



Risk Analysis of Cost for Replacing Online Monitoring Devices Based on Monte Carlo Simulation

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Abstract. With the growth in electricity demand and the advancement of smart grid initiatives, replacing online monitoring devices as a technical transformation project plays a crucial role in the real-time monitoring and intelligent management of transmission line operation status. However, due to various uncertainties such as equipment unit prices, quantities, and technical scheme selection, the cost risks of such projects exhibit significant volatility. This paper focuses on the online monitoring device replacement project completed in 2023 in S Province, China. It applies Monte Carlo simulation, combining kernel density estimation, Bernoulli distribution, and discrete uniform distribution, to fit and simulate the distribution of key risk factors. Through simulation results, the study identifies unit price and quantity as the major risk factors affecting the total cost of such projects and offers suggestions for optimizing budget preparation and risk control for each risk factor. The research findings can provide decision-making support for cost control in similar projects and contribute to the efficient construction of smart grid systems.

Keywords: Online Monitoring Device, Cost Risk, Monte Carlo Simulation, Kernel Density Estimation, Sensitivity Analysis.

1 Introduction

With China's rapid urbanization and growing electricity demand, ensuring the safety and reliability of the power grid, a key infrastructure for socio-economic development, has become increasingly important. Transmission lines, as critical links between power plants and users, face challenges such as faults caused by environmental conditions, equipment aging, and external damage. To address these issues, online monitoring devices have become essential for real-time operation monitoring, integrating advanced sensing, communication, and data analytics technologies.

Replacing these devices, a key technical transformation project, is vital for enhancing grid reliability and achieving sustainable development. However, uncertainties in equipment costs, installation fees, construction environments, and external factors like climate and terrain contribute to significant cost risks^[1]. Poor cost management can lead to budget overruns, project delays, and hinder smart grid construction.

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This study examines an online monitoring device replacement project in S Province, China, completed in 2023 with a cost overrun rate exceeding 10%. Using Monte Carlo simulation, it identifies key cost risk factors, fits their parameter distributions, and quantifies their impact. The findings aim to improve project cost estimation and support decision-making for similar grid transformation projects, contributing to a safer and more efficient smart grid.

2 Analysis of Risk Factors in the Cost of Replacing Online Monitoring Devices

Identifying and analyzing risk sources is essential for assessing cost risks in online monitoring device replacement projects. These projects involve equipment removal, installation, and debugging, with static investment comprising installation, procurement, and other costs. Key risks arise from technical scheme selection, construction environment, equipment procurement, and external policies, as also discussed in global risk assessment techniques^[2]. Based on engineering data from S Province, this section categorizes these risks, laying the groundwork for distribution fitting and risk quantification.

2.1 Identification of Risk Factors

The cost risks of replacing online monitoring devices arise from a variety of sources, which are diverse and complex. Based on actual data analysis and project characteristics, this paper identifies the following core risk factors for the cost of such projects:

Unit Price Fluctuations.

Equipment unit price directly affects total costs and is influenced by factors like raw material price changes, supply chain stability, and market demand. For instance, rising raw material costs or supply chain disruptions can significantly increase procurement expenses. In the sample project, unit prices ranged from 5,900 to 17,300 CNY per set, indicating substantial volatility.

Quantity Fluctuations.

The number of devices varies based on transmission line scale and technical requirements, leading to significant cost differences across projects. For example, smart line projects often require more devices due to higher functional demands. In the sample data, device quantities ranged from 5 to 370, highlighting the uncertainty and its cost impact.

Technical Schemes.

The technical scheme is critical in the decision-making and design phases of online monitoring device replacement projects^[3]. Without fully considering device functionality, operational environments, and future upgrades, mismatches can occur, leading to design flaws, rework, and unstable device operation, ultimately resulting in cost overruns, delays, and increased maintenance.

Key factors influencing technical scheme risks include:

(1) Smart Line Projects: Higher technical standards and broader coverage increase cost uncertainty.

(2) Self-Implemented Projects: While potentially reducing costs by avoiding outsourcing, resource constraints may lower efficiency and extend timelines.

(3) Device Functionality: Costs vary by device type, with video devices being common but more complex devices, like wire movement and wind deviation monitoring, having higher unit costs.

These factors significantly affect project costs, making technical scheme selection a major risk consideration.

2.2 Classification of Risk Factors

Based on the identification of risk factors, this study classifies the risk factors into three categories: market risks, technical risks, and management risks, each of which affects the project cost in different ways. Since the study focuses on projects completed in the same province in the same year, risks from the construction environment and external policies are not considered.

