Risk Assessment and Prognosis of Onshore Wind Power Projects Utilizing Fault Tree Analysis and Bayesian Network Methodology

Jingyi Huang[a], Yi Wang[b]*

North China Electric Power University (Baoding), Baoding 071003, China

[a]13477945425@163.com, [b*]wangyizj@ncepu.edu.cn

Abstract. As the energy mix evolves, the share of wind power is increasing. Presently, the risk assessment of onshore wind projects predominantly relies on expert judgment. To enhance this process, our study commences with a clear definition of project objectives, followed by an analysis of risk sources and events. We systematically map these elements into a Bayesian network utilizing a fault tree model. By integrating fuzzy expert evaluations, we develop a comprehensive risk assessment model and perform a sensitivity analysis. Case studies demonstrate that the risk factors identified by our model align closely with real-world scenarios, providing robust references for the management of onshore wind projects.

Keywords: Onshore wind power project; Risk evaluation; Fault tree; Bayesian network modeling

1 Introduction

With the ongoing transformation of China's energy sector, the proportion of renewable energy generation methods, particularly wind power and hydropower, has been progressively increasing. Wind power currently stands as one of the most rapidly developing and technologically mature renewable energy sources. However, wind power projects are characterized by substantial capital investments and complex environmental conditions, which expose them to multiple risk factors. Failure to effectively manage these risks may lead to escalated project costs, prolonged construction timelines, and potentially result in project failure with significant financial losses. Consequently, implementing comprehensive risk assessment throughout the project lifecycle and proactively addressing critical risk factors is of paramount importance.

Owing to the substantial variations in site selection, construction, design, and other critical aspects of onshore wind power projects, the risk profiles of different onshore wind power projects exhibit significant heterogeneity. The scientific classification of risk factors and comprehensive understanding of wind power project risks are of paramount importance. Previous studies [1]-[7] have predominantly focused on external risk factors, primarily investigating wind power project risk assessment through

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dimensions including policy risk, environmental risk, economic risk, technical risk, and natural disaster risk. Notably, Mei [8]and Hu et al. [9] have extended this research scope by incorporating internal risk factors, particularly project management risk, in addition to the aforementioned external risks.

To accurately evaluate the risks associated with wind power projects, it is imperative to not only precisely identify the risk factors inherent in such projects but also to select appropriate risk assessment methodologies. Currently, the most commonly employed risk assessment methods include the AHP (Analytic Hierarchy Process), Fuzzy Comprehensive Evaluation, and the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution). However, these methods are often criticized for their excessive reliance on the expertise and experience of specialists. In contrast, Bayesian networks offer the advantage of integrating expert knowledge with prior probabilities, thereby mitigating subjectivity. References [10]-[13] have all utilized traditional Bayesian networks for risk assessment research, yet the construction of directed acyclic graphs in these networks presents significant challenges. Consequently, recent studies have increasingly focused on integrating Bayesian networks with other methodologies. For instance, Sun[14] employed influence diagrams to identify the risk transmission chain in PPP (Public-Private Partnership) projects and constructed a Bayesian network model, leveraging the learning and reasoning capabilities of Bayesian networks to deduce the key risk sources in PPP projects. Similarly, Zhang et al.[15] combined the fault tree model with Bayesian networks to establish a Bayesian network model, utilizing the reverse reasoning diagnosis of Bayesian networks to identify the critical risk factors in the metro shield construction process.

Leveraging the inherent advantages of Bayesian networks in addressing uncertainty issues, this methodology excels in explicitly illustrating the interrelationships among multiple variables through graphical representations, demonstrating superior objectivity compared to alternative evaluation approaches. Consequently, this study integrates Bayesian networks with fault tree analysis, utilizing the fault tree to establish causal relationships among diverse risk factors and subsequently transforming the causal relationship diagram into a directed acyclic graph within the Bayesian network framework. Through the application of Bayesian network reasoning and diagnostic capabilities, the research identifies critical risks in wind power projects, with empirical validation conducted using the Ye County FN wind power project as a case study.

2 Development of Fault Tree Analysis Model

A fault tree is a graphical representation that employs diverse event symbols to delineate the causal relationships among events within a system. This analytical tool comprises fundamental components, including top events, intermediate events, and basic events[16]. Based on the logical interrelationships among various risk factors in onshore wind power projects, this study utilizes the “OR gate”, which signifies that the occurrence of any single event will trigger the upper-level event.

