



Research on the Influence Assessment Technology of Cost Market Elements in Construction Stage Based on Gray Correlation Method

Ye Ke^{1a*}, Mengqian Zhang^{1b}, Fangshun Xiao^{1c}, Xuemei Zhu^{1d}, Yonghong Li^{1e}

¹State Grid Fujian Economic Research Institute, Fuzhou, Fujian Province, 350013, China

^{a*}ky20230203@163.com, ^b1536178547@qq.com,
^cxiao_fangshun@fj.sgcc.com.cn, ^d8862585@qq.com,
^e357041190@qq.com

Abstract. The operational advancement of China's integrated national market framework has systemically facilitated cross-regional mobilization of production factors, enhancing resource allocation efficiency within domestic economic ecosystems. For the study of the national unified market transmission project cost component evolution trend, and cause transmission project cost fluctuation of internal and external factors, reveal to adapt to the low carbon construction cost transmission mechanism, not only to analyze the project cost market factors. This research further integrates cost surveillance mechanisms within power transmission infrastructure development processes. By systematically examining operational implementation characteristics of such projects, the study conducts a systematic deconstruction of critical market-driven variables impacting construction expenditures. Utilizing grey relational analysis techniques, the investigation quantitatively assesses the relative dominance of these factors through comparative sequencing methodologies.

Keywords: National unified market, Resource flow, Transmission project cost

1 Introduction

Systematically investigating the operational dynamics of national integrated market frameworks on power infrastructure expenditure structures, while advancing multidimensional evaluation methodologies for capital allocation efficiency and revenue generation frameworks in transmission projects, establishes critical conceptual foundations for enhancing grid operators' expenditure governance and analytical competencies. This dual-focused exploration enables the formulation of evidence-based strategies for optimizing resource deployment in evolving energy market ecosystems

Literature [1] qualitatively analyzes the influencing factors of power grid project cost from several aspects such as technical scheme, design, equipment and material price, and environment, and puts forward relevant strategic suggestions based on the problems existing in project cost review. Literature [2] takes overhead power line

engineering as the research object, adopts qualitative analysis method, studies and analyzes the main factors of overhead power line engineering cost, and proposes relevant improvement measures to improve the level of project cost control. The literature [3] divides the engineering cost influencing factors during the construction phase of substations are categorized into three types: fundamental influencing factors, immediate influencing factors, and external influencing factors. The paper further analyzes the impact process of each category. The literature [4] summarizes the factors affecting profits into three aspects: supply and demand relationship, competition mode and bidding strategy, and the cost is attributed to raw material cost, labor cost, fixed cost, R&D cost and financing cost, in order to provide reference for reasonable control of project cost and reduction of engineering investment risk. The literature [5] analyzes the importance of power grid engineering cost management, and gives a specific overview of the main influencing factors of engineering cost management, and also puts forward several specific control strategies for power grid engineering cost management for reference. Literature [6] establishes a multi-regional input-output (MRIO) framework to quantify embodied carbon flows within China's manufacturing trade, employing decomposition techniques to analyze emission drivers through efficiency improvements, technological advancements, and structural-scale dynamics in export sectors. Building upon existing low-carbon building assessment research, literature [7] identifies methodological limitations in lifecycle carbon accounting for construction projects and proposes enhanced evaluation protocols. Literature [8] applies structural decomposition analysis to isolate key factors influencing embodied carbon growth in Sino-US trade, revealing that energy efficiency gains and production technology upgrades significantly offset emission increases caused by export volume and composition changes. Literature [9] develops a multidimensional analytical framework to examine Sino-Japan trade-related carbon transfers across five operational dimensions. Through constructing virtual importer technical coefficients, literature [10] measures embodied carbon in China's bilateral trade, identifying sectoral concentration patterns: export-related emissions predominantly originate from heavy chemical and labor-intensive industries, while import-related emissions cluster in technology-intensive sectors.

This study develops a methodological framework for embodied carbon quantification and systematic decomposition in power infrastructure projects, leveraging structural analytical techniques. The proposed approach establishes theoretical foundations for refining project categorization mechanisms and optimizing strategic decision-making processes within evolving operational paradigms of modern grid operators.

