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Research on the Improved Large-Scale Group Decision Making of Engineering Project Operation

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Abstract: The operation process of engineering projects is essentially a process of information flow and processing, which is complex and uncertain. It is necessary to fully consider the subjective initiative characteristics such as the behavioral preferences of the decision-making subjects. However, traditional decision-making methods are based on the assumption of complete rationality but ignore the reality of limited rationality caused by individual psychological factors. Especially in group decision-making, the preference differences among multiple subjects are prone to cause result deviations. Therefore, in the face of the challenges of uncertainty, complexity and the integration of opinions in the operation of engineering projects, this paper constructs an engineering project operation evaluation method that integrates behavioral decision-making characteristics, providing decision support for the improvement of engineering project operation management. Traditional decision-making methods express preferences through language, but they are difficult to capture dynamic psychological changes, resulting in evaluation biases. Meanwhile, as the scale of the participating entities expands, the operation and investment decision-making of engineering projects has gradually evolved into a large-scale group decision-making problem involving the interests of multiple parties, which puts forward higher requirements for the rationality of the decision-making process.

Keywords: Engineering project operation; Large-scale group decision-making; Behavioral preferences

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1. Introduction

In the actual management of project operation optimization, the operator not only needs to take into account the goal of enhancing passenger satisfaction, but also must confront practical constraints such as limited budgets and uncertain risks. When making service investment decisions, operators often encounter complex situations involving multiple factors; On one hand, they hope to enhance passenger satisfaction by improving service quality; On the other hand, they must comprehensively assess various investment plans within a limited budget to avoid waste of resources [1]. Often, systematic trade-offs need to be made among multiple conflicting attributes such as passenger revenue, operating costs, risk levels, and implementation cycles. This issue not only constitutes a typical multi-attribute decision-making problem but also a behavioral decision-making process full of subjectivity and uncertainty.

As the number of participants in engineering project decision-making gradually increases, for instance, multiple decision-making members from various functional departments such as finance, technology, operation, and safety take part in the evaluation and voting of plans, this process is gradually evolving into a large-scale group decision-making problem. Due to the diversity of opinions and differences in professional positions among participants, the evaluation results often vary significantly, further exacerbating the complexity of the model in consensus generation and opinion integration.

Operators do not always aim for maximum revenue or the highest passenger satisfaction. Instead, they strive to achieve the optimal allocation of resources within an acceptable budget and management risks. Traditional decision-making methods, such as AHP, TOPSIS, and fuzzy comprehensive evaluation, although they can provide certain operability in multi-scheme comparisons, often ignore the psychological motivations and preference influences of decision-makers [2,3]. When dealing with the subjective preferences of operators, these methods usually rely on language terms as expression tools, making it difficult to accurately depict the irrational behavioral responses of operators in high-risk and uncertain situations. For instance, when considering whether to introduce a new automated ticketing system or increase train services, the operator needs to comprehensively assess the technical feasibility, cost-effectiveness and potential social impact [4].

In such situations, the operator often exhibits a significant risk-averse behavior. That is, when confronted with potential uncertainties, they tend to avoid solutions that may lead to negative outcomes, even if these solutions might bring about a higher increase in passenger satisfaction. This risk-averse tendency is widespread in real decision-making. However, most current service optimization models usually assume that individuals are “completely rational” or hold “static preferences”, and fail to fully consider the behavioral psychological characteristics exhibited by group members in an uncertain information environment [5]. This psychological tendency is widespread in real operational scenarios. However, in the current operation optimization models of engineering projects, it is often overlooked or simplified.

To address the above issues, this paper attempts to introduce a language subscript term set to more accurately depict the evaluation behavior of operators in large-scale group decision-making scenarios, thereby more accurately reflecting the risk aversion characteristics exhibited by project operators in the actual decision-making process [6]. This article aims to achieve breakthroughs in the following aspects as follows:

(1) Enhance the authenticity of the opinions expressed by the operators, making their decision-making process closer to their actual psychological state;

(2) Strengthen the fitting ability of the group opinion integration model for real preferences and reduce the problem of preference distortion caused by the assumption of complete rationality in traditional methods;

(3) Provide more behavioral pattern-compliant auxiliary decision-making tools for the allocation of operational resources in engineering projects.

2. Construction of a scheme optimization evaluation Model for large-scale group decision-making

This paper constructs a risk-averse operator group decision support model for the operation optimization of engineering projects based on the background of large-scale group decision-making. For instance:

(1) Use language assessment models to quantify the impact of psychological biases on decision-making

outcomes, thereby achieving more accurate expression of preferences;

(2) A questionnaire survey was designed for the operation and management personnel of engineering projects to collect their subjective evaluations of investment plans and express them in the form of fuzzy language. To simplify the complexity of group opinions, the K-means algorithm is used to group decision-makers and assign weights. On this basis, an improved large-scale group decision-making algorithm is introduced;

(3) We adopt the weighted aggregation operator to integrate and process the evaluation information provided by the group members, and conduct aggregated analysis on the different attributes of each scheme within and between groups respectively.