As onshore wind power projects constitute large-scale engineering undertakings, they are susceptible to a multitude of risk factors and diverse accident types stemming

from these factors. This study develops a fault tree model from the perspective of achieving the objectives of onshore wind power projects. The occurrence of risks in onshore wind power projects is designated as the top event, while the generation of economic risks, quality risks, schedule risks, safety risks, and environmental risks are established as intermediate events. Subsequently, the five intermediate events and their underlying causes are subjected to in-depth analysis, resulting in the identification of 13 basic events. To construct the fault tree model, logical relationships are established between the intermediate events and the basic events. Through case analysis, literature review, and expert consultation, a four-level fault tree system is systematically organized. The occurrence of risks in wind power projects occupies the first level, while the occurrence of economic risks, quality risks, schedule risks, safety risks, and environmental risks, which represent the target risk occurrences, are positioned at the second level. The third level comprises various classifications of the upper-level risks, as illustrated in **Table 1**.

Table 1. Risk Factor Logic Table for Onshore Wind Power Projects.

<table>
<tr><td rowspan="13">A
Risks occur in onshore wind power projects.</td><td rowspan="5">B
Economic risks</td><td rowspan="4">B1
Cost risk</td><td rowspan="3">B11
Cost risks during the construction period</td><td colspan="2">B111 Financial risk</td></tr>
<tr><td rowspan="2">B112
Engineering cost risk</td><td>B1121
The risk of rising labor costs</td></tr>
<tr><td>B1122
The risk of rising equipment rental costs</td></tr>
<tr><td colspan="3">B12 Operation and maintenance cost risk</td></tr>
<tr><td rowspan="2">B2
Revenue risk</td><td colspan="3">B21 Subsidy policy and electricity price policy risks</td></tr>
<tr><td colspan="3">B22 Wind resource risk</td></tr>
<tr><td rowspan="3">C
Quality risks</td><td>C1
Construction quality risk</td><td colspan="3">C11 Contractor's risk</td></tr>
<tr><td rowspan="2">C12 Managerial capability risk</td><td colspan="3"></td></tr>
<tr><td>C2
Fan quality risk</td><td colspan="3">C21 Contractor's risk</td></tr>
<tr><td rowspan="3">D
Schedule risks</td><td>D1
Equipment progress risk</td><td colspan="3">D11 Contractor's risk</td></tr>
<tr><td rowspan="3">D2
Construction progress risk</td><td colspan="3">D21 Address condition risk</td></tr>
<tr><td colspan="3">D22 Risk of adverse weather conditions</td></tr>
<tr><td colspan="3">D23 Contractor's risk</td></tr>
<tr><td>E
Safety risks</td><td colspan="4">E1 Managerial capability risk</td></tr>
<tr><td></td><td colspan="4">E2 Safety construction risks</td></tr>
<tr><td>F
Environmental risks</td><td colspan="4">F1 Ecological balance risk</td></tr>
</table>

Through systematic analysis of the causal relationships between basic events and intermediate events, coupled with logical classification, the risk assessment framework for onshore wind power projects can be effectively transformed into a comprehensive fault tree model, as illustrated in **Figure 1**. As depicted in Figure 1, the risk factors associated with onshore wind power projects are systematically categorized into five primary domains: economic risks, quality risks, schedule risks, safety risks, and environmental risks, based on project objectives. Specifically, economic risks are evaluated through two distinct components: cost risks and revenue risks. The cost risk component primarily comprises construction period costs and operation and maintenance costs, which are interconnected through an "OR" gate, signifying that the occurrence of either component will trigger cost risk. Similarly, the revenue risk component is primarily composed of subsidy policy risks and wind resource risks, which are also connected through an "OR" gate, indicating that the occurrence of any single basic event will result in revenue risk. The structural relationships between other intermediate events and basic events within this fault tree model can be interpreted following the same logical framework.