Market Risks.

Market risks primarily include fluctuations in unit price and quantity. Unit price changes can result from shifts in raw material markets, labor costs, and transportation fees. Quantity fluctuations often arise from miscalculations during the initial design phase or discrepancies between planned and actual project conditions. Due to the unpredictability of market conditions, project managers must continuously monitor trends and adjust budgets accordingly.

Technical Risks.

Technical risks are linked to uncertainties in the technical scheme and implementation process, particularly with innovative technologies like smart line projects and device functionality. The maturity and applicability of the technology can impact costs. If challenges arise during implementation, additional costs may be incurred for technical adjustments.

Management Risks.

Management risks involve issues in project organization, contract management, and personnel management. In self-implemented projects, the absence of external professional contractors can lead to a shortage of technical staff and project delays, affecting cost control and budget execution.

2.3 Interaction Between Risk Sources

It should be noted that risk sources are not independent but exhibit significant interactions. An unreasonable technical scheme could increase construction difficulty, amplifying the fluctuations in unit price and quantity. Quality issues in equipment procurement could increase installation and debugging efforts, thereby extending project timelines and adding complexity to implementation. Therefore, when conducting distribution fitting and Monte Carlo risk assessments, the interactions between different risk sources should be considered comprehensively in the overall risk assessment.

3 Construction of the Cost Risk Simulation Model for the Replacement of Online Monitoring Devices

In cost risk analysis, precise model construction and appropriate analysis methods are key to ensuring the reliability of results. This paper primarily adopts the Monte Carlo simulation method, which has been widely applied in infrastructure cost estimation globally^[4], combined with the distribution fitting of risk factors, simulating the impact of different risk factors on the total cost. and then conducting risk assessment. The advantage of this method lies in its ability to handle complex nonlinear relationships and random variables, providing a comprehensive risk assessment result.

3.1 Sample Overview

This paper selects the total static investment settlement data for the replacement of online monitoring devices in a 110kV voltage level technological transformation project in Province S, China, completed in 2023, where the cost overrun rate exceeded 10%. Based on the aforementioned analysis of risk sources, the main cost risk factors identified include "whether it is a smart line special project," "whether it is a self-implemented project," "device function," "unit price," and "quantity." The specific data is shown in the Table 1.

Table 1. Sample Project Data

No.	Smart Line Special Project	Self-Implemented Project	Device Function	Unit Price (10,000 yuan/set)	Quan- tity (sets)	Static Invest- ment (10,000 yuan)	Overrun Rate (%)
1	Yes	No	Video	0.83	119	109.63	10.13
2	Yes	Fully Self-Imple- mented	Video	0.60	156	93.70	11.80
3	Yes	Fully Self-Imple- mented	Video	0.59	370	220.20	10.38
4	Yes	Fully Self-Imple- mented	Image	0.70	238	166.60	14.09
5	No	Fully Self-Imple- mented	Image	0.59	274	162.16	12.42
6	Yes	Fully Self-Imple- mented	Video	0.70	169	118.30	19.62
7	Yes	Fully Self-Imple- mented	Image	1.73	25	43.25	11.43
8	No	Fully Self-Imple- mented	Video	0.64	260	235.65	25.88
9	Yes	Fully Self-Imple- mented	Conductor Swing	0.96	15	14.40	10.91
10	Yes	Fully Self-Imple- mented	Tower Tilt	0.59	5	2.95	13.35
11	Yes	Fully Self-Imple- mented	Wind Off- set	1.36	5	6.80	10.47

3.2 Distribution Fitting of Cost Risk Factors

In Monte Carlo simulation, accurate distribution fitting is crucial for reliable results. This paper uses kernel density estimation for continuous variables (e.g., unit price and quantity), Bernoulli distribution for binary variables (e.g., smart line or self-implemented projects), and discrete uniform distribution for categorical variables (e.g., device function).

Kernel Density Estimation.

