Optimizing Competency-Based Human Resource Allocation in Construction Project Scheduling: A Multi-Objective Meta-Heuristic Approach

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ABSTRACT: Effective allocation of human resources to project activities is crucial in optimizing project schedules and resource utilization. This paper addresses the challenge of competency-based workforce allocation in construction project scheduling by integrating multi-criteria decision-making with meta-heuristic optimization. A three-objective mathematical planning model aimed at minimizing project completion time, reducing implementation costs, and enhancing workforce competency is proposed. By leveraging expert opinions and multi-criteria decision-making techniques the relevant competency criteria are identified and prioritized. Our approach involves solving a sample problem precisely using GAMS software and developing two meta-heuristic algorithms—Non-Dominated Sorting Genetic Algorithm (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO). The algorithms' parameters were optimized using Taguchi design techniques to ensure robust performance. The effectiveness of our proposed methods is validated by comparing their results with exact solutions and conducting extensive tests on large-scale problems. The results demonstrate that both meta-heuristic algorithms effectively address the competency-based allocation challenge, with NSGA-II showing superior performance in achieving optimal solutions. This study highlights the potential of integrating competency-based approaches with advanced optimization techniques to enhance project management in construction.

Keywords: Construction project scheduling, Human resource assignment, Meta-heuristic algorithm, multi-criteria decision making

I. INTRODUCTION

In today's rapidly evolving landscape of science and commerce, the significance of timing cannot be overstated [1, 2]. This importance is particularly evident in domains such as transportation, production, and project management, where precise scheduling is crucial for efficiency and competitiveness [3 and 4]. Among the myriad scheduling challenges in these fields, the multi-skill project scheduling dilemma stands out as a well-recognized conundrum [5]. This dilemma revolves around the allocation of resources and the coordination of various skills required to complete a set of tasks [6]. Real-time scheduling issues have emerged as a critical consequence of this evolving complexity in project management [4].

In the realm of construction projects, manpower allocation typically unfolds in three key stages: project selection, project scheduling, and resource allocation [7]. Notably, the literature identifies three distinct labor modalities: single-skill labor, high-skill labor, and multi-skill labor with proficiency in two or more specialized fields [8 and 9]. While machinery, equipment, and tools may be readily acquired with the necessary funds, specialized labor remains a unique and invaluable resource for organizations [10]. The expertise of a company's workforce is its primary asset, differentiating it from competitors. Effective resource management, enhanced performance, and innovation are achievable only when employees possess the knowledge and intelligence to drive these outcomes [11].

Effective management of human and non-human resource competencies facilitates improved workforce planning, cost reduction, and higher-quality output [4]. Moreover, the adoption of competence management systems empowers businesses to make strategic decisions, identify underutilized skills, forecast future capabilities, enhance employment opportunities, and boost employee performance [12]. In addressing the intricate challenges of balancing time and cost while optimizing task sequences to enhance project efficiency and productivity, various methodologies have been proposed. These methods encompass mathematical programming models [13], innovative approaches [14, 15], and meta-heuristic techniques [16].

However, in the context of multi-objective and multi-mode project scheduling challenges, each activity presents numerous implementation options, greatly expanding the problem-solving space, especially in medium- and large-scale projects. These multi-objective balancing problems fall under the category of NP-hard problems [17]. Many studies in the field of project scheduling have turned to meta-heuristic algorithms to address mathematical models [18-29].

Despite the wealth of research in project scheduling and resource allocation, certain critical gaps persist in the literature. Notably, there is a scarcity of studies addressing the intricate interplay between project scheduling and human resource assignment, particularly within the context of construction projects. This gap is significant because it leaves a crucial aspect of project management unexplored, hindering the development of effective strategies for optimizing workforce allocation. Furthermore, recent advances in technology and the evolving nature of skill sets have opened new opportunities for optimizing human resource allocation based on competency levels. However, this facet remains underrepresented in existing research.

Recognizing these research gaps, our study aims to bridge these deficiencies by introducing a comprehensive framework that integrates project scheduling and human resource assignment while considering competency-based allocation. The main contributions of the current study are as follows:

- To address the project scheduling and human resource assignment problem within the context of construction projects, filling a critical research gap in this domain.
- To introduce multi-objective optimization techniques, including objectives related to project completion time, project execution cost, and deviation from competency levels, thus advancing the field.
- To employ two evolutionary algorithms, namely, the non-dominated sorting genetic algorithm and multi-objective particle swarm optimization, to tackle the challenges of large-scale scheduling problems in this context.

The rest of the research is divided into the following categories. Section 2 reviews the pertinent literature. The proposed mathematical model is described in section 3, along with the problem's assumptions, constraints, and goals. Section 4 discusses Moore's suggested methods for solving these problems. The proposed mathematical model's computational findings and sensitivity analysis are discussed in section 5. Section 6 concludes with conclusions and recommendations for future research.

II. LITERATURE REVIEW

Due to the importance of the topic, several studies in the area of human resource assignment have been conducted using various theories. According to some research, human resources have a range of skills and are distributed to different departments based on the firm's requirements. Recent studies, however, have taken into account the timing and simultaneous allocation of people to projects.

