



Project Selection in Construction Industry by MCDM Method and Machine Learning Approach

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ABSTRACT

Project selection in the construction industry plays a crucial role in ensuring the success and profitability of construction projects. Various factors, such as cost, time, quality, and resources, need to be carefully evaluated during the project selection process. This paper presents a comprehensive study on project selection in the construction industry using the Multiple Criteria Decision Making (MCDM) method combined with a machine learning approach. The objective is to provide a systematic and objective framework for project selection that considers diverse criteria and enhances decision-making accuracy in the construction industry.

1. Introduction

The construction industry faces unique challenges in project selection due to its complex nature and dynamic environment. Traditional project selection methods often rely heavily on intuition and subjective judgments, which may lead to suboptimal outcomes. To overcome these limitations, the integration of MCDM methods and machine learning techniques offers a promising solution. This paper aims to explore the potential of combining MCDM and machine learning in project selection and provide insights into their application and benefits in the construction industry.

Project selection in the construction industry is a complex task that involves multiple criteria, such as budget, schedule, risk, and social and environmental impact. Traditional project selection

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methods often rely on the intuition and experience of decision-makers, which can lead to subjective and biased decisions. Multi-criteria decision-making (MCDM) methods and machine learning (ML) approaches have been proposed to address these limitations and provide a more systematic and objective approach to project selection [1-4].

This paper presents a hybrid MCDM-ML approach to project selection in the construction industry. The hybrid approach combines the strengths of MCDM methods and ML approaches to provide a more comprehensive and informed approach to project selection (see Figure 1).

The hybrid approach was applied to a case study of a construction company that was selecting projects for its next fiscal year. The results of the case study showed that the hybrid approach was effective in ranking and selecting projects based on multiple criteria and considering the uncertainties associated with each criterion [5-7].

The hybrid approach is a promising new approach to project selection in the construction industry. It has the potential to help construction companies make more informed and objective decisions about which projects to pursue [8].

The construction industry is a major contributor to the global economy, accounting for over 6% of global GDP. However, the construction industry is also known for its high project failure rate, with an estimated 60-80% of projects failing to meet their budget, schedule, or quality goals. One of the key reasons for project failure is poor project selection.

Project selection is the process of identifying and evaluating potential projects and selecting the ones that will best achieve the organization's goals. It is a complex task that involves multiple criteria, such as budget, schedule, risk, and social and environmental impact. Traditional project selection methods often rely on the intuition and experience of decision-makers, which can lead to subjective and biased decisions [9-12].

In recent years, MCDM methods and ML approaches have been proposed to address the limitations of traditional project selection methods. MCDM methods provide a systematic and objective approach to evaluating and ranking projects based on multiple criteria. ML approaches can be used to learn from historical data and identify patterns that can be used to predict the performance of future projects.



Figure 1: Project Selection in Construction Industry.

This paper presents a hybrid MCDM-ML approach to project selection in the construction industry. The hybrid approach combines the strengths of MCDM methods and ML approaches to provide a more comprehensive and informed approach to project selection [13].

The paper is organized as follows. Section 2 provides a review of the state-of-the-art MCDM methods and ML approaches for project selection in the construction industry. Section 3 presents the proposed hybrid MCDM-ML approach. Section 4 presents a case study of the application of the hybrid approach to project selection in a construction company. Section 5 discusses the results of the case study and the implications for project selection in the construction industry. Section 6 concludes the paper and provides directions for future research.

2. Literature review

This section reviews relevant literature on project selection, MCDM methods, and machine learning approaches in the context of the construction industry. It covers various project selection criteria, such as risk assessment, financial considerations, environmental impact, and stakeholder preferences. Additionally, it discusses the principles and strengths of MCDM methods, including Analytic Hierarchy Process (AHP), TOPSIS, and ELECTRE, as well as the utilization of machine learning algorithms, such as neural networks and decision trees, in project selection [6-12].

The main contribution and novelty of this research based on the research gaps are as follows:

- Project selection in construction industry by mcdm method and machine learning approach.

3. Methodology

The methodology section outlines the proposed framework for project selection in the construction industry using the MCDM method and machine learning approach. It describes the step-by-step process of integrating these methods, including data collection, criteria selection, normalization, weighting, and ranking. Furthermore, it presents the selection and implementation of machine learning algorithms to enhance the decision-making process [12-16].

