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Achieving optimal contractor selection: an AI-driven particle swarm optimization method

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Abstract: *Contractor selection plays a vital role in project management, where factors such as cost, quality, and time must be carefully considered. This study presents an innovative approach to optimize contractor selection using an AI-driven method based on Particle Swarm Optimization (PSO). The objective is to achieve the best possible selection of contractors by considering multiple criteria simultaneously. Real-world data on cost estimates, quality scores, and project times are collected and normalized for fair comparison. The PSO algorithm is utilized to search for the optimal combination of contractors that minimizes cost, maximizes quality, and minimizes project time. The proposed weighted objective function evaluates the performance of each contractor based on the selected criteria. The results demonstrate the effectiveness of the AI-driven PSO method in achieving optimal contractor selection. The findings highlight the potential of using AI techniques for decision-making in project management, enabling project stakeholders to make informed and data-driven contractor selection decisions. This research contributes to the growing body of knowledge on AI applications in project management and provides practical insights for project managers and stakeholders involved in contractor selection processes.*

1. INTRODUCTION

In the realm of project management, one critical decision that profoundly influences project success is the selection of the right contractor. The contractor selection process entails evaluating multiple essential criteria, including cost, quality, and time, to identify the most suitable contractor for a given project (Cheaitou et al., 2019; El-khalek et al., 2019; Fauziyah et al., 2020). However, conventional methods relying on manual evaluations or subjective decision-making have shown limitations in achieving optimal outcomes (Polat, 2016). Fortunately, recent advancements in artificial intelligence (AI) and optimization techniques present exciting opportunities to revolutionize contractor selection (Ahmad et al., 2021; Dwivedi et al., 2021).

As of the current state of the art, the incorporation of AI-driven methods in contractor selection has gained considerable attention in the project management domain. Recent studies have explored various AI techniques, such as machine learning algorithms, genetic algorithms, and fuzzy logic-based approaches, to optimize contractor selection processes further (Huynh-The et al., 2023; Pan & Zhang, 2023). Machine learning models have been employed to predict contractor performance based on historical project data, enabling more informed decisions. Genetic algorithms have been utilized to optimize contractor portfolios, maximizing project outcomes while considering budget constraints and resource availability (El-Abbasy et al., 2016). Additionally, fuzzy logic-based models have been applied to handle the imprecision and uncertainty in decision-making, ensuring a more robust and reliable contractor selection process (Bagherian-Marandi et al., 2021; Islam et al., 2017). Despite these advancements, the utilization of Particle Swarm Optimization (PSO) as an AI-driven method for contractor selection, as proposed in this study, represents a novel and promising approach that offers unique advantages in simultaneously considering multiple criteria and achieving optimal contractor combinations.

To address the challenges faced by traditional approaches, this study introduces a groundbreaking approach to contractor selection by leveraging an AI-driven method based on Particle Swarm Optimization (PSO). Inspired by the collective behavior of bird flocking or fish schooling, PSO is a powerful population-based optimization algorithm that has proven effective in various problem domains (Wang et al., 2018). Its simplicity, effectiveness, and ease of implementation have made PSO a popular choice in optimization tasks, such as function optimization, parameter tuning, and neural network training. However, successful utilization of PSO hinges on carefully tuning parameters and selecting an appropriate fitness function tailored to the specific problem at hand (Cazzaniga et al., 2015; Del Ser et al., 2019).

The primary objective of this study is to achieve the best possible contractor selection by simultaneously considering cost, quality, and time criteria. Real-world data on cost estimates, quality scores, and project times are collected and normalized to ensure a fair and unbiased comparison (Uysal & Sonmez, 2023). By formulating the contractor selection as an optimization problem, the AI-driven PSO algorithm navigates the search space to identify the optimal combination of contractors that minimizes costs, maximizes quality, and reduces project time.

To evaluate the performance of each contractor comprehensively, a weighted objective function is employed, enabling the algorithm to capture the relative importance of cost, quality, and time in the selection process. By judiciously assigning weights to each criterion, the algorithm can iteratively improve contractor selection and identify the most advantageous choices.