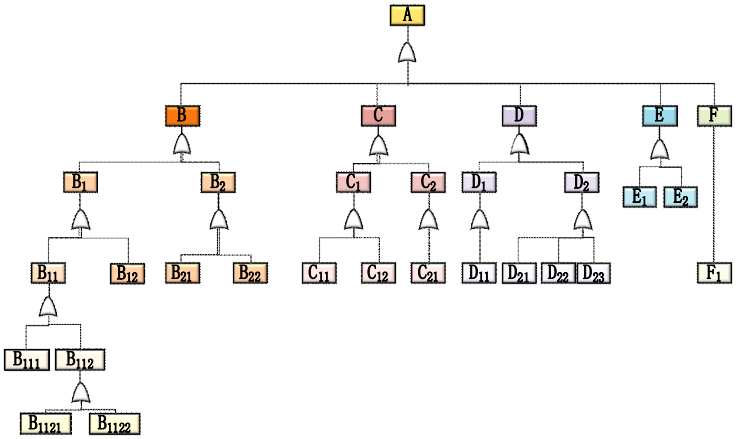

Fig. 1. Fault tree model of onshore wind power projects.

3 Improving The Construction of Bayesian Network

3.1 The Establishment of a Directed Acyclic Graph in Bayesian Networks

To translate the fault tree model into a directed acyclic graph (DAG) of a Bayesian network, the events in the fault tree are mapped to nodes in the Bayesian network, while the causal relationships between nodes in the fault tree are converted into directed edges in the DAG. Specifically, the top event in the fault tree corresponds to a leaf node in the Bayesian network DAG, intermediate events become intermediary nodes, and basic events are transformed into root nodes.

Taking quality risk as an example, as shown in **Figure. 2**, the onshore wind power project risk (A) is the top event, corresponding to a leaf node (A) in the Bayesian network. Quality risk (C) is an intermediate event, mapped to an intermediary node (C) in the Bayesian network. Construction risk (C1) and wind turbine risk (C2) are intermediate events, converted into intermediary nodes (C1, C2). Contractor risk (C11) and management capability risk (C12) are basic events, transformed into root nodes (C11, C12) in the Bayesian network. The directed acyclic graph of this Bayesian network indicates that contractor risk (C11) and management capability risk (C12) contribute to construction risk (C1), while contractor risk (C21) leads to wind turbine quality risk (C2). Wind turbine quality risk (C2) and construction risk (C1) jointly cause quality risk (C). Finally, quality risk (C) and four other risks collectively result in the occurrence of onshore wind power project risk (A).

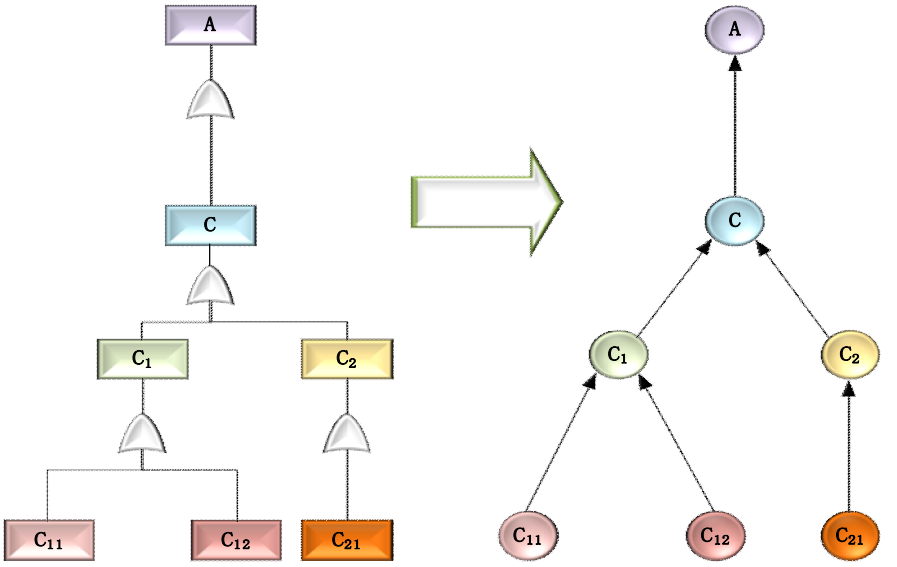

Fig. 2. Example of Fault Tree Conversion to Bayesian Network

In accordance with the aforementioned transformation principles from fault tree analysis to Bayesian networks, the existing fault tree model is systematically converted into a directed acyclic graph structure within the Bayesian network framework.