Correia and Saldana Gamma [30] delved into the cost-effective scheduling of multi-skill projects. They introduced a mathematical planning model framework to understand the impact of cost-centered perspectives on the final solution. Chen et al. [31] examined the multi-project scheduling problem and human resource allocation, emphasizing the impact of workforce on activity scheduling and introducing the concept of the human resources working time coefficient. Fernandez-Viagas and Framinan [32] proposed an integrated approach for project scheduling and human resource allocation that accounted for controlled processing durations.

Almeida et al. [33] addressed project scheduling with restricted multi-skill resources within the Resource-Constrained Scheduling Problem (RCPSP) context. They introduced the concepts of resource weight and group activity for scheduling with constrained multi-skill resources. Maghsoudlou et al. [34] explored multi-mode project scheduling with multi-skill restricted resources, employing the Multi-Objective Invasive Weeds Optimization method (MOIWO) to improve project efficiency. Bahlouli et al [12] assessed human resource management competence, utilizing software technology and statistical methodologies to evaluate and analyze competence.

Kianto et al. [35] conducted research on knowledge-based human resource management and its impact on organizational performance. Batarlien et al. [36] examined the influence of human resource management on competitive advantage in the transportation industry. Berk et al. [37] examined human resources planning while accounting for uncertainty in revenue forecasts, using the robust optimization approach. Lian et al. [38]

considered the allocation of multi-skilled human resources in a ceramic manufacturing facility, including grouping, loading, and activity allocation based on varied degrees of expertise and efficiency. They developed a linear mathematical planning model and applied the Non-Dominated Sorting Genetic Algorithm (NSGA-II) to address this NP-hard problem.

Zabihi et al [39] introduced a multi-objective teaching-learning-based meta-heuristic algorithm to tackle the Multi-Skill Project Scheduling Problem (MSPSP). Myszkowski et al. [40] explored MSRCPSP in a software library, developing Greedy and Genetic algorithms. Chen et al. [11] investigated a competence-time-quality scheduling model for multi-skilled workers in IT projects, utilizing a multi-objective ant colony optimization method.

Chen et al. [41] conducted a quasi-experiment to assess the potential implementation of motorcycle bans in 11 prefecture cities of Zhejiang Province. Chen et al. [42] tackled project scheduling issues with stochastic resource constraints using a hyper-heuristic genetic programming approach. Xie et al. [43] used a genetic algorithm to solve the scheduling issue for prefabricated building projects, resulting in efficient outcomes.

Yang et al. [44] investigated participant performance by evaluating autonomous navigation and working memory. Zhang et al. [45] proposed a novel ultrasonic tomography reconstruction method, and Mou et al. [46] addressed a distributed permutation flow-shop inverse scheduling issue to reduce adjustment and energy use. Zenggang et al. [47] proposed a two-stage incentive algorithm for socially aware networks. Yan et al. [48] introduced a new method to enhance social co-governance of food safety, and Wang et al. [49] investigated the electromagnetic induction effects of coupled memristive Hindmarsh–Rose neurons.

Zheng et al. [49] integrated a multi-layer semantic representation network with a deep fusion matching network, and Wang et al. [51] designed a combined teleoperation system using a bilateral continuous finite-time adaptive terminal sliding mode control method. Milika et al. [20] created a bilevel optimization model for multi-agent project scheduling and resource allocation, offering an algorithm based on mathematical programming. Table 1 summarizes the literature review.

Table 1. Summary of related papers

Author(s)	Project scheduling	Staff assignment	Multi-skill	Solution method
Fernandez-Viagas and Framinan [32]	*	*		ILP GRASP
Chen et al [11]	*	*		DP
Almeida et al [33]	*	*	*	Heuristic
Maghsoudlou et al. [34]	*		*	MOIWO
Berk et al [37]		*		Robust Optimization
Lian et al [38]		*	*	ILP NSGA-II
Zabihi et al [39]	*		*	MOPSO MOIWO
Myszkowski et al [40]	*		*	GA DE
Chen et al. [11]	*	*	*	MOACO
Xie et al. [43]	*		*	GA
Mika et al. [20]	*	*		Heuristic
Current Study	*	*	*	BWM/ε-constraint NSGA-II/MOPSO

According to Table 1, few studies have examined competency factors in human resource allocation. However, their effect on resource assignment and project scheduling has not been considered simultaneously. Moreover, no research has applied multi-criteria decision-making to identify competency criteria, whereas this study employs the Best-Worst Method (BWM) to prioritize these factors. Additionally, a Mixed-Integer Linear Programming (MILP) model is proposed and solved exactly, alongside the development of a Non-Dominated Sorting Genetic Algorithm II (NSGA-II). Finally, this study investigates a time-cost-quality tradeoff for competency-based human resource assignment and project scheduling, an aspect not previously explored.

III. PROBLEM STATEMENT

In the current research, a model of human resource allocation based on skill in the scheduling of construction projects has been developed. Human resources in this context possess varying degrees of skill. To address this, it is first necessary to determine the competency criteria of human resources. Competency indicators were extracted based on expert opinions and previous studies. The Best-Worst Method (BWM), a multi-criteria decision-making technique, was then used to balance and rank these indicators. The most important metrics were selected and incorporated as model inputs.

The three objectives of the proposed model are to reduce project completion time, minimize project implementation costs, and enhance the projected competence level. The project includes several activities with prerequisite relationships, meaning an activity can begin only when its prerequisite activities have been completed. It is also not permissible to interrupt activities; once an activity starts, it cannot be postponed or stopped, and it requires all human resources with the necessary skill levels to be engaged from start to finish. The ultimate goal of the proposed model is to allocate human resources to project activities based on their competency and implementation schedule, achieving minimum time and cost while maximizing the level of expected competency. The following sections explain the mathematical model, including indices, parameters, and variables.