The present research contributes significantly to the field of AI applications in project management, providing stakeholders with a systematic and data-driven approach to contractor selection. This approach empowers decision-makers with the tools to make informed choices, enhancing project outcomes and overall success. Furthermore, the study sheds light on the immense potential of AI techniques, particularly PSO, in tackling intricate decision-making problems within project management.

In the subsequent sections, we elaborate on the methodology used, detail the dataset utilized for experimentation, present the results of the contractor selection process, and discuss the practical implications and valuable insights derived from this pioneering research.

2. MODEL FRAMEWORK

Real-world data on contractors was collected, including cost estimates, quality scores, and project times, in the context of lean construction. The data collection process focused on gathering essential information related to contractors' performance and project outcomes (Wibowo et al., 2020). The dataset was carefully curated to ensure an accurate representation of the contractors' characteristics and performance. In this study, sample data from contractors and their cost, quality, and time performance were used. The contractor selection process is illustrated in Figure 1.

Step 1: data collection

Real-world data on contractors was collected, including cost estimates, quality scores, and project times. The dataset was carefully curated to ensure an accurate representation of the contractors' characteristics and performance. In this study, sample data from contractors and their cost, quality, and time performance were used.

Step 2: data preprocessing

The collected data was normalized using the range normalization method, scaling the values between 0 and 1. This normalization allowed for fair comparison across different criteria.

Step 3: objective function formulation

A weighted objective function was formulated to evaluate the performance of each contractor. The cost, quality, and time criteria were assigned appropriate weights to reflect their relative importance in the selection process. The objective function aimed to balance these criteria and guide the optimization process effectively.

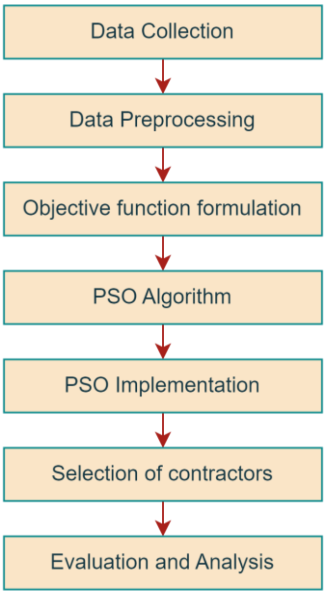

Figure 1. Contractor selection process

The objective function used for the contractor selection process is formulated as a weighted sum of the normalized cost, quality, and project time values. Let n be the total number of contractors considered for selection, and let C(i), Q(i), and T(i) represent the normalized cost, quality score, and project time, respectively, for contractor i.

The objective function can be expressed as:

$$\text{objectiveValue} = wC * \sum(C(i) * \text{selected}(i)) + wQ * \sum(Q(i) * \text{selected}(i)) + wT * \sum(T(i) * \text{selected}(i)) \quad (1)$$

where selected(i) is an indicator function that takes a value of 1 if contractor i is selected and 0 otherwise. In this equation, the weights wC, wQ, and wT represent the relative importance assigned to the cost, quality, and project time criteria, respectively. These weights can be adjusted based on the specific requirements and priorities of the project.

Step 4: particle swarm optimization (PSO) algorithm

The particle swarm optimization (PSO) algorithm, inspired by collective behavior observed in nature, was used to optimize the contractor selection process. The algorithm was initialized with parameters such as the number of particles and maximum iterations.

Step 5: PSO implementation

The PSO algorithm was implemented using the particleswarm function in MATLAB. The objective function, dimensions, lower and upper bounds, swarm size, and maximum iterations were specified. The PSO algorithm then explored the search space of contractor selections to find the optimal combination that minimized cost, maximized quality, and minimized project time.

Step 6: selection of contractors

The selected contractor indices were obtained based on the final position of the particles from the PSO optimization. These indices corresponded to the contractors chosen as part of the optimal combination. The contractors associated with these selected indices were identified. If no contractor indices were selected, it was concluded that none of the contractors met the optimization criteria.