3.2 The Establishment of Parameters for Bayesian Networks

3.2.1 The Principle of Bayesian Network.

The Bayesian network model is fundamentally grounded in probability theory. Formally, a Bayesian network can be mathematically represented as G = {(I, E) P}, where "I" denotes the set of vertices (nodes), "E" signifies the set of directed edges, and "P" represents the joint probability distribution over the nodes. Specifically, I = {Xi | i ∈ I}, where each Xi corresponds to a distinct node, and each node is associated with a

conditional probability table (CPT). The Bayesian network optimizes its parameters through the computation of prior and posterior probabilities within a given network topology. The mathematical foundation of the Bayesian network is established by Bayes' theorem, which can be expressed as follows:

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \tag{1}$$

The posterior probability can be computed by applying the prior probability through the following mathematical formulation:

Assume that in the set I = (Xi)i∈I, each node exhibits independence with respect to the others, which can be formally expressed as:

$$P(X_1, X_2, \cdots, X_n) = \prod_{i=1}^{I} P(X_i \mid parents(X_i)) \tag{2}$$

Then the joint distribution probability under this condition is:

$$P(B = b_j, A = a_i) = P(A = a_i) \times P(B = b_j \mid A = a_i) \tag{3}$$

Subsequently, the marginal probability can be derived as follows:

$$P(B) = \sum_i P(A = a_i) \times P(B = b_j \mid A = a_i) \tag{4}$$

Based on this, the posterior probability can be derived as follows:

$$P(A = a_i \mid B = b_j) = \frac{P(A = a_i) \times P(B = b_j \mid A = a_i)}{P(B = b_j)} \tag{5}$$

Consequently, Bayesian networks are capable of rectifying the original dataset by leveraging prior probabilities and posterior probabilities.

3.2.2 Computation of the Occurrence Probability for the Root Node.

The determination of Bayesian network parameters can be achieved through two primary methodologies. The first approach involves parameter estimation through the collection and analysis of extensive empirical data. In scenarios where acquiring sufficient empirical data proves infeasible, the alternative method of expert elicitation can be implemented. This study employs the expert elicitation methodology for parameter determination. Grounded in fuzzy set theory, industry experts were engaged to provide assessments using a 7-level natural language scale. Subsequently, these linguistic evaluations were transformed into corresponding triangular fuzzy numbers, as illustrated in **Table 2**.

Table 2. The semantic representations of event occurrence probabilities and their corresponding triangular numerical values.

Serial Number	Semantic significance	Triangular fuzzy number
1	Very low	(0,0,0.1)
2	Low	(0,0.1,0.1)
3	Relatively low,	(0.1,0.3,0.5)
4	Medium	(0.3,0.5,0.7)
5	Relatively high	(0.5,0.7,0.9)
6	High	(0.7,0.9,1.0)
7	Very high	(0.9,1.0,1.0)

To ensure the accuracy of the data and further eliminate the subjectivity of experts, this paper employs the similarity aggregation method (SAM) to process the acquired triangular fuzzy numbers.

Let Ek denote the natural language assessment of the occurrence probability for each risk factor provided by the k-th expert (k = 1, 2, 3, …, m), where all linguistic assessments are subsequently transformed into corresponding triangular fuzzy numbers.

Compute the consistency degree S between any two experts within the expert panel. Specifically, determine the consistency degree S (Em, En) between experts En and Em. Let Rm = (a, b, c) and Rn = (e, f, g) represent the fuzzy numbers corresponding to the evaluation outcomes of the m-th and nth experts, respectively. The computation is as follows:

$$S(R_m, R_n) = 1 - \frac{1}{3}\sum_{i=1}^{3} | r_{mi} - r_{ni} | \tag{6}$$

Among these variables, r_{mi} denotes the fuzzy number corresponding to the assessment result of the *i*-th risk factor evaluated by expert Em, while r_{ni} represents the fuzzy number corresponding to the assessment result of the *i*-th risk factor evaluated by expert En.

Compute the mean consistency index across the expert evaluation outcomes.

$$AA(E_m) = \frac{1}{\lambda - 1}\sum_{v=1}^{\lambda} S(R_m, R_n) \tag{7}$$

Compute the relative consistency index of the expert evaluation results.

$$RA(E_m) \frac{AA(E_m)}{\sum_{u=1}^{k} AA(E_m)} \tag{8}$$

Compute the consistency coefficient for the expert panel.

$$CC(E_m) = \beta w(E_m) + (1 - \beta) \times RA(E_m) \tag{9}$$

Among these parameters, represents the weight assigned to each expert, while β denotes the relaxation factor, which quantifies the relative significance of the expert's weight in relation to the consistency measure. In this study, the relaxation factor is empirically set to 0.5.