1. SETS AND INDICES

I: set of human resource
J: set of activities
K: Set of criteria
T: time horizon
i: Human Resource Index i=1,2,…,I
j: activity index j=1,2,…,J
k: index of competency criterion k=1,2,…,K
t: time period index t=1,2,…,T

2. PARAMETERS

wk: the weight of criterion *k*
bik: the competency level of human source *I* in criterion *k*
ebjk: the expected competency level of activity *j* in criterion *k*
cij: the cost of human source i to perform activity *j*
dij: the time needed for performing activity j by human source *i*
aij: if human source i is able to perform activity *j* the value of index equals to 1 otherwise 0
prjj': f j activity is performed immediately after *j* 'activity, the value of index equals to 1 otherwise 0
N: a very large number

3. VARIABLES

xijt: If human resource i is allocated to activity j in period t, the value of index equals to 1 otherwise 0
yij: If human resource i is allocated to activity j, the value of index equals to 1 otherwise 0
zjt: If activity j starts in period, the value of index equals to 1 otherwise 0
Cmax: project completion time
stj: starting time of activity j
ctj: completion time of activity *j*

The mathematical model of present study is three-objective and includes minimizing project completion time and human costs while maximizing the expected competency level. The proposed mathematical model is as follow.

$$\boldsymbol{Min\ C_{max}} \tag{1}$$

$$Min \sum_{j=1}^{J}\sum_{i=1}^{I} c_{ij} \times d_{ij} \times y_{ij} \tag{2}$$

$$Min \sum_{j=1}^{J}\sum_{i=1}^{I}\sum_{k=1}^{K} w_k \times |eb_{jk} - b_{ik}y_{ij}| \tag{3}$$

$$\sum_{i=1}^{I} y_{ij} = 1 \qquad \forall j \tag{4}$$

$$y_{ij} \le a_{ij} \qquad \forall i,j \tag{5}$$

$\sum_{j=1}^{J} x_{ijt} \leq 1$	$\forall i, t$	(6)
$st_j = \sum_{t=1}^{T} z_{jt} \times t$	$\forall j$	(7)
$ct_j = st_j + \sum_{i=1}^{I} d_{ij} \times y_{ij} - 1$	$\forall j$	(8)
$C_{max} \geq ct_j$	$\forall j$	(9)
$st_j - st_j \geq \sum_{i=1}^{I} d_{ij} \times y_{ij} \times pr_{jj} - N \times (1 - pr_{jj})$	$\forall j, j$	(10)
$x_{ijt}, y_{ij}, z_{jt} \in \{0,1\}$	$\forall i, j, t$	(11)
$C_{max}, st_j, ct_j \geq 0$	$\forall j, t$	(12)

Equation (1) indicates the minimization of project completion time. Equation (2) relates to minimizing the total cost of the project, including the cost of human resources. Equation (3) indicates the maximization of the expected competency level, calculated as the minimization of the difference between expected competency and the competency level of human resources. Equation (4) states that each activity is assigned to only one human resource. Equation (5) guarantees that only a human resource with the proper competency level is allocated to an activity. Equation (6) ensures that each human resource in each period can only work on the activity assigned to them. Equation (7) and (8) represent the calculation of the start and end of each activity, respectively. Equation (9) describes how to calculate project completion time. Equation (10) represents the prerequisite relationships between activities. Finally, Equation (11) and (12) represent the binary and integer variables of the problem, respectively.

V. SOLUTION METHODS

To address the challenge, a three-objective mathematical planning model was developed. The Epsilon constraint approach was chosen to solve the proposed model exactly, as it is suitable for multi-objective problems. To solve large-scale problems, two meta-heuristic algorithms were devised. The following sections describe the phases of the Epsilon constraint method and the parameterization of the proposed algorithms.

1. E-CONSTRAINT METHOD

The ε-constraint approach is a well-known method for handling multi-objective problems by transforming all objective functions, except one, into constraints at each step to solve the problem. This method generates a set of non-dominated solutions, which are situated on the Pareto frontier formed by the ε constraint [52].

$$\begin{gathered} \text{Min } f1(X) \\ x \in X \\ f2(X) \leq \varepsilon 2 \\ \ldots \\ fn(X) \leq \varepsilon n \end{gathered} \tag{13}$$

The steps of the ε-constraint method are as follows:

- One of the objective function is selected as main target.
- Problem is solved based on one of the sub-objective function each time and its optimal value is obtained.
- The interval between two values of the sub-objective functions is divided by a predefined number and created a table of values for $\varepsilon 2, \ldots, \varepsilon n$.
- Main problem is solved by values $\varepsilon 2, \ldots, \varepsilon n$.
- Pareto solution obtained is reported.

2. PARAMETER SETTING OF THE SUGGESTED PROBLEM'S META-HEURISTIC METHODS

In addition to providing a mixed-integer programming model, this work developed two metaheuristic algorithms: the Non-Dominated Sorting Genetic Algorithm (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO). In this section, how to establish the parameters for the proposed algorithms is demonstrated.

