1.0000 |
| Company L | 0.202 | 0.278 | 0.2400 |
| Company S | 0.145 | 0.532 | 0.3385 |
| Company T | 0.227 | 1.000 | 0.6135 |
| Company K | 0.064 | 0.159 | 0.1115 |

Based on the weighted average evaluation methodology, Company M demonstrates superior comprehensive performance, achieving a perfect weighted score of 1.0000. This reflects its balanced excellence in both economic expansion metrics and energy efficiency improvements per capital expenditure. Company H secures the second position, exhibiting strong energy output gains per investment unit but lagging in macroeconomic growth indicators. In contrast, Company Q underperforms across all measured dimensions, resulting in the lowest overall ranking.

This study utilizes operational performance metrics collected from eleven administrative regions within Z Province during the 2016-2017 observation period. The complete dataset, including detailed variable measurements, is presented in Appendix Table 3.

**Table 3.** Statistics of basic data of indicators.

| Years | DMU | (I) Total assets (100 million yuan) | (I) Invest-ment in fixed assets (10,000 yuan) | (I) Capaci-ty to load ratio | (I) Line loss rate | (O)GDP growth rate (%) | (O) Unit invest ment increas es power supply |
|---|---|---|---|---|---|---|---|
| 2016 | Company H | 115.89 | 187093.68 | 2.25 | 3.23 | 10.47 | 1.85 |
| | Company J | 65.18 | 103014.20 | 2.12 | 3.57 | 7.83 | 1.89 |
| | Company N | 79.86 | 136303.21 | 1.87 | 3.44 | 7.62 | 2.51 |
| | Company Q | 26.72 | 40819.43 | 2.31 | 3.70 | 6.30 | 0.45 |
| | Company W | 75.52 | 112327.75 | 2.22 | 4.76 | 7.26 | 1.23 |
| | Company K | 63.69 | 89224.53 | 2.09 | 2.78 | 6.89 | 2.09 |
| | Company M | 27.32 | 44839.31 | 1.9 | 3.70 | 7.98 | 2.58 |
| | Company L | 36.96 | 78269.03 | 2.88 | 5.56 | 7.49 | 1.17 |
| | Company S | 44.39 | 69041.70 | 2.27 | 2.78 | 7.07 | 1.81 |
| | Company T | 61.29 | 95418.79 | 2.07 | 5 | 7.29 | 2.51 |
| | Company K | 10.32 | 7935.56 | 3.24 | 5 | 6.32 | 0.82 |
| 2017 | Company H | 123.96 | 200107.68 | 2.41 | 3.03 | 11.2 | 1.98 |
| | Company J | 68.35 | 108020.95 | 2.22 | 3.45 | 8.21 | 1.98 |
| | Company N | 86.79 | 148138.89 | 2.03 | 3.13 | 8.28 | 2.79 |
| | Company Q | 28.44 | 43444.97 | 2.46 | 3.45 | 6.7 | 0.48 |
| | Company W | 78.03 | 116059.04 | 2.29 | 4.55 | 7.5 | 1.27 |
| | Compan | 65.79 | 92170.08 | 2.16 | 2.7 | 7.12 | 2.16 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Company K | | | | | | |
| | Company M | 28.55 | 46860.17 | 1.99 | 3.57 | 8.34 | 2.7 |
| | Company L | 38.46 | 81444.09 | 3 | 5.26 | 7.779 | 1.22 |
| | Company S | 45.96 | 71485.56 | 2.35 | 2.70 | 7.32 | 1.87 |
| | Company T | 67.28 | 104746.57 | 2.27 | 4.55 | 8 | 2.76 |
| | Company K | 11.27 | 8663.19 | 3.54 | 4.55 | 6.9 | 0.9 |

The model's theoretical foundation indicates that regions achieving a comprehensive efficiency score of unity demonstrate optimal input-output conversion, with all resources being utilized at maximum effectiveness. Conversely, lower efficiency scores reflect diminishing relative performance, where at least one input variable exhibits divergence between observed and target values. This discrepancy represents potential improvement opportunities for suboptimal units, providing actionable insights for optimizing fixed-asset investment allocations. The detailed regional input-output analysis outcomes are documented in Appendix Table 4.

**Table 4.** Efficiency Assessment of Corporate Input-Output Performance Using DEA Methodology.

| **Years** | **DMU** | **Comprehensive efficiency** | **Pure technical efficiency** | **Scale efficiency** | |
|---|---|---|---|---|---|
| 2016 | Company H | 0.763 | 0.902 | 0.846 | irs |
| | Company J | 0.741 | 0.939 | 0.789 | irs |
| | Company N | 1 | 1 | 1 | - |
| | Company Q | 0.224 | 1 | 0.224 | irs |
| | Company W | 0.497 | 0.951 | 0.523 | irs |
| | Company K | 1 | 1 | 1 | - |
| | Company M | 1 | 1 | 1 | - |
| | Company L | 0.473 | 0.876 | 0.54 | irs |
| | Company S | 0.898 | 1 | 0.898 | irs |
| | Company T | 1 | 1 | 1 | - |

| | | | | | |
|---|---|---|---|---|---|
| | Company K | 1 | 1 | 1 | - |
| average value | | 0.783 | 0.972 | 0.806 | - |
| 2017 | Company H | 0.751 | 0.897 | 0.837 | irs |
| | Company J | 0.733 | 0.94 | 0.78 | irs |
| | Company N | 1 | 1 | 1 | - |
| | Company Q | 0.223 | 1 | 0.223 | irs |
| | Company W | 0.493 | 0.952 | 0.518 | irs |
| | Company K | 0.969 | 1 | 0.969 | irs |
| | Company M | 1 | 1 | 1 | - |
| | Company L | 0.477 | 0.9 | 0.53 | irs |
| | Company S | 0.889 | 1 | 0.889 | irs |
| | Company T | 1 | 1 | 1 | - |
| | Company K | 1 | 1 | 1 | - |
| average value | | 0.775 | 0.974 | 0.796 | - |