Ultimately, the clustering outcomes are derived.

$$R_{AG} = CC(E_1) \times R_1 + CC(E_2) \times R_2 + \cdots + CC(E_k) \times R_k \tag{10}$$

Ultimately, the clustering outcomes derived from the aforementioned similarity aggregation approach remain fuzzy numbers, necessitating defuzzification to transform them into precise probability values. This study employs the "mean area method" for the defuzzification process:

$$F = \frac{a + 2b + c}{4} \tag{11}$$

3.2.3 The Probabilities of Intermediate Nodes and Leaf Nodes Are Determined.

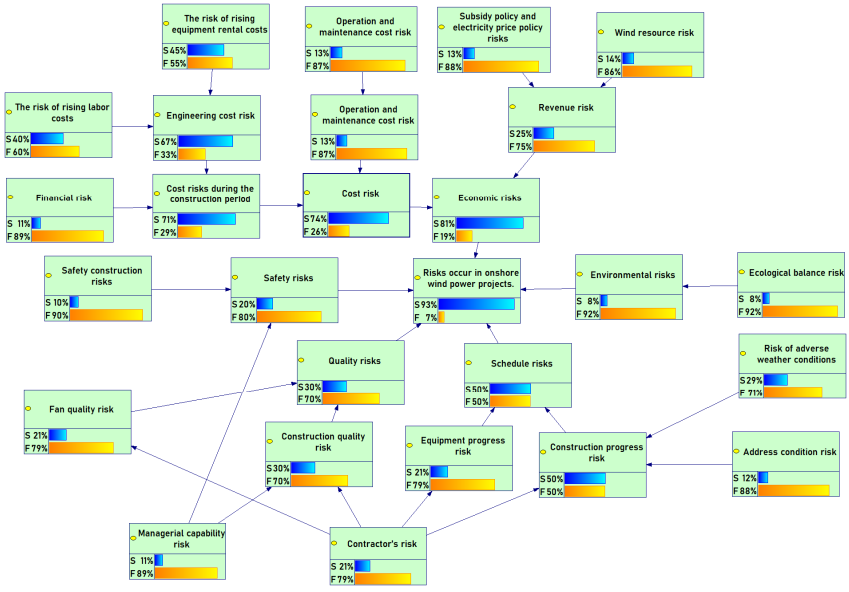

Fig. 3. Forward reasoning of the Bayesian network model

By employing the fault tree analysis model, the causal relationships between the root node and intermediate nodes, as well as between intermediate nodes and leaf nodes, can be systematically established. Subsequently, the probabilities associated with intermediate nodes and leaf nodes can be quantitatively derived from the probabilities of basic events and their logical interrelationships.

Considering the intermediate node quality risk (C) illustrated in Figure 3 as a case study, the construction risk (C1) and the wind turbine risk (C2) constitute the intermediate nodes, while the contractor risk (C11) and the management personnel capability risk (C12) represent the root nodes. Furthermore, C11 and C12 are interconnected with C via an "OR" logical gate, signifying that the occurrence of any one of these three events will trigger the occurrence of C. Consequently, if we define A = 1 as the event occurrence and A = 0 as the event non-occurrence, then $P(C=1|C_{11}=1,C_{12}=1)$, $P(C=1|C_{11}=0,C_{12}=1)$, $P(C=1|C_{11}=1,C_{12}=0)$, $P(C=0|C_{11}=0,C_{12}=0)$ all are equal to 1.Subsequently, in accordance with the law of total probability, it can be deduced that $P(C=1)=P(C_{11}=1)\bullet P(C_{12}=1)+P(C_{11}=1)\bullet P(C_{12}=0)+P(C_{11}=0)\bullet P(C_{12}=1)$. The probability of event C occurrence can therefore be derived.

By integrating the acquired probability distributions with the directed acyclic graph, the Bayesian network model illustrated in **Figure. 3** can be effectively constructed.