The parameters of the genetic algorithm, including population size, crossover rate, mutation rate, and number of iterations, as well as those of the particle swarm optimization algorithm, including the number of particles, number of iterations, individual cognitive coefficient, and social coefficient, were adjusted using the Taguchi experiment design method in MINITAB software. The values for the genetic algorithm parameters are detailed in Table 2, divided into three phases. The values for the parameters of the multi-objective particle swarm optimization technique are provided in Table 3.

Table 2. NSGAII algorithm parameter values

Parameter	Definition	Amounts		
Npop	Number of initial population	70	150	200
Max_iteration	Number of generations (repeat)	150	300	500
Cross_rate	Intersection operator rate	0,75	0,85	0,95
Mut_rate	Mutation operator rate	0,006	0,009	0,01

Table 3. Values of MOPSO algorithm parameters

Parameter	Definition	Amounts		
Npop	Number of initial population	70	150	200
Max_iteration	Number of generations (repeat)	150	300	500
Personal Best Learning Coefficient	Intersection operator rate	1,5	1,8	2
Global Best Learning Coefficient	Mutation operator rate	1,5	1,8	2

Equation 14. (GAP)'s relative deviation percentage (RPD) approach has been used as the difference criteria to assess how well the recommended genetic algorithm performed.

$$GAP = \left(\frac{alg_{sol} - best_{sol}}{best_{sol}}\right) \times 100 \quad (14)$$

The best value of the objective function obtained between these states is best _sol, and alg _sol is the value of the objective function created from a combination of algorithm parameters. Table 4 lists the findings and distinct states that may be created by mixing various NSGA-II algorithm parameter settings.

Table 4. The result obtained from the design of Taguchi experiment for NSGA-II algorithm

GAP Amount	The number of repetitions	Mutation Rate	collective micro rate	Individual micro rate	Mode number
0.5032	150	0.006	0.75	70	1
0.1259	300	0.009	0.85	70	2
0.7419	500	0.01	0.95	70	3
0.6635	500	0.009	0.75	150	4
0.4917	150	0.01	0.85	150	5
0.0045	300	0.006	0.95	150	6
0.7124	300	0.01	0.75	200	7
0.7280	500	0.006	0.85	200	8
0.2942	300	0.009	0.95	200	9

Table 4 lists the nine scenarios that were considered and analyzed, including three population sizes (70, 150, and 200), three crossover rates (0.75, 0.85, and 0.95), three mutation rates (0.006, 0.009, and 0.01), and three iteration counts (150, 300, and 500). It is important to note that each scenario was run 10 times, with average results reported. Figure 1 illustrates the application of the Taguchi method to determine the parameters for the proposed evolutionary algorithms. According to the graph in the top left, the impact value of the population size on the mean of the third state was at its lowest, leading to the selection of 200 as the optimal population size. Consequently, 300, 0.01, and 0.85 were chosen as the optimal values for the number of iterations, mutation rate, and crossover rate, respectively.

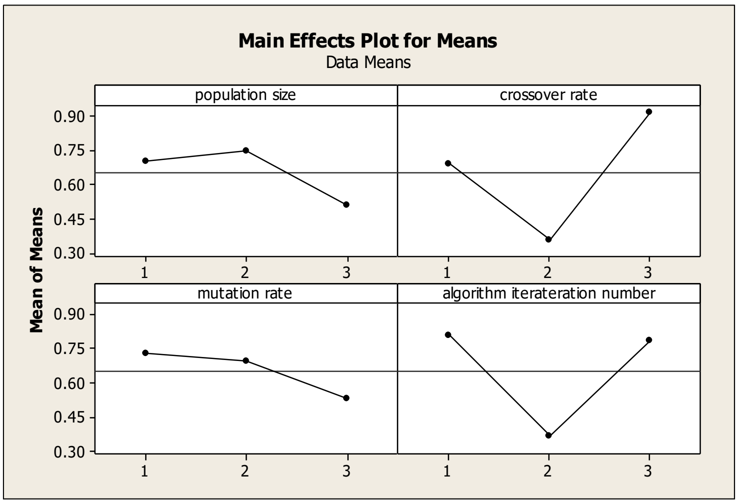

FIGURE 1. Effect of mean parameters of NSGA-II algorithm

Following are several states created by mixing various MOPSO algorithm parameter values. The results are shown in Table 5.

Table 5. The result obtained from the design of Taguchi experiment for MOPSO algorithm

GAP Amount	The number of repetitions	Collective learning rates	Individual learning rates	Population size	Mode number
0.4053	150	1.5	1.5	70	1
0.1259	300	1.8	1.8	70	2
0.0019	500	2	2	70	3
0.3635	500	1.5	1.5	150	4
0.6317	150	1.8	1.8	150	5
0.0136	300	2	2	150	6
0.7124	300	1.5	1.5	200	7
0.7810	500	1.8	1.8	200	8
0.2942	300	2	2	200	9

The effect of the mean parameters of the MOPSO algorithm is also shown in Figure 2.