Kernel density estimation is a non-parametric probability density estimation method that smooths the data points to estimate their probability density function. The kernel density estimation is shown in formula (1):

$$f(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x-x_i}{h}\right) \quad (1)$$

Where:

$f(x)$ is the estimated probability density function,

n is the sample size,

x_i represents the i -th sample data,

h is the smoothing parameter,

$K(\cdot)$ is the kernel function, commonly the Gaussian kernel, as shown in formula (2):

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right). \quad (2)$$

Kernel density estimation generates a continuous probability distribution by calculating the smoothed density for each data point. In this study, kernel density estimation is used to fit the unit price and quantity of the online monitoring devices. Kernel density estimation was chosen because it provides a flexible, non-parametric way to estimate probability distributions of continuous variables like unit price and quantity, which often exhibit irregular patterns. The Bernoulli distribution is employed for binary variables (e.g., whether it is a smart line special project), as it represents two possible outcomes. The discrete uniform distribution is used for categorical variables (e.g., device functions), as it assumes equal probability for each category, aligning with the project's data distribution.

Bernoulli Distribution.

For whether the project is a smart line special project (X_1) and whether it is a self-implemented project (X_2), we assume these two factors follow a Bernoulli distribution. The probability mass function of a Bernoulli distribution is given by formula (3):

$$P(X = 1) = p, P(X = 0) = 1 - p \quad (3)$$

Where represents the probability of the event occurring, which can be calculated from the sample data.

Discrete Uniform Distribution.

The categorical variable for device function (F) can be considered to follow a discrete uniform distribution. Suppose the possible values of the device function are $\{1, 2, 3, 4, 5\}$, the probability mass function of this distribution is shown in formula

(4). This distribution assumes that each device function has an equal probability of occurring:

$$P(F = k) = \frac{1}{5}, k = 1, 2, 3, 4, 5 \quad (4)$$

3.3 Monte Carlo Simulation

Monte Carlo simulation is a statistical method that uses random sampling for numerical computation and has been extensively applied in risk evaluations for engineering projects^[5]. In cost risk analysis, Monte Carlo simulation can generate a large number of random samples to simulate the impact of different risk factors on the total cost and obtain the distribution characteristics of the cost through numerous simulations.

Simulation Process.

The basic process of Monte Carlo simulation is as follows:

(1) Distribution Fitting and Sampling: Based on the previous distribution fitting results, this study generates simulated values for each risk factor through random sampling.

(2) Total Cost Calculation: The total cost for each simulation is calculated using formula (5):

$$C = \sum_{i=1}^E (P_i \times Q_i) \quad (5)$$

Where:

C is the total cost,

P_i is the unit price of the i -th device,

Q_i is the quantity of the i -th device,

E is the total number of devices.

(3) Repeated Sampling: By performing repeated random sampling, the total cost for each simulation is calculated, and the distribution of total cost is derived.

Overrun Probability Calculation.

A key indicator in the Monte Carlo simulation of engineering cost risk is the probability of cost overrun, which is the probability that the total cost exceeds the budget. If a budget limit C_{limit} is set, the overrun probability can be calculated using formula (6):

$$P_{over} = \frac{1}{N} \sum_{i=1}^N \mathbb{1}(C_i > C_{limit}) \quad (6)$$

Where:

$\mathbb{1}(C_i > C_{limit})$ is the indicator function, taking a value of 1 when $C_i > C_{limit}$ and 0 otherwise,

N is the number of simulations.

3.4 Total Cost Risk Assessment

Through Monte Carlo simulation, the total cost distribution is analyzed, extracting key risk characteristics such as the mean (expected cost), standard deviation (cost fluctuation range), and overrun probability (likelihood of exceeding the budget), as emphasized in probabilistic cost estimation methods^[6]. The results also quantify the impact of various risk factors on total cost, identifying the most sensitive contributors to cost fluctuations and completing the risk assessment for online monitoring device replacement projects. To evaluate the performance of the Monte Carlo simulation framework, it can be compared against other risk analysis methods such as scenario analysis and sensitivity analysis. Scenario analysis, for instance, allows for examining extreme cases, while sensitivity analysis identifies the most critical factors affecting costs. These methods, however, lack the probabilistic depth provided by Monte Carlo simulations, which consider the entire distribution of risk factors.

4 Case Study Analysis

Based on the risk distribution fitting model and Monte Carlo simulation model constructed earlier, this section will elaborate on the distribution fitting results, simulation results, and their analysis. MATLAB will be used to fit the risk factors of the sample data and simulate 1000 iterations to quantify and explain the cost risk of the online monitoring device replacement project.

4.1 Distribution Fitting Results of Risk Factors

Distribution Fitting Results of Unit Price.

The device unit price (P) is modeled using kernel density estimation (KDE) to fit its probability distribution. Most unit price data is concentrated between 0.59 and 0.83 ten thousand CNY per set, while high-tech devices, such as those for wire swinging and wind deviation monitoring, reach up to 1.73 ten thousand CNY per set, resulting in a multimodal distribution. The fitted distribution (Fig. 1) highlights the variability in procurement costs, with a mean of 0.85 ten thousand CNY per set and a variance of 0.1449.