Subsequently, the comprehensive integration is completed by combining attribute weights to generate the priority ranking of each improvement plan, thereby obtaining the optimal service investment decision result based on the risk-averse behavior orientation of the operator.

2.1. Linguistic evaluation modeling for preference expression

Linguistic methods are an approximate technique in the field of linguistic research, consisting of two parts: linguistic descriptive semantics and the linguistic terminology set. The structure of a linguistic term is a letter with a subscript, which forms the basis for describing decision operators in language. At present, the most common sets of linguistic terms are divided into two types: addition and multiplication. The additive linguistic terminology set is an assessment method that simply adds up various language ability indicators to obtain an individual's overall performance. However, because it adopts a simple additive method, it may lead to certain aspects of ability having a greater impact on the overall assessment result. Conversely, the multiplicative linguistics terminology set assessment more accurately reflects an individual's language proficiency level in all aspects by taking the weighted average of the performance of various language ability indicators.

$$f: s_{\mu_1}^{(2\tau_1+1)} \rightarrow s_{\mu_2}^{(2\tau_2+1)} \tag{1}$$

$$\mu_2 = f(\mu_1) = \mu_1 \frac{|V(x_{-\tau_2})|+|V(x_{\tau_2})|}{|V(x_{-\tau_1})|+|V(x_{\tau_1})|} \tag{2}$$

2.2. Clustering of decision-makers using the K-means algorithm

The fundamental concept of the K-means algorithm is to divide the dataset into k clusters, ensuring that data points within the same cluster are as similar as possible while maintaining the uniqueness among data points within different clusters. The reasons for choosing the k-means method for clustering in this paper are as follows:

(1) K-means clustering is an unsupervised learning algorithm that can automatically identify potential groups and effectively cluster similar data points in chaotic survey and evaluation data. This method shows considerable feasibility when dealing with the dataset collected in this study;

(2) The composition of decision-makers includes stakeholders from different departments.

By clustering decision-makers using K-means, these groups show similarities in certain features. Therefore, decision-makers can be divided into different groups to form a spherical clustering dataset, which usually leads to better clustering results.

$$D(B^h, c_k) = \frac{1}{M \times N} \sum_{m=1}^{M} \sum_{n=1}^{N} D_M(b_{mn}^h, c_t^k) \tag{3}$$

$$E = \sum_{k=1}^{K} \left[\frac{1}{M \times N} \sum_{m=1}^{M} \sum_{n=1}^{N} D_M(c_t^k, c_t^{k'}) \right] \tag{4}$$

2.3. Intra-group and inter-group information aggregation mechanisms

After the clustering process, the collective evaluation process of information aggregation involves two methods: intra-group opinion aggregation and inter-group opinion aggregation. Intra-group opinion aggregation refers to the integration of the opinions of decision-makers within the same subgroup, while inter-group opinion aggregation refers to the integration of the opinions of decision-makers within different subgroups. In order to conduct subsequent opinion aggregation, weights need to be assigned to each decision-maker during the intra-group integration process, and weights need to be assigned to each subgroup during the inter-group integration process.

This study determines the weight of decision-makers by considering the following two factors:

(1) Within subgroups, as the number of decision-makers in a cluster increases, the weight used to represent the group's opinion also increases, following the majority principle;

(2) Within a group, if a cluster shows greater cohesion, indicating that the differences among the decision-makers within the cluster are smaller, it should be given a higher weight.

$$d_{G_k}^{+} = \sqrt{\sum_{h_k=1}^{H_k}\left(Z_{G_k}^{+} - S(F^{h_k})\right)^2},\ \ d_{G_k}^{-} = \sqrt{\sum_{h_k=1}^{H_k}\left(Z_{G_k}^{-} - S(F^{h_k})\right)^2} \tag{5}$$

$$\omega_{G_k}^{h_k} = \frac{c_{h_k}}{\sum_{h_k=1}^{H_k} c_{h_k}} \tag{6}$$

3. Examples and analysis of results

To verify the feasibility of the risk-averse decision-making model for project operators proposed in the previous text, this paper takes the operation of a certain expressway as the research background and focuses on the optimization of operation quality. Based on the six operational indicators extracted and summarized from comprehensive market research, five of them (transfer convenience, C_1; temperature comfort, C_2; network connection quality, C_3; ticket price rationality, C_4; and handrail humanization, C_5) were selected as the alternative solutions for improvement by the operator. Meanwhile, from the perspective of evaluating attributes, six dimensions were selected (input cost, A_1; technical feasibility, A_2; maintenance convenience, A_3; implementation period, A_4; expected improvement in satisfaction, A_5; compatibility with existing facilities, A_6) to conduct a comprehensive assessment of the alternative schemes.

3.1. Data collection and linguistic standardization of evaluation information

A total of 80 questionnaires were distributed, and 73 valid questionnaires were ultimately retrieved, with an effective rate of 91.3%. After collecting the questionnaires, two preprocessing steps were conducted to ensure suitability for subsequent mathematical modeling and analysis. The linguistic expressions provided by respondents were transformed into interval-valued linguistic tuples. All linguistic assessments were then standardized to a unified granularity level. For decision-makers who employed three-granularity linguistic terms, specifically the 4^{th}, 5^{th}, 10^{th}, 16^{th}, and 19^{th} respondents, the five-granularity linguistic term set was adopted as the common linguistic scale for the multi-attribute group decision-making process. Using the transformation rules defined in Equations (1) and (2), their original assessments were normalized accordingly.