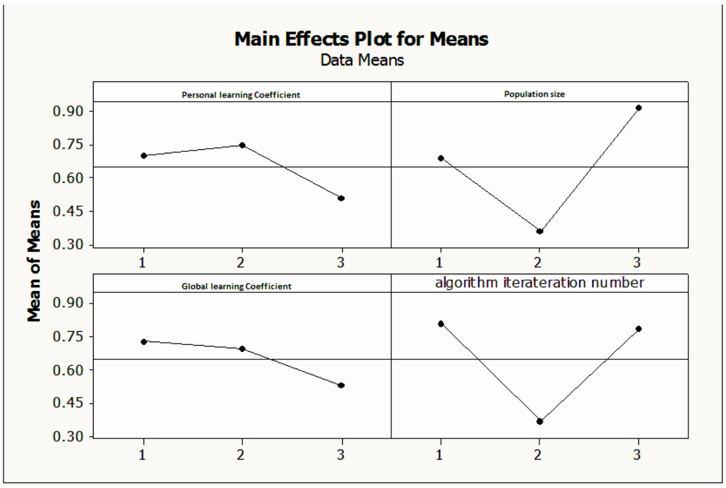

FIGURE 2. The effect of the average parameters of the MOPSO algorithm

According to the graph in the top left of Figure 2, the impact value of the mean base case for the third scenario was the lowest for the individual cognitive coefficient; consequently, a value of 2 was selected for the individual cognitive coefficient. As a result, 2, 150, and 300 were determined to be the optimal values for the individual cognitive coefficient, initial population size, and number of iterations, respectively.

VI. DATA COLLECTION

In the following, the weights of the criteria were calculated using the Best-Worst Method (BWM). These calculated weights were then used to solve the model exactly through a genetic meta-heuristic algorithm with non-dominated sorting.

1. IDENTIFYING THE HUMAN RESOURCE COMPETENCY CRITERIA

In this section, the human resource competency criteria were extracted based on expert opinions and previous studies in the field, with the results presented in Table 6.

Table 6. Criteria and sub-criteria of human resource competency

Professional competency	Managerial competency	Ability to move forward	C1
		Ability to create participation	C2
		Team making	C3
		Flexibility	C4
	Commercial orientation	Business Intelligence	B1
		Market orientation	B2
		Customer orientation	B3
		Financial awareness	B4
	Work-related skills	Committed to outcome	J1
		Technical knowledge	J2
		Training and development	J3
		Technology	J4
Creative competency	Communication	Communication and service	U1
		Verbal communication	U2
		Written communication	U3
		Culture, planning and politics	U4
	Creativity and holistic thinking	Innovation	I1
		Curiosity	I2
		Ability to view	I3
		Innovative thinking	I4
	Entrepreneurship	Interact with people	E1
		Search for opportunities	E2
		Use creativity	E3
		Strategic planning and market development	E4
	Activity	Vision	A1
		Action	A2
		Relationship	A3
		Cooperation	A4
	Variability	Challenge Management	V1
		Flexibility	V2
		Improvement	V3
		Adaptation	V4
Social competency	Teamwork	Work with others	T1
		personal attributes	T2
		The role of team	T3
		Relationship	T4
	Professionalism	Consequentialism	P1
		Obligation	P2
		Skills and ability	P3
		Sympathy	P4
	Interpersonal skills	Social skills	S1
		Communication skills	S2
		Flexibility	S3
		Dispute Resolution	S4
	Learning motivation	Continuous improvement	M1
		Learning motivation	M2

	Curiosity	M3
	Continuous learning	M4

2. PRIORITIZATION OF CRITERIA USING MULTI-CRITERIA DECISION-MAKING BEST WORST METHOD (BWM)

The multi-criteria decision-making Best-Worst Method was used at this stage to rank the sub-criteria associated with each criterion. The most and least significant criteria were first identified. Subsequently, the other criteria were compared against the least significant criterion after the most significant criterion had been compared to the others. Next, the mathematical model for weighting the criteria was formulated, and the optimal weight for each criterion was calculated. The calculation process for one of the criteria is shown as a sample in Tables 7 and 8, while the remaining criteria were calculated in the same manner, and their results are also presented.

- Managerial competency

The most crucial criterion and the least crucial criterion were determined to be flexibility and the capacity to go ahead.

Table 7. Pair wise comparison for the best criterion of managerial competency

Other / Thebest	C1	C2	C3	C4
C1	**1**	**3**	**5**	**7**

Table 8. Pair wise comparison for the worst criterion of managerial competency

The worst / Other	C_4
C_1	7
C_2	5
C_3	3
C_4	1

The relations between criteria were written as follows and the optimal weight of criteria was obtained by solving the written mathematical model in GAMS software.

$$\min X \qquad (15)$$

$$\left|\frac{W_1}{W_2} - 3\right| \le X \qquad \left|\frac{W_2}{W_4} - 5\right| \le X$$

$$\left|\frac{W_1}{W_3} - 5\right| \le X \qquad \left|\frac{W_3}{W_4} - 3\right| \le X$$

$$\left|\frac{W_1}{W_4} - 7\right| \le X \qquad W_1 + W_2 + W_3 + W_4 = 1$$

W1= 0.533 W2= 0.267 W3= 0.133 W4= 0.067

This process was repeated for each of the other criteria, resulting in the calculation of weights for all criteria. After applying the Best-Worst Method to each competency criterion and determining the optimal weight, the criterion with the highest weight in each category was selected as the primary criterion for assessing human resource competency. The selected sub-criteria are bold in Table 9.