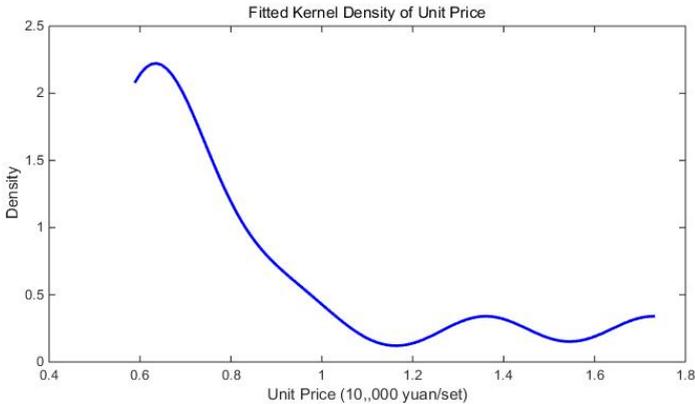


Fig. 1. Fitted Kernel Density of Unit Price

Distribution Fitting Results for Quantity.

The fluctuation range of equipment quantity is large, mainly determined by project scale and technical requirements, with sample quantities ranging from 5 to 370 units. The probability density function for quantity was obtained through kernel density estimation (KDE), and the fitting results are shown in Fig. 2. The mean quantity is 151.27 units, with a variance of 27,110.88.

Fitting Results for Other Cost Risk Factors.

The factors "whether it is a smart line special project" (X_1) and "whether it is a self-implemented project" (X_2) are both fitted to a Bernoulli distribution, with the probabilities as follows:

$$P(X_1 = 1) = p_1 = 0.81818, \quad P(X_2 = 1) = p_2 = 0.90909$$

The device function (F) is fitted to a discrete uniform distribution, assuming that each function has an equal probability of occurrence.

Total Cost Distribution.

The total cost distribution shows a right-skewed characteristic, with a mean of 1.204 million yuan and a standard deviation of 0.456 million yuan, reflecting the significant impact of different project characteristics on cost. The distribution histogram is shown in Fig. 3.

Overrun Probability Analysis.

Based on the budget data for the 110kV online monitoring device replacement project in S Province, a budget limit of 1.5 million yuan was set. The simulation results show an overrun probability of 18.6%, meaning that nearly 20% of the projects could

exceed the budget. This highlights the necessity of incorporating adequate contingencies into the budget to account for uncertainties.

$$P_{over} = \frac{1}{N} \sum_{i=1}^N \mathbb{1}(C_i > 150) \quad (7)$$

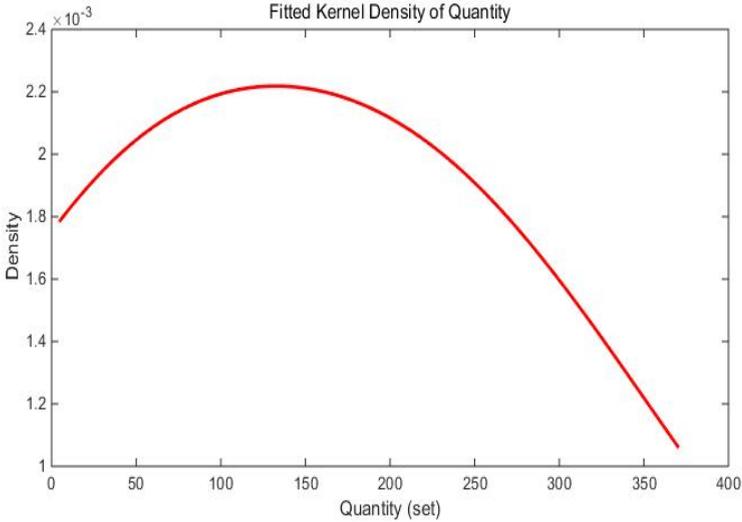


Fig. 2. Fitted Kernel Density of Quantity

Analysis of the Impact of Risk Factors on Costs.

The sensitivity of risk factors (unit price, quantity, whether it is a smart line special project, whether it is a self-implemented project and device function) to total cost fluctuations was analyzed by calculating the correlation coefficients between each risk factor and the total cost. The specific results are shown in Fig. 4.