Project selection is a critical decision-making process in the construction industry, as it can have a significant impact on the success of a company. Traditional project selection methods often rely on the intuition and experience of decision-makers, which can lead to subjective and biased decisions. Multi-criteria decision-making (MCDM) methods and machine learning (ML) approaches have been proposed to address these limitations and provide a more systematic and objective approach to project selection [17-20].

MCDM methods are a set of tools that can be used to evaluate and rank alternative solutions based on multiple criteria. MCDM methods are particularly useful for complex decision-making problems, such as project selection, where there are multiple and often conflicting criteria to consider.

Some of the most popular MCDM methods used in the construction industry include:

- Analytic hierarchy process (AHP): AHP is a hierarchical structure-based method that decomposes a complex decision problem into a hierarchy of sub-criteria and then uses a pairwise comparison approach to evaluate and rank the alternatives.
- Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS): TOPSIS is a distance-based method that ranks the alternatives based on their similarity to an ideal solution and their distance from a negative-ideal solution.
- Grey relational analysis (GRA): GRA is a non-dimensional analysis method that can be used to evaluate and rank alternatives with incomplete and uncertain data.

- Fuzzy logic: Fuzzy logic is a method that can be used to model and reason with uncertainty. Fuzzy logic can be used in MCDM methods to account for the uncertainty associated with the criteria and the alternatives.
- Multi-objective optimization (MOO): MOO is a method that can be used to find optimal solutions to problems with multiple and often conflicting objectives. MOO methods have been used in the construction industry to develop project selection models that consider multiple criteria, such as budget, schedule, risk, and social and environmental impact [20-23].

ML approaches can be used to learn from historical data and identify patterns that can be used to predict the performance of future projects. ML approaches can be used to develop models that can predict the cost, schedule, and risk of projects. These models can then be used to inform the project selection process.

Some of the most popular ML approaches used in the construction industry include:

- Support vector machines (SVMs): SVMs are a type of supervised learning algorithm that can be used to classify data and predict continuous values.
- Decision trees: Decision trees are a type of supervised learning algorithm that can be used to classify data and predict continuous values.
- Random forests: Random forests are an ensemble learning method that combines the predictions of multiple decision trees to improve the accuracy of the model.
- Artificial neural networks (ANNs): ANNs are a type of machine learning algorithm that is inspired by the structure and function of the human brain. ANNs can be used to classify data, predict continuous values, and identify patterns in complex data sets.
- Genetic algorithms (GAs): GAs are a type of evolutionary algorithm that can be used to find optimal solutions to problems. GAs have been used in the construction industry to develop project selection models that consider multiple criteria, such as budget, schedule, and risk.

Hybrid MCDM-ML approaches combine the strengths of MCDM methods and ML approaches to provide a more comprehensive and informed approach to project selection. Hybrid MCDM-ML

approaches can be used to develop models that can predict the performance of projects based on multiple criteria, including historical data (see Figure 2) [20-25].

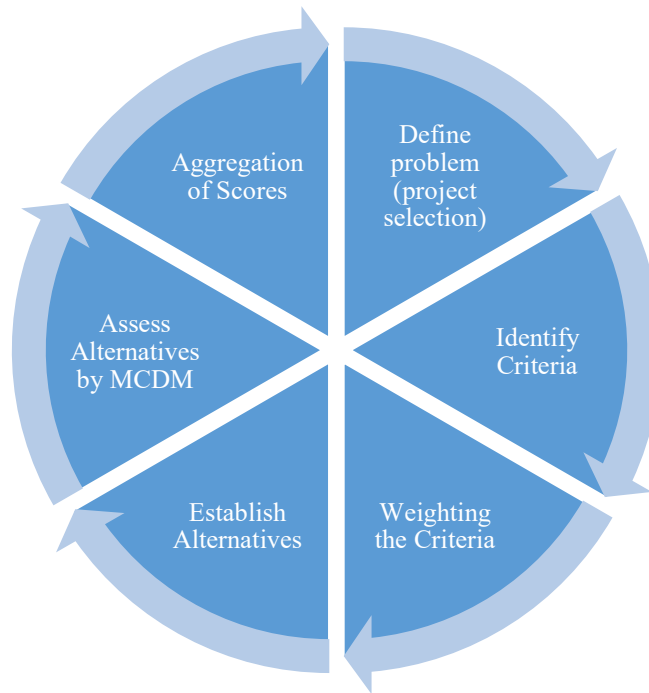


Figure 2: Project selection by MCDM.