3.2. Clustering of decision-makers and weight assignment using the K-means algorithm

The k-means cluster analysis was conducted on the processed data using MATLAB2023a. The termination threshold is 0.05 (i.e., ε = 0.05). Through cluster analysis, the 20 subgroups of decision-makers from the operation party are divided into: $G_1 = \{E_1, E_2, E_5, E_8, E_{15}, E_{18}\}$, $G_2 = \{E_3, E_4, E_7, E_{13}, E_{16}, E_{19}, E_{20}\}$, $G_3 = \{E_6, E_{10}, E_{12}, E_{17}\}$ and $G_4 = \{E_9, E_{11}, E_{14}\}$. Subsequently, different weights were assigned to each group using Equation (3) to (4), and the results are shown in **Table 1**. According to the majority principle, G_2 has the largest number of members and the greatest weight. Next is G_1, while G_4, which has the fewest members, has the lowest weight.

Table 1. The weights of each group

Group	Inter-group weight	Intra-group weight	
G_1	$\omega_{G_1} = 0.30$	$\omega_{G_k}^{1} = 0.09$	$\omega_{G_k}^{2} = 0.17$
		$\omega_{G_k}^{5} = 0.22$	$\omega_{G_k}^{8} = 0.19$
		$\omega_{G_k}^{15} = 0.14$	$\omega_{G_k}^{18} = 0.18$
G_2	$\omega_{G_2} = 0.35$	$\omega_{G_k}^{3} = 0.13$	$\omega_{G_k}^{4} = 0.15$
		$\omega_{G_k}^{7} = 0.13$	$\omega_{G_k}^{13} = 0.11$
		$\omega_{G_k}^{16} = 0.14$	$\omega_{G_k}^{19} = 0.24$
		$\omega_{G_k}^{20} = 0.10$	/
G_3	$\omega_{G_3} = 0.20$	$\omega_{G_k}^{6} = 0.19$	$\omega_{G_k}^{10} = 0.31$
		$\omega_{G_k}^{12} = 0.16$	$\omega_{G_k}^{17} = 0.34$
G_4	$\omega_{G_4} = 0.15$	$\omega_{G_k}^{9} = 0.35$	$\omega_{G_k}^{11} = 0.50$
		$\omega_{G_k}^{14} = 0.15$	/

3.3. Aggregation of evaluation results and priority ranking of optimization schemes

The evaluation results of each operation optimization plan in each attribute were weighted and aggregated. Furthermore, the score function was applied to calculate the value score of each service investment plan, thereby achieving the priority ranking of each plan. The final assessment results and the corresponding score values are shown in **Table 2**. According to the ranking of the scores, the service optimization schemes under the current conditions are in the following order: $C_3 > C_2 > C_5 > C_4 > C_1$. It can be seen from this that scheme C_3 performs the best in the comprehensive evaluation that takes into account multiple attributes such as cost, technology, and implementation cycle, and is thus regarded as the highway operation service scheme with the most priority investment value at present.

Table 2. The final comprehensive evaluation value

Alternatives	The final comprehensive evaluation value	Priority
G_1	$[(s_{-2}^{5}, -0.3), (s_{2}^{5}, -0.5)]$	5
G_2	$[(s_{-2}^{5}, 0), (s_{2}^{5}, -0.2)]$	2
G_3	$[(s_{-2}^{5}, 0.2), (s_{2}^{5}, -0.2)]$	1
G_4	$[(s_{-2}^{5}, 0.4), (s_{2}^{5}, -0.3)]$	4
G_5	$[(s_{-2}^{5}, -0.1), (s_{2}^{5}, -0.4)]$	3

4. Conclusion

Based on domestic and international research and in accordance with the actual situation of engineering enterprises in China, this paper analyzes the main influencing factors of digital transformation of engineering enterprises, constructs an evaluation index system for the maturity of digital transformation of engineering enterprises from four aspects, uses the G_1 method to obtain the index weights, and finally uses the cloud model to evaluate the maturity of digital transformation of engineering enterprises.

This paper focuses on the investment evaluation problem of the operator under the background of project service optimization and constructs a multi-attribute group decision-making model considering the risk-averse behavior of the operator. In real management practice, project operators not only need to enhance passenger satisfaction within a limited budget, but also make investment decisions that align with their own risk preferences when confronted with diversified service demands and complex operational environments. Traditional multi-attribute group decision-making methods are often based on the assumption of complete rationality and are difficult to effectively reflect the psychological and behavioral characteristics of operators in real situations, especially the psychological characteristics of being more sensitive to potential losses and tending to avoid uncertain risks. Therefore, this paper introduces the framework of prospect theory and constructs an investment evaluation model for project operators based on a language evaluation model to more accurately depict their psychological characteristics of risk aversion.

Disclosure statement

The author declares no conflict of interest.

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