The results highlight that unit price and quantity are the most critical factors influencing total costs, while project type (smart line or self-implemented) and device function have comparatively less impact. Key findings include:

(1) Unit Price ($\rho=0.82$): The strongest factor, directly impacting total costs due to equipment procurement forming the largest cost component. Market fluctuations, supply chain issues, and technological upgrades significantly increase cost risks.

(2) Quantity ($\rho=0.64$): The second major factor, influenced by project scale and technical requirements. Quantity fluctuations amplify unit price impacts and increase other costs, such as construction, due to economies of scale.

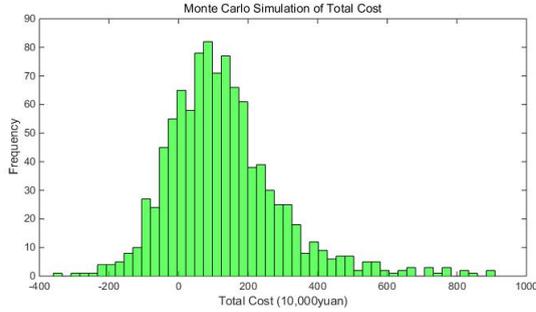


Fig. 3. Monte Carlo Simulation of Total Cost

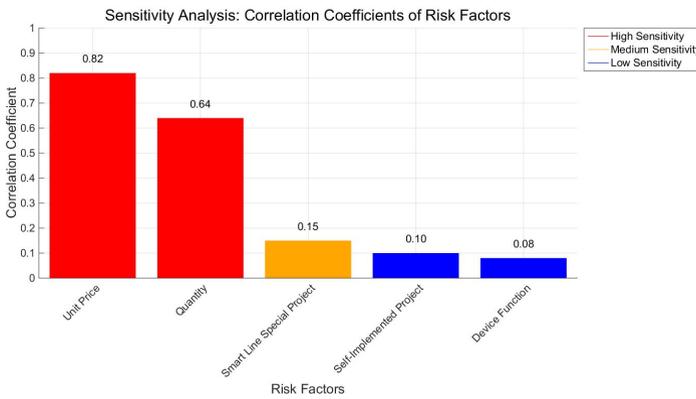


Fig. 4. Correlation Coefficient Between Each Risk Factor and Total Construction Cost

(3) Smart Line Special Projects ($\rho=0.15$): Moderate impact, mainly through indirect effects on unit price and quantity. These projects demand higher technical standards, but their overall cost volatility remains limited.

(4) Self-Implemented Projects ($\rho=0.10$): Minimal impact, as self-implementation improves technical control and resource use, primarily affecting construction costs rather than overall cost fluctuations.

(5) Device Function ($\rho=0.08$): Least impact, with complex devices like line swing or wind deflection monitoring having higher unit costs but lower quantities, limiting their effect on total cost variability.

Focusing on controlling unit price and quantity can effectively mitigate cost risks in similar projects.

5 Conclusion

This study employs an engineering cost risk assessment framework, integrating risk factor identification, distribution fitting, and Monte Carlo simulation methods. Based

on project data, we identified market, technical, and management risks, fitted their distributions, and analyzed the total cost's sensitivity. The key findings are:

(1) Unit price and quantity are the primary cost drivers, with correlation coefficients of 0.82 and 0.64, respectively. Other factors, such as Smart Line Special Projects (0.15), Self-Implemented Projects (0.10), and Device Functions (0.08), have minimal impact.

(2) Monte Carlo simulations indicate an 18.6% probability of exceeding a 1.5 million RMB budget, emphasizing the need for redundancy in budget planning.

(3) The combined use of distribution fitting and Monte Carlo simulation effectively captures uncertainties and quantifies risk factors, demonstrating strong practical value.

Based on the above conclusions, we offer the following four recommendations for grid projects:

(1) Mitigate unit price fluctuations through long-term price locking or price alert mechanisms during procurement. For instance, price locking can be implemented through long-term procurement contracts with suppliers, ensuring stable costs for critical equipment.

(2) Reduce quantity uncertainties with precise demand forecasting during project planning. Demand forecasting can leverage historical data and advanced algorithms, such as machine learning models, to accurately predict device quantities required for future projects. For example, using past data from similar projects in S Province, forecasting tools can identify seasonal demand trends and adjust procurement strategies accordingly.

(3) Optimize technical solutions for Smart Line projects and enhance internal management for Self-Implemented Projects to avoid unnecessary cost increases.

(4) Expand the sample size in future studies to improve the model's robustness and applicability across different regions and project types.

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