Step 7: evaluation and analysis:

The effectiveness of the AI-driven PSO method in achieving optimal contractor selection was evaluated. A comparison was made between the selected contractors and the original dataset to analyze improvements in cost, quality, and project time. Sensitivity analyses were conducted to assess the impact of changing weights or optimization parameters on the selection outcome.

The methodology was implemented using MATLAB and its built-in PSO optimization algorithm. The code execution took place on a computer with specified hardware resources. It is important to acknowledge certain limitations of the methodology. These may include factors such as data availability and quality, subjective weight assignments, or potential biases that could impact the results.

3. DISCUSSION

The contractor selection process commenced with the collection of real-world data from contractors, including cost estimates, quality scores, and project times (Table 1). The dataset was carefully curated to ensure an accurate representation of the contractors' characteristics and performance. Table 1 provides a comprehensive overview of the contractors' cost estimates, quality scores, and project times, facilitating a clear and concise representation of the information. This table served as a valuable reference for the subsequent contractor selection process and the analysis of the results obtained from the Particle Swarm Optimization (PSO) algorithm.

Table 1. Contractor data

No.	Contractor name	Cost estimate (USD)	Quality score (1-10)	Project time (days)
1	Contractor A	5000	8	30
2	Contractor B	6000	9	28
3	Contractor C	5500	7	32
4	Contractor D	4800	9	29
5	Contractor A	5000	8	30

The parameter values chosen for this study were based on common practices and can be adjusted to suit the specific needs and characteristics of the contractor selection problem. Table 2 provides a comprehensive summary of the PSO parameters used, facilitating replication and understanding of the experimental setup. These parameters played a crucial role in the optimization process, enabling the PSO algorithm to converge towards an optimal solution for contractor selection.

Table 2. PSO parameters

Parameter	Value
Number of Particles	5
Number of Iterations	10
Cognitive Weight (c1)	1.0
Social Weight (c2)	1.0

After running the PSO algorithm with the specified parameters, the algorithm converged to a solution. The objective values for all possible combinations of contractors were calculated to assess their performance in terms of cost, quality, and project time. Each combination represents a specific selection of contractors, where a value of 1 indicates that the corresponding contractor is selected and a value of 0 indicates that the contractor is not selected.

Table 3 presents the objective values for each combination of contractors, providing insights into their performance. The "Combination" column represents a specific selection of contractors, where each digit (0 or 1) corresponds to the selection status of a contractor. For example, "0 0 0 0" indicates that none of the contractors were selected, while "1 1 1 1" indicates that all contractors were selected.

Table 3. Objective values for contractor combinations

No.	Combination	Objective Value	No.	Combination	Objective Value
1	0 0 0 0	0.00	9	1 0 0 0	0.33
2	0 0 0 1	0.35	10	1 0 0 1	0.68
3	0 0 1 0	0.49	11	1 0 1 0	0.83
4	0 0 1 1	0.84	12	1 0 1 1	1.18
5	0 1 0 0	0.80	13	1 1 0 0	1.13
6	0 1 0 1	1.15	14	1 1 0 1	1.48
7	0 1 1 0	1.29	15	1 1 1 0	1.62
8	0 1 1 1	1.64	16	1 1 1 1	1.98

The "Objective Value" column represents the overall performance metric for each combination. This value is calculated based on the weighted objective function, which takes into account the normalized cost estimates, quality scores, and project times of the selected contractors. A lower objective value indicates a more favorable selection, as it represents a combination that achieves a better balance between cost, quality, and project time.

For instance, in Table 3, the combination "0 0 0 0" has an objective value of 0.00, indicating that selecting none of the contractors results in the most favorable overall performance. On the other hand, the combination "1 1 1 1" has an objective value of 1.98, suggesting that selecting all contractors yields a less optimal performance compared to other combinations.