2 This paper studies the technical route

This paper takes the construction stage of power transformation project as the research object, and takes improving the level of cost control in the construction stage as the research purpose, and systematically analyzes the influence degree of various market elements on the project cost in the construction stage, so as to provide support

for the power grid to formulate targeted measures of cost control. The research idea is as shown in the following figure:

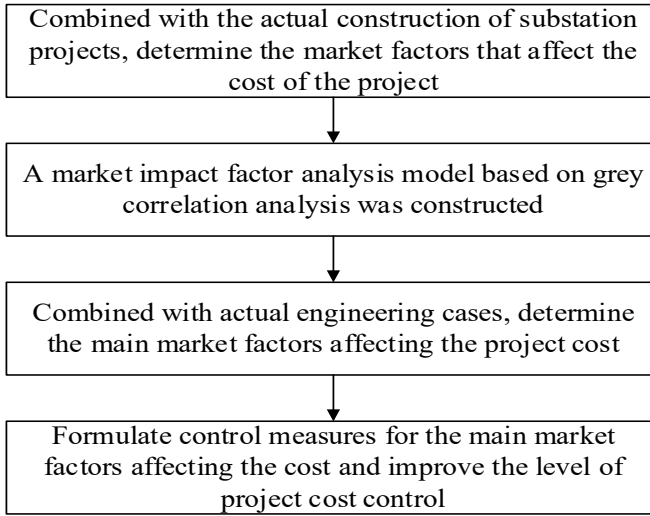


Fig. 1. Technical idea diagram of this paper.

According to Figure 1, this research employs a systematic analytical protocol comprising four operational phases. Initially, critical expenditure drivers during power infrastructure construction are identified through multi-source data triangulation. Subsequently, a grey relational analytical model is developed to quantify interdependencies among these variables. Empirical case studies are then conducted to validate the model's efficacy in isolating dominant cost determinants. Finally, targeted mitigation strategies are formulated and operationalized through iterative feedback mechanisms, enabling adaptive cost governance in subsequent infrastructure development cycles.

3 Model construction of influence factors evaluation based on the grey correlation degree method

3.1 Model parameters and the main step flow

(1) Grey correlation degree analysis theory

For a system, "black" means a lack of information, "white" means complete information, and "gray" means that some information is known and some are unknown. In response to the analytical challenges posed by complex socioeconomic systems, Professor Deng Julong established the grey system theory in 1982 as a methodological framework for modeling systems with partial information transparency. Grey relational analysis (GRA) represents a multivariate analytical technique that evaluates inter-factor relationships through comparative sequence proximity metrics. The

methodology operationalizes this concept by transforming observational data into geometric curves, where relational intensity between variables is quantitatively assessed through curve similarity measurements. Higher geometric congruence between sequence curves corresponds to stronger inter-variable associations, thereby enabling systematic prioritization of influential factors in complex systems.

(2) Operational Protocol for Grey Relational Analysis

1) Establish a reference sequence representing core system characteristics and comparative sequences corresponding to operational influencers. Within power infrastructure cost analysis frameworks, the reference sequence encapsulates historical expenditure patterns, while comparative sequences contain temporal data of identified cost determinants.

2) Implement dimensionless processing for both reference and comparative sequences. Given the heterogeneous measurement units across system variables, this preprocessing step eliminates scalar discrepancies through standardized transformation protocols.

Let $X_i = (x_i(1), x_i(2), \dots, x_i(n))$ be the sequence of behavior of X_i . The reference and comparison sequences need to be dimensionless. To eliminate the influence of dimension, the standardized transformation method is applied for normalization.

$$x'_i(j) = \frac{x_i(j) - \mu}{\sigma} \quad (1)$$

where μ and σ are the mean and variance of the sequence, respectively. The standardized transformation converts all data into a standard normal distribution with a mean of 0 and a standard deviation of 1, thereby eliminating the influence of different dimensions and units. This normalization process is crucial for ensuring the accuracy of the gray correlation analysis results, and must be strictly followed.

3) Correlation Coefficient Computation

Following data standardization, the reference sequence and comparative sequences undergo differential quantification analysis. For discrete temporal observations, relational coefficients are mathematically derived through comparative proximity evaluation between normalized sequence values.

$$\delta_{0i}(j) = \frac{\Delta_{\min} + \rho \Delta_{\max}}{\Delta_{0i}(j) + \rho \Delta_{\max}}, i = 1, 2, \dots, k; j = 1, 2, \dots, n \quad (2)$$

$$\delta_{0i}(j) = |x_0(j) - x_i(j)| \quad (3)$$

$$\begin{aligned} \Delta_{\min} &= \min_i \min_j \Delta_{0i}(j), \\ \Delta_{\max} &= \max_i \max_j \Delta_{0i}(j) \end{aligned} \quad (4)$$

ρ serves as a calibration parameter designed to mitigate computational distortions arising from excessive value magnitudes in multivariate datasets. $\Delta_{\max}$ value magnitude disparities in datasets while enhancing the discriminative capacity among derived relational metrics. $0 < \rho < 1$, generally take 0.5. The correlation coefficient quantifies the degree of spatial congruence between sequence pairs within multivariate analytical frameworks X_0 and X_i are at time t , $0 < \delta_{0i} \leq 1$.

4) Seek correlation degree

In a coordinate plot where the abscissa is time t and the ordinate is the correlation coefficient, the correlation coefficient curve is plotted. The area between the curve and the abscissa is called the associative area. Note that the correlation area of the reference sequence (1 at the correlation coefficient) is S_{00} , and the correlation area of the comparison sequence is S_{0i} .