Table 9. Final weight of criteria and the selected criteria

Managerial competency	Ability to move forward	C1	0.533
	Ability to create participation	C2	0.267
	Team making	C3	0.133
	Flexibility	C4	0.067
Commercial orientation	Business Intelligence	B1	0.267
	Market orientation	B2	0.133
	Customer orientation	B3	0.067

Professional competency		Financial awareness	B4	0.533
		Committed to outcome	J1	0.533
	Work-related skills	Technical knowledge	J2	0.267
		Training and development	J3	0.133
		Technology	J4	0.067
		Communication and service	U1	0.133
	Communication	Verbal communication	U2	0.267
		Written communication	U3	0.067
		Culture, planning and politics	U4	0.533
		Innovation	I1	0.133
	Creativity and holistic thinking	Curiosity	I2	0.067
		Ability to view	I3	0.267
		Innovative thinking	I4	0.533
		Interact with people	E1	0.067
Creative competency	Entrepreneurship	Search for opportunities	E2	0.533
		Use creativity	E3	0.267
		Strategic planning and market development	E4	0.133
		Vision	A1	0.067
	Activity	Action	A2	0.267
		Relationship	A3	0.533
		Cooperation	A4	0.133
		Challenge Management	V1	0.533
	Variability	Flexibility	V2	0.133
		Improvement	V3	0.067
		Adaptation	V4	0.267
		Work with others	T1	0.533
	Teamwork	personal attributes	T2	0.133
		The role of team	T3	0.067
		Relationship	T4	0.267
		Consequentialism	P1	0.267
Social competency	Professionalism	Obligation	P2	0.533
		Skills and ability	P3	0.133
		Sympathy	P4	0.067
		Social skills	S1	0.133
	Interpersonal skills	Communication skills	S2	0.267
		Flexibility	S3	0.067
		Dispute Resolution	S4	0.533
		Continuous improvement	M1	0.533
	Learning motivation	Learning motivation	M2	0.133
		Curiosity	M3	0.067
		Continuous learning	M4	0.267

3. EXPLAIN THE SAMPLE PROBLEM

Two different types of example problems were created to solve the proposed model. First, a small-scale case study problem was developed to address the issue precisely and verify the proposed metaheuristic algorithms. Then, based on Taheri Amiri et al. [53], several large-scale sample problems were generated randomly. In this section, a small-scale sample problem is explained after identifying and extracting the competency criteria of human resources. In this problem, a project with 7 activities was considered.

To implement this project, 9 human resources with different levels of competency were considered and allocated to various activities based on skill level and cost, aiming to complete the project in the shortest possible time and at the lowest cost, while minimizing the deviation from the expected competency of the project. Table 10 represents the project network and the prerequisite relationships between activities.

Table 10. The prerequisite relationship between activities

Activity	A	B	C	D	E	F	G
Precedence	-	A	A	A	B,C	D	E,F

Since each human resource has different levels of competency and ability, not all of them may be able to perform every activity. Accordingly, Table 11 represents the feasibility of each activity for each human resource. The highlighted boxes indicate that a worker can perform that activity.

Table 11. Feasibility of activity by human resource

Activity / Human resource	A	B	C	D	E	F	G
1	✓	✓			✓	✓	
2	✓	✓	✓		✓	✓	✓
3			✓	✓	✓		
4		✓	✓	✓	✓	✓	✓
5	✓	✓		✓	✓	✓	
6	✓			✓			✓
7		✓			✓		
8	✓		✓			✓	
9		✓	✓	✓			✓

Also, the time and cost of each activity by each of the human resources have been reported in Table 12, respectively.

Table 12. Activities processing time and execution cost by human resource (day & Thousand Tomans)

Activity / Human resource	A	B	C	D	E	F	G
1	7 3500	10 4200			8 4800	13 3800	
2	5 4500	7 5500	4 5100		5 6000	9 5200	8 4400
3			6 4300	8 3500	8 5000		
4		7 5000	4 5500	6 4800	5 6000	12 4500	7 5000
5	5 4500	10 4200		7 4000	7 5500	12 4500	
6	9 3000			9 3800			11 3500
7		11 3500			10 4000		
8	9 3000		6 4000			13 3200	
9		10 4200	7 4100	8 3500			10 4000

After presenting the time and cost associated with the activities, the competency of each human resource in each criterion was determined and is presented in Table 13. As mentioned earlier, 12 criteria with the highest weight were selected after identifying and weighing the competency criteria. It should be noted that the highest competency score assigned to human resources is 10.

Table 13. The competency level of human resources

Human resource / Criterion	1	2	3	4	5	6	7	8	9
Ability to move forward	8	8	6	10	9	4	5	7	9
Financial awareness	9	7	8	8	6	5	3	6	6
Committed to outcome	8	10	7	9	8	7	4	8	9
Culture, planning and politics	5	8	6	7	9	5	2	6	8

Innovative thinking	9	9	8	10	5	6	4	8	7
Search for opportunities	6	9	9	9	10	5	4	5	8
Relationship	8	7	6	8	8	7	5	9	9
Challenge Management	7	9	5	10	9	5	4	5	5
Work with others	10	10	7	9	6	8	6	6	8
Obligation	9	10	6	9	8	4	5	7	9
Dispute Resolution	6	9	5	7	10	5	4	5	8
Continuous improvement	8	8	8	10	7	3	4	4	7

Also, the level of expected competency for each project activity has been reported in Table 14.