4 Bayesian Network Reasoning

4.1 Reverse Reasoning of Bayesian Networks

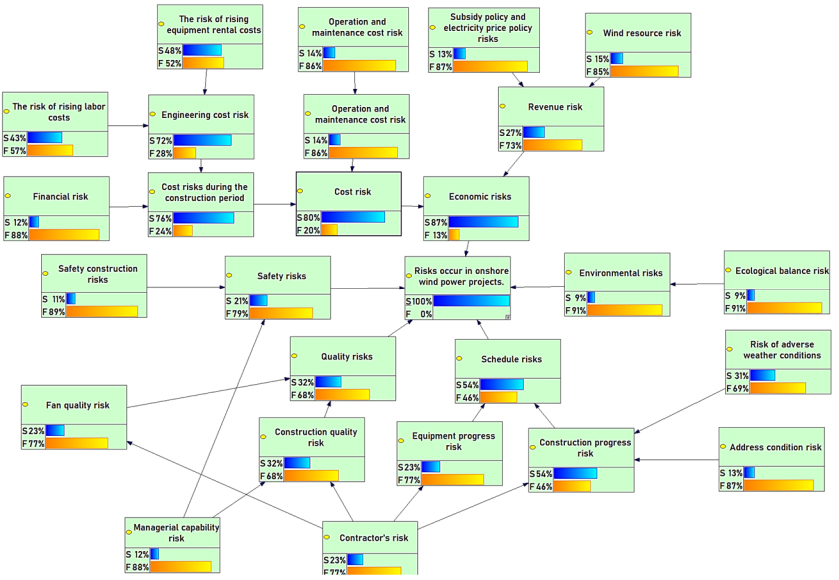

Fig. 4. Backward reasoning of the Bayesian network model

Reverse reasoning constitutes a deductive process that proceeds from effect to cause, operating in the inverse direction of the Bayesian network's directed graph. Specifically, by elevating the risk value of the terminal outcome, we identify nodes with

elevated risk values to deduce the principal risk factors. In this study, the probability of risk occurrence in wind power projects is established at 100%, with the posterior probabilities of each node illustrated in **Figure. 4**. Based on the reverse reasoning analysis, the posterior probabilities for economic risk and schedule risk in wind power projects are determined to be 87% and 60%, respectively, significantly surpassing those of quality risk, environmental risk, and safety risk, which stand at 33%, 9%, and 11%. Consequently, in the context of wind power project risks, economic risk and schedule risk warrant prioritized attention. It is imperative to investigate the underlying causes of these two risk events and implement targeted measures to mitigate their probability of occurrence.

4.2 Sensitivity Analysis of Bayesian Networks

Sensitivity analysis serves as a crucial methodology for evaluating the responsiveness of final outcomes to variations in individual nodes, while simultaneously elucidating the relative interdependencies and significance among these nodes. The metrics derived from sensitivity analysis exhibit remarkable sensitivity; indeed, even marginal alterations can exert substantial influence on project completion, necessitating targeted management interventions. As established through reverse inference in Section 4.1, the posterior probabilities associated with economic risk and schedule risk demonstrate the highest magnitudes. Consequently, sensitivity analysis is imperative for further pinpointing the fundamental factors that exert the most substantial impact on these two risk events.