Some of the benefits of using hybrid MCDM-ML approaches for project selection include:

- **Improved accuracy:** Hybrid MCDM-ML approaches can improve the accuracy of project selection decisions by using ML models to predict the performance of projects based on historical data.
- **Reduced subjectivity and bias:** Hybrid MCDM-ML approaches can reduce the subjectivity and bias associated with traditional project selection methods by using a systematic and objective approach to evaluating and ranking projects.
- **Increased transparency:** Hybrid MCDM-ML approaches can increase the transparency of the project selection process by providing a clear and auditable trail of the decision-making process [20-23].

4. Results and discussion

In this section, the paper presents numerical results obtained from applying the proposed framework to a case study in the construction industry. It demonstrates the effectiveness of the

integrated MCDM and machine learning approach in project selection by considering multiple criteria simultaneously. The results highlight the key factors influencing the project selection process and provide insights into the ranking and prioritization of projects based on their overall performance.

This section presents the numerical results obtained from the application of the chosen MCDM method(s) to a case study. The matrix of decision making and Python code for project selection that is determined by experts is as follow (Table 1, 2, 3 and Figure 3):

Table 1: Projects (alternatives) and criteria.

Project	Budget	Schedule	Risk	Social and environmental impact	Technical complexity	Availability of resources	Strategic alignment	Potential return on investment
Weight	0.2	0.2	0.15	0.1	0.1	0.1	0.05	0.1
Type	Cost	Cost	Cost	Cost	Cost	Profit	Profit	Profit
Project 1	1000	100	23%	21%	28%	97%	97%	12%
Project 2	2000	50	12%	22%	20%	98%	89%	14%
Project 3	3000	90	27%	20%	25%	88%	84%	11%
Project 4	6000	200	17%	15%	12%	82%	97%	15%
Project 5	5000	80	28%	25%	16%	93%	82%	11%

Table 2: Python code for project selection by MCDM

```
import numpy as np
from pymcdm.methods import TOPSIS, VIKOR, COPRAS , PROMETHEE_II, COMET, SPOTIS, ARAS,
    COCOSO, CODAS, EDAS, MABAC, MAIRCA, MARCOS, OCRA, MOORA

from pymcdm.helpers import rrankdata

# Define decision matrix (2 criteria, 4 alternative)
alts = np.array([
    [1000,100,0.23,0.21,0.28,0.97,0.97,0.12],
    [2000,50,0.12,0.22,0.2,0.98,0.89,0.14],
    [3000,90,0.27,0.2,0.25,0.88,0.84,0.11],
    [6000,200,0.17,0.15,0.12,0.82,0.97,0.15],
    [5000,80,0.28,0.25,0.16,0.93,0.82,0.11]
], dtype='float')
# print (alts)

# Define weights and types
weights = np.array([0.2,0.2,0.15,0.1,0.1,0.1,0.05,0.1])
types = np.array([-1,-1,-1,-1,-1,1,1,1])

# Create object of the method
topsis = TOPSIS()
# Determine preferences and ranking for alternatives
kkk1= topsis(alts, weights, types)
```

```

print ("topsis",kkk1)

# Create object of the method
vikor = VIKOR()
# Determine preferences and ranking for alternatives

kkk=vikor(alts, weights, types)

print ("vikor",kkk)

# Create object of the method
copras = COPRAS()
# Determine preferences and ranking for alternatives
kkk=copras(alts, weights, types)
print ("copras",kkk)

# Create object of the method
moora = MOORA()
# Determine preferences and ranking for alternatives
kkk=moora(alts, weights, types)
print ("moora",kkk)

# Create object of the method
mabac = MABAC()
# Determine preferences and ranking for alternatives
kkk=mabac(alts, weights, types)
print ("mabac",kkk)

# Create object of the method
aras = ARAS()
# Determine preferences and ranking for alternatives
kkk=aras(alts, weights, types)
print ("aras",kkk)