The following evaluation conclusions can be drawn from Table 4 above:

(1) During the 2016-2017 period, Companies N, M, T, and K consistently achieved the maximum comprehensive efficiency score of one, demonstrating superior performance in converting inputs to outputs. These firms established themselves as industry leaders in operational efficiency. Conversely, Companies H, J, Q, W, L, and S failed to reach full efficiency, with their scores remaining below unity, suggesting deficiencies in resource allocation and technology implementation that require corrective measures.

(2) Company J exhibited perfect technical efficiency in 2016, attaining the highest possible score. However, by mid-2017, its scale efficiency deteriorated, resulting in a decline in overall efficiency. The presence of increasing returns to scale suggests that expanding operational capacity would enhance both scale efficiency and comprehensive performance metrics.

(3) Throughout the two-year study period, Companies Q and S maintained perfect pure technical efficiency while demonstrating suboptimal scale efficiency. The observed increasing returns to scale condition indicates that these enterprises would

benefit from expanding their operational scale to improve both scale-specific and overall efficiency measures.

(4) For Companies H, J, W, L, and S, both pure technical efficiency and scale efficiency scores remained below the optimal level. The simultaneous occurrence of increasing returns to scale reveals a fundamental mismatch between technological capabilities and operational scale. This imbalance manifests as redundant scale investments, the elimination of which would lead to improvements in both pure technical efficiency and comprehensive performance.

(5) The efficiency analysis identified significant input redundancies and output deficiencies among all underperforming firms. Company H exhibited the most severe case of fixed asset investment redundancy during 2017, followed closely by Company J, with their respective inefficiency levels reaching fifty-three point two percent and thirty-four point thirty-seven percent.

By comparing the ranking results of the weighted average method and the DEA method, we found that there are some differences in assessing the efficiency of each company. For example, Company M ranks high in both methods, showing its efficiency in terms of resource utilization and output. On the other hand, although company Q performs poorly in the weighted average method, it is less efficient in the DEA method, which fully reflects that DEA can more accurately reflect the inefficiency of the company in resource input. In general, the DEA method can provide more comprehensive and accurate evaluation results by comprehensively considering the relationship between inputs and output, while the weighted average rule may overestimate or underestimate the actual efficiency of the company in some cases. Therefore, the application of the DEA method is more effective in identifying and addressing the potential problems in resource use.

Combined with the characteristics of DEA model, the following application suggestions are put forward. First, considering the economic level, technological development and policy environment differences of power grid construction in different regions, the input parameters of the model can be adjusted accordingly to ensure the adaptability of the model. In addition, in the face of missing or inconsistent data, it is recommended to use data interpolation or weighted average to deal with missing data, while using standardized techniques to ensure the consistency of all data. Finally, it is suggested to implement the model step by step by stages. In the initial stage, feedback should be collected in a small pilot to ensure the effect of the model, and continuous optimization in the subsequent promotion to gradually adapt to the changing actual needs.

## 5 Conclusion

This study makes significant theoretical and practical contributions in multiple dimensions. Primarily, it innovatively integrates the distinctive features of power grid project investment and construction with Data Envelopment Analysis theory, thereby developing a novel comprehensive evaluation framework. This methodological advancement substantially enriches the theoretical foundation for assessing power grid investment efficiency. This innovative evaluation method effectively overcomes the shortcomings of traditional assessment approaches, enabling a more comprehensive and objective reflection of the investment benefits of power grid projects. Particularly in cases of limited resources, it helps decision-makers precisely identify inefficient areas in the investment process, improving resource allocation efficiency and optimizing investment returns. Secondly, through empirical analysis of the power grid project in Z province, this paper reveals issues such as management gaps and suboptimal benefits in current power grid investments, providing targeted improvement suggestions for grid companies and related enterprises. This guidance helps them avoid similar issues in future projects, thereby increasing investment effectiveness and project success rates. Furthermore, the research not only offers scientific and rational decision support for grid companies, optimizing their investment strategies but also contributes to the sustainable development of the power grid industry. By conducting reasonable investment benefit evaluations, it ensures the efficient use of funds, thereby promoting the stable and long-term development of grid infrastructure and reducing waste and resource misallocation. Additionally, the research method and evaluation index system proposed in this paper have strong applicability, extending beyond the power grid sector to other infrastructure fields such as transportation, energy, and telecommunications. This broadens its potential application and impact. Lastly, the findings of this paper provide valuable references for policy formulation and industry standards. By deeply analyzing the investment benefits of power grid projects, this paper offers data support and empirical evidence for government agencies, industry associations, and other stakeholders, helping them create more scientific, reasonable, and actionable investment management policies. This, in turn, promotes industry standardization, technological progress, and improved investment efficiency. In conclusion, this paper not only enriches the theoretical system for evaluating power grid investment benefits but also provides methodological support for practical applications. It holds significant theoretical, practical, and application value, with a profound impact on the healthy development of the power grid industry and the enhancement of project investment management levels.

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