Table 14. The expected competency level of activities

Human resource / Criterion	A	B	C	D	E	F	G
Ability to move forward	9	8	8	9	7	8	5
Financial awareness	8	9	8	8	6	7	7
Committed to outcome	10	10	7	10	8	9	6
Culture, planning and politics	8	8	9	9	9	7	8
Innovative thinking	9	9	8	7	6	9	7
Search for opportunities	7	8	7	9	10	8	6
Relationship	8	8	6	6	8	7	8
Challenge Management	7	9	10	8	9	5	6
Work with others	10	8	7	9	6	8	9
Obligation	9	10	9	6	8	9	5
Dispute Resolution	8	10	7	7	10	5	8
Continuous improvement	9	8	8	10	7	3	7

Finally, the Best-Worst Method was used to determine the weight of each criterion. The most significant criterion was identified as "commitment," while the least important was "culture, planning, and politics." The appropriate weight for each criterion was then calculated and is presented in Table 15.

Table 15. Weight of criteria

Criterion	Weight
Ability to move forward	0.155
Financial awareness	0.027
Committed to outcome	0.052
Culture, planning and politics	0.016
Innovative thinking	0.075
Search for opportunities	0.04
Relationship	0.036
Challenge Management	0.155
Work with others	0.116
Obligation	0.171
Dispute Resolution	0.134
Continuous improvement	0.02

VII. RESULT AND DISCUSSION

1. EXACT SOLUTION APPROACH

The proposed problem had three objectives, as previously mentioned. Therefore, it was resolved using the ε-constraint method. With this approach, each objective function is first optimized independently. The suggested mathematical model was initially solved three times for this purpose. The initial model was created as follows, in accordance with the existing constraints, with the goal of minimizing project completion time as the primary objective function.

$$Min\, C_{max} \quad (16)$$
$$S.t.$$
$$Eq.(4-12)$$

The best value of the objective function (minimum completion time) was saved as the first objective function's optimal value after solving the initial model. The values of the other two objective functions were also noted simultaneously. The second model was then created in accordance with the existing constraints, with the primary objective function based on the second objective, which is minimizing the cost of project execution.

$$Min \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I} c_{ij} \times x_{ijt} \quad (17)$$
$$S.t.$$
$$Eq.(4-12)$$

Similarly, the best value of the second objective function (minimum execution cost) and the values of the other functions were recorded. Finally, the third objective function, which is maximizing the expected competency level or, in other words, minimizing the difference between the expected competency and the obtained competency, was considered as the objective function. The third model was then formed accordingly.

$$Min \sum_{j=1}^{J}\sum_{i=1}^{I}\sum_{k=1}^{K} w_k \times |eb_{jk} - b_{ik}y_{ij}| \quad (18)$$
$$S.t.$$
$$Eq.(4-12)$$

The optimal value of main objective function and values of other objective functions of each model have been presented in Table 16.

Table 16. Objective functions value

Objective function / minimizing	(Z_1)	(Z_2)	(Z_3)
Z_1^*	29	35700000	10.839
Z_2^*	42	24700000	17.236
Z_3^*	29	35700000	10.839

As can be seen from Table 17, the optimal solution for the first and third problems was the same. This implies that the higher the competency level of a human resource, the less time is required to perform an activity, reflecting the learning effect. In fact, maximizing the expected competency can be equivalent to minimizing project completion time. However, this is not always the case. It is also possible for a person with high levels of competency and skills to require more time to perform a particular activity or project under certain conditions. Table 17 represents the optimal allocation of human resources to activities in the first and third models when the project completion time has been minimized and the maximum expected competency has been considered.

Table 17. Human resources assignment in the first and third models (✓) and second model (*)

Activity / Human resource	A	B	C	D	E	F	G
1							
2	✓	✓				✓	
3							
4			✓		✓		✓
5				✓			
6	*						*
7		*			*		
8			*			*	
9				*			

As shown in Table 17, activities A, B, and F have been allocated to human resource No. 2. Additionally, activities C, E, and G have been allocated to human resource No. 4. Finally, human resource No. 5 performs activity D. Table 13 represents the optimal allocation of human resources to activities, taking into account the minimized project implementation cost. After calculating the optimal values for each function, one of the objectives was considered the primary objective, and the other objectives were applied as constraints on the problem. According to the research subject, maximizing the expected competency was considered the main objective in the present study. Therefore, the final model can be rewritten as follows.

$$Min \sum_{j=1}^{J}\sum_{i=1}^{I}\sum_{k=1}^{K} w_k \times |eb_{jk} - b_{ik}y_{ij}| \tag{19}$$

S.t.

$$Eq.(4-12)$$

$$C_{max} \leq \varepsilon_1 \tag{20}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I} c_{ij} \times x_{ijt} \leq \varepsilon_2 \tag{21}$$

The range of changes in the first and second objective functions was split into 12 sections (points) as previously explained, and the problem was solved once for each of these values. The results of solving the problem are shown in Table 18.

Table 18. Pareto solutions obtained from the exact solving of the sample problem

Solution number	Objective function		
	Z_1	Z_2	Z_3^*
1	42	24700000	17.236
2	40	25700000	16.891
3	39	26700000	-
4	38	27700000	15.976
5	37	28700000	-
6	36	29700000	14.971
7	35	30700000	-
8	34	31700000	13.672
9	33	32700000	13.072
10	32	33700000	-
11	31	34700000	11.664
12	29	35700000	10.843

Only 8 of the issues provided a workable solution, as indicated in Table 18. As a result, Figure 3 illustrates the 8 Pareto solutions to the aforementioned issue.