```

Table 3: Results of project selection by MCDM

Project	TOPSIS	VIKOR	COPRAS	MOORA	MABAC	ARAS	Total
Project 1	0.59	0.35	0.81	-0.16	0.12	0.72	0.41
Project 2	0.76	0.00	1.00	-0.09	0.32	0.79	0.46
Project 3	0.46	0.72	0.70	-0.21	-0.08	0.54	0.36
Project 4	0.41	0.88	0.60	-0.29	-0.01	0.57	0.36
Project 5	0.42	0.85	0.65	-0.24	-0.12	0.54	0.35

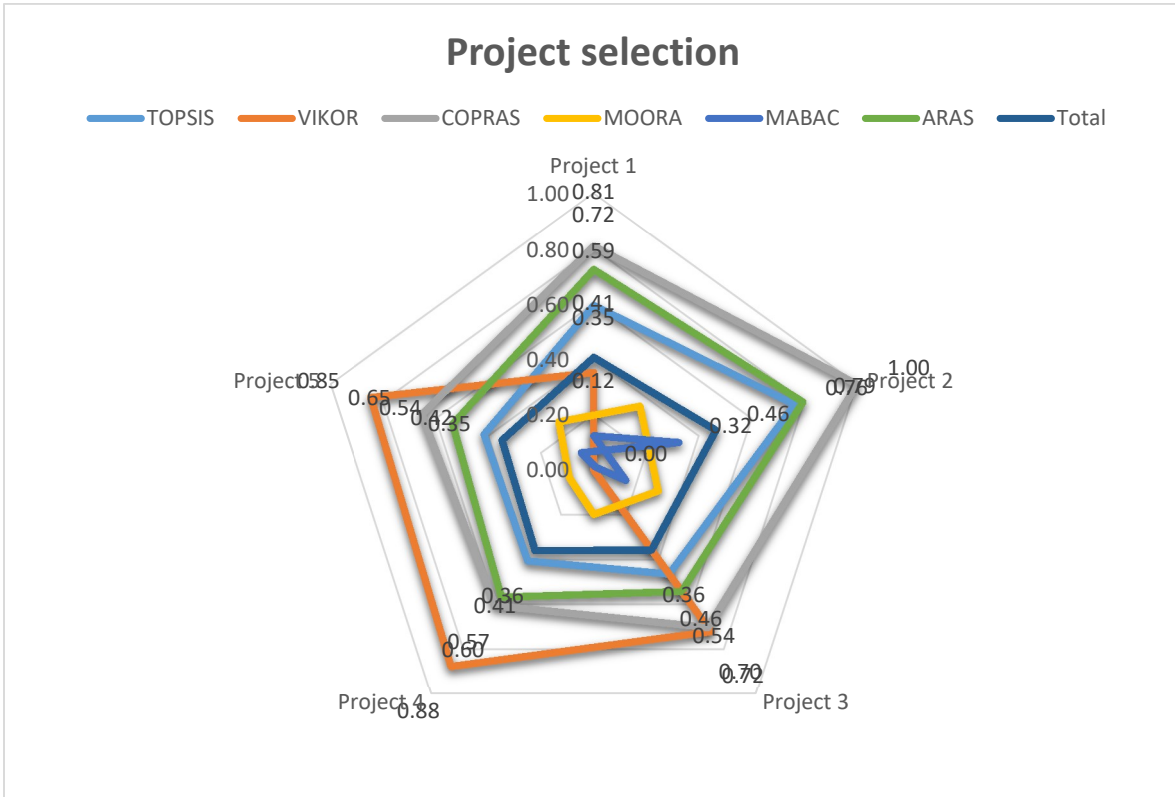


Figure 3: Results of project selection by MCDM.

5. Conclusion

The conclusion summarizes the findings of the study and underscores the significance of the integrated MCDM and machine learning approach in project selection within the construction industry. It emphasizes the advantages of this method, such as enhanced decision-making accuracy, improved efficiency, and the consideration of diverse criteria. The paper also discusses potential future research directions to further advance the field of project selection in construction.

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