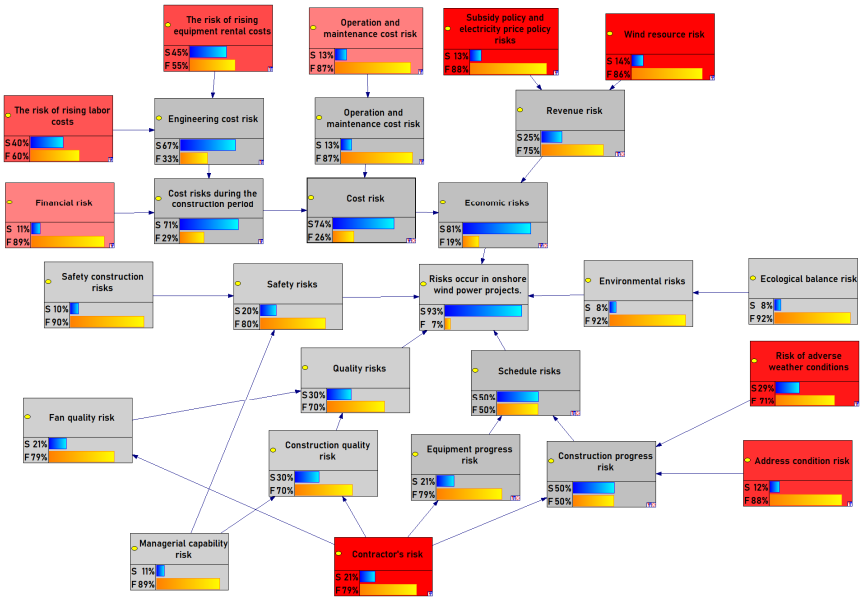

Fig. 5. Sensitivity analysis

To further identify root causes, economic risk, schedule risk, and all their parent nodes were set as target nodes. Sensitivity analysis was then conducted using Genie software, with results illustrated in **Figure. 5**. In Figure 5, darker node colors indicate higher sensitivity levels, providing an intuitive visualization of risk factors with greater sensitivity.

Based on the sensitivity analysis results, economic risk demonstrates higher sensitivity to labor wages (B_{1121}), equipment leasing (B_{1122}), and wind resources (B_{22}) compared to other risk factors. For schedule risk, the highest sensitivities are observed for adverse climate risks (D_{22}) and contractor risks (D_{11}). Therefore, to reduce the probability of risks in the wind power project, these key risk factors require prioritized management and control.

5 Instance Validation

To validate the applicability of fault tree analysis and Bayesian network models in risk assessment for wind power projects, this study employs the completed and operational Ye County FN wind power project as a case study. Through systematic analysis, the risk factors associated with the project were identified, followed by the establishment of a fault tree and the construction of a Bayesian network model for probabilistic inference analysis. The analysis reveals that the occurrence probabilities of economic risk (89%) and schedule risk (83%) significantly exceed those of other intermediate nodes. Further investigation indicates that these elevated probabilities primarily stem from engineering cost risk, adverse weather conditions, and contractor-related risks, necessitating targeted risk mitigation strategies. The obtained results were subsequently compared with actual project outcomes:

Through analysis of financial data during the project's construction phase, it was found that the primary cost overruns occurred in the engineering construction phase. These were mainly due to opposition from local residents and other enterprises, which obstructed construction progress, as well as rising prices of construction materials, equipment leasing, and land, leading to increased project budgets.

A comparison between the project's actual operational production indicators and the feasibility study design targets revealed a significant gap between the actual grid-connected electricity output and the designed output, severely diminishing the project's economic benefits. This discrepancy arose because the feasibility study phase inadequately accounted for various uncertainty factors, such as issues caused by turbine location changes, resulting in a substantial deviation between actual economic performance and the feasibility study projections.

By comparing actual construction progress with planned schedules, the project experienced four delays. The most impactful delays were caused by extreme weather conditions (e.g., thunderstorms, rain, and snow) leading to work stoppages, as well as contractor wage arrears triggering strikes and worker protests, which prolonged the timeline.

Finally, comparing the risk factors encountered in the Ye County FN project with the key risk factors identified by the Bayesian network risk assessment model in this study shows substantial overlap, validating the model's applicability.

6 Conclusion

Through a systematic analysis of risk sources and their formation mechanisms in wind power projects, this study, employing case studies and expert consultations, has identified 26 distinct risk factors. The research has systematically organized the logical interrelationships among these risk factors, constructed a fault tree model, and subsequently transformed it into a Bayesian network model. By conducting expert surveys and applying fuzzy processing to the results, the occurrence probabilities of each root node were determined. Utilizing the logical relationships within the fault tree model, the conditional probabilities were established, thereby formulating a comprehensive risk assessment model for onshore wind power projects. The principal findings are as follows:

Through expert consultation and case analysis, this study identifies 26 risk factors for large-scale wind power projects, categorized into five dimensions: economic, scheduling, quality, environmental, and safety risks. Analytical results highlight five prioritized risks: labor cost inflation, equipment rental price volatility, wind resource instability, contractor reliability deficiencies, and extreme weather disruptions, requiring targeted mitigation strategies.

(2) Validation through evaluation of completed and operational projects indicates that the identified key risk factors align with practical scenarios, thereby substantiating the model's applicability.

(3) Given the substantial heterogeneity among wind power projects and their diverse environmental contexts, risk events exhibit considerable variability. While this model focuses on assessing and analyzing common risks prevalent in most wind power projects, specific projects necessitate more granular classification of risk factors. Future research endeavors should prioritize this objective to enhance the model's specificity and applicability.

Acknowledgments

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