Correlation formula:

$$r_{0i} = \frac{S_{0i}}{S_{00}} = \frac{1}{n} \sum_{j=1}^n \delta_{0i}(j) \quad (5)$$

5) Order the correlation degree of the cost by several factors. The greater the correlation degree, the greater the influence of the factors on the cost.

3.2 Empirical analysis

This paper takes a 220k V new power transformation project as an example, combined with the identification results of market influence factors, calculates the GDP growth rate (x_1), mechanical construction price (x_2), main transformer price (x_3), material price level (x_4), labor price (x_5), transportation cost price (x_6), inflation rate (x_7).

The raw dataset underwent normalization procedures through standardized transformation techniques, with the transformed dataset systematically documented in Table 1.

Table 1. Standardization treatment of market impact factors of a 220k V new power transformation project

order number	X1	X2	X3	X4	X5	X6	X7	Y
1	1.9255	-0.6440	0.9582	0.2421	1.9164	0.8573	0.9758	1.8169
2	-0.6367	0.3710	0.9582	1.8560	0.3194	-0.6556	-1.1151	0.1149
3	-0.2902	-0.6176	-0.9582	-0.5649	0.3194	-0.6556	0.9758	-0.8803
4	-0.2785	-0.6176	-0.9582	-0.5649	0.3194	0.3530	0.9758	-0.7269
5	-0.3123	-0.0150	0.9582	0.2421	-1.2775	0.3530	-1.1151	-0.8389
6	-0.7389	-0.6949	0.9582	1.0490	0.3194	1.3616	-0.0697	0.9263
7	-1.0114	-0.7118	0.9582	0.2421	0.3194	1.3616	0.6273	1.1948
8	-0.1384	1.5479	-0.9582	0.2421	-1.2775	-1.6642	-1.1151	-0.5677

9	1.7710	-0.6365	-0.9582	-1.3718	-1.2775	-0.6556	-1.1151	0.0772
10	-0.2902	2.0187	-0.9582	-1.3718	0.3194	-0.6556	0.9758	-1.1163

Through systematic integration of the dataset presented in Table 1 and methodological application of grey relational theory, the operational influence magnitudes of diverse market variables on infrastructure expenditure parameters are systematically documented in Table 2.

Table 2. Gray correlation degree table.

factor	X1	X2	X3	X4	X5	X6	X7
r_{oi}	0.610	0.562	0.747	0.648	0.642	0.613	0.556

As can be seen from Table 2, the gray correlation ranking: main variable price> material price level> labor price> transportation cost price> GDP growth rate> mechanical construction price> inflation rate.

4 Conclusion

In this paper to improve the level of substation engineering construction stage cost control for the research goal, based on the grey correlation method of engineering cost market influence factor analysis model, and combined with the actual case, analyzes the influence of the market factors on the construction stage cost, so as to develop targeted for the power grid enterprise cost control measures to provide reference.

References

1. Wang liping. Identification and evaluation technology of influencing factors of power grid overhaul project cost [J]. Power and Energy, 2023,44 (01): 91-94.
2. Zhang Hua. Analysis of several factors affecting the cost of overhead power line project [J]. Residence, 2021 (02): 152-153.
3. Zhang Xiang. Analysis of influencing factors of project cost in substation construction stage [J]. Low-carbon World, 2017, No.171(33): 64-65. DOI:10.16844/j.cnki.cn10-1007/tk.2017.33.039.
4. Lu Yanchao, Wen Weining, Zhao Biao, Zheng Yan. Analysis of influencing factors of power grid engineering equipment materials [J]. Electric Power Construction, 2013,34 (04): 74-78.
5. Zhang Yan. Analysis of the cost management and control strategy of power grid engineering [J]. Small and Medium-sized Enterprise Management and Technology (Shanghai Ten-day Journal), 2016 (12): 164-165.
6. Zhang Juan. Economic emission scheduling of microgrid considering demand side response index [J]. Journal of Northeast Electric Power University, 2020,40(06):1-10.
7. Zhang Junjian. Analysis on power investment and technological transformation strategies from the perspective of carbon emission [J]. Market Weekly, 2020, (02):43-44.
8. Tian Xin, Li Xueliang, Zhao Long, et al. Carbon emission reduction path and effect evaluation of hybrid power grid based on GRA model [J]. Practice and Understanding of Mathematics, 2020,50(02):130-140.

9. Nagasawa K, Rhodes D J, Webber E M. Assessment of primary energy consumption, carbon dioxide emissions, and peak electric load for a residential fuel cell using empirical natural gas and electricity use profiles[J]. *Energy & Buildings*,2018,178:242-253.
10. Sechilariu M, Molines N, Richard G, et al. Electromobility framework study: infrastructure and urban planning for EV charging station empowered by PV-based microgrid[J]. *IET Electrical Systems in Transportation*,2019,9(4):176-185.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