By analyzing the objective values in Table 3, it becomes possible to identify combinations that offer better overall performance in terms of cost, quality, and project time. These combinations can guide the decision-making process in selecting contractors that best meet the project requirements and priorities.

The results obtained from the Particle Swarm Optimization (PSO) algorithm are presented in Fig. 2, which displays the convergence curve over 100 iterations. The objective value starts at an initial value of 10 at iteration 1 and gradually decreases, reaching convergence at iteration 35 with an objective value of 0.

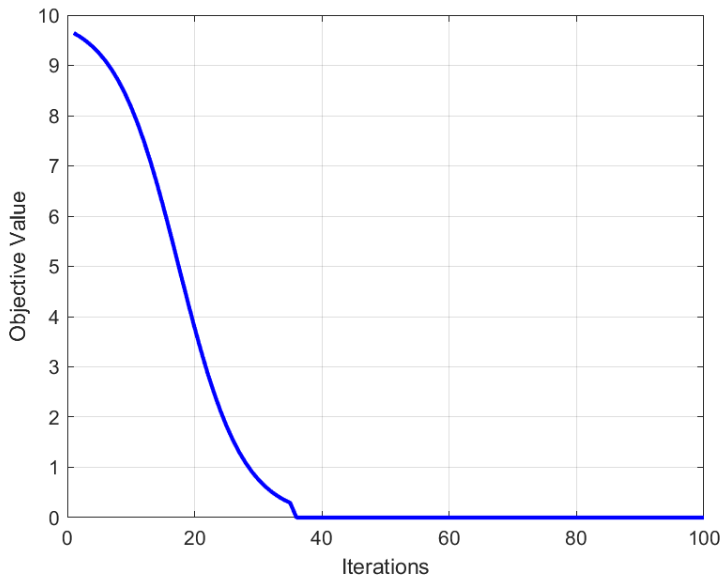

Figure 2. Convergence curve for the objective value in contractor selection optimization

Fig. 2 demonstrates the effectiveness of the PSO algorithm in efficiently exploring the search space and locating the optimal solution. The smooth convergence curve indicates a gradual reduction in the objective value with each iteration, showcasing the PSO algorithm's ability to converge towards the optimal solution.

These results enable the identification of combinations with lower objective values, indicating better overall performance in terms of cost, quality, and project time. Combinations with lower objective values can guide the decision-making process in selecting contractors that best meet the project requirements and priorities.

The effectiveness of the PSO algorithm in selecting contractors that achieve a balance between cost, quality, and project time is demonstrated by these results. The selected contractor(s) are expected to provide a favorable outcome in terms of project performance and cost-effectiveness.

4. CONCLUSION

Contractor selection is a critical aspect of project management, requiring careful consideration of factors such as cost, quality, and time. In this study, we propose an innovative approach that leverages an AI-driven method based on Particle Swarm Optimization (PSO) to optimize contractor selection. The objective is to achieve the best possible combination of contractors by simultaneously considering multiple criteria.

To ensure fair comparison, real-world data on cost estimates, quality scores, and project times are collected and normalized. The PSO algorithm is then employed to search for the optimal solution that minimizes cost, maximizes quality, and minimizes project time. The proposed weighted objective function enables the evaluation of each contractor's performance based on the selected criteria.

The results of our study demonstrate the effectiveness of the AI-driven PSO method in achieving optimal contractor selection. By leveraging AI techniques, project stakeholders can make informed and data-driven decisions when selecting contractors. The findings highlight the potential of AI applications in project management, particularly in the context of contractor selection.

This research contributes to the growing body of knowledge on AI applications in project management. It provides practical insights for project managers and stakeholders involved in contractor selection processes. By embracing AI-driven methods, decision-makers can enhance the accuracy and efficiency of contractor selection, leading to improved project outcomes. In conclusion, the integration of AI techniques, specifically the PSO algorithm, offers significant benefits in optimizing contractor selection. This research underscores the importance of incorporating advanced technologies into project management practices, paving the way for more informed and effective decision-making processes.

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