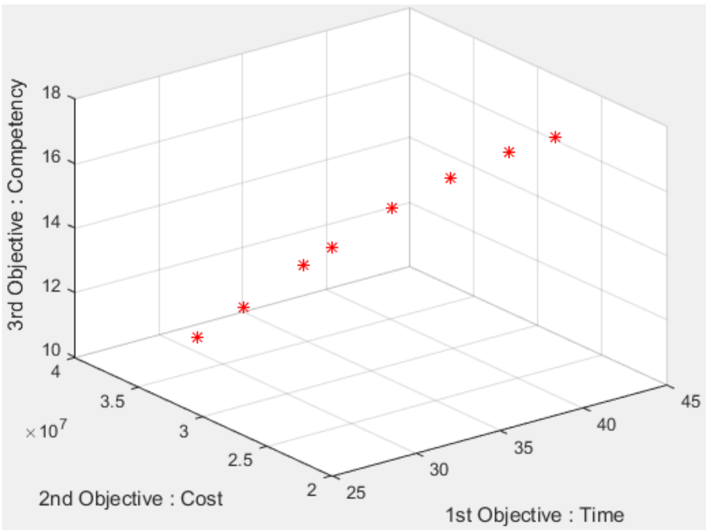

FIGURE 3. Pareto solutions obtained from exact solving of the sample problem

2. VALIDATION OF PROPOSED ALGORITHMS

The proposed meta-heuristic methods are supported by a case study. This section demonstrates that the suggested meta-heuristic method successfully addresses the case study, which is accurately handled by GAMS software. Table 19 displays the results of the two proposed metaheuristic algorithms for the example problem. The first column shows the solutions obtained by solving the example problem 100 times using the two algorithms in three modes: best, worst, and average. The subsequent three columns present the objective function values obtained by the NSGA-II algorithm, along with the mean deviation from the exact solution shown in the following column. The MOPSO algorithm follows a similar procedure.

Table 19. Pareto solutions obtained from the proposed algorithms

Solution	NSGA-II				MOPSO			
	Objective function			Mean deviation (%)	Objective function			Mean deviation (%)
	Z_1	Z_2	Z_3		Z_1	Z_2	Z_3	
Best	42	24900000	17.027	0.08	42	25000000	17.038	0.1
Average	40	26000000	16.523	0.19	40	26200000	16.534	0.21
Worst	38	27700000	15.894	0.27	38	27800000	15.902	0.31

The proposed meta-heuristic algorithms demonstrate strong performance when comparing the solutions of the two methods based on the mean deviation, which is derived from the average deviations of the three objectives. The mean deviation for both methods was less than 1%, indicating their ability to achieve results close to the exact solution. Figure 4 is provided to help the reader better understand the comparison of the results, showing the Pareto front for each of the three approaches.

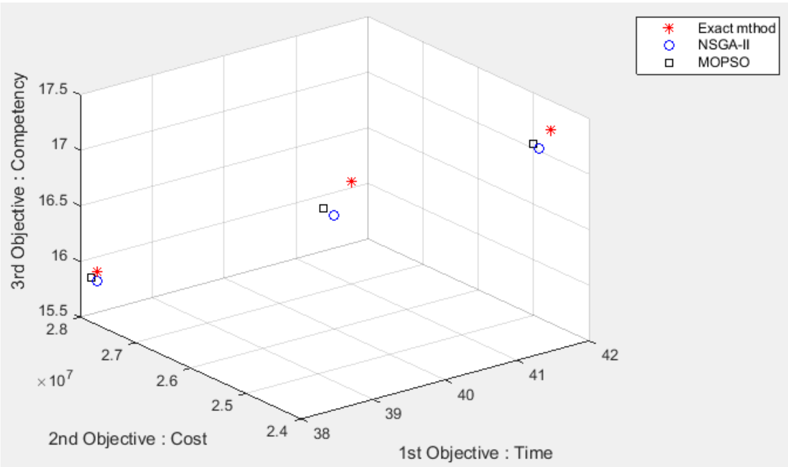

FIGURE 4. Pareto solutions obtained from three approaches

3. SOLVING THE PROBLEM IN LARGE SCALES

A number of problems were randomly generated and solved to assess the problem-solving capability of the proposed algorithm for large-scale problems. The method for generating problem parameters is presented in Table 20.

Table 20. Sample problems generation

Parameter	Generation range
Number of human resources	5-20
Number of activities	10-30
Duration of activity (day)	5-15
Cost of activity	300-700

The proposed NSGA-II and MOPSO algorithms were used to generate and solve a number of large-scale sample problems based on the specified parameter values. The results are shown in Table 21.

Table 21. Pareto solutions obtained by the proposed algorithms for large scale samples

Problem number	Number of human resources	Number of activities	NSGA-II			MOPSO			Deviation (%)
			Z_1	Z_2	Z_3	Z_1	Z_2	Z_3	
1	5	10	41	39200000	11.326	42	39100000	11.333	0.11
			51	27700000	16.859	51	27800000	16.857	0.17
2	10	15	53	63000000	14.612	55	62900000	14.622	0.16
			74	46500000	19.341	73	46800000	19.334	0.09
3	15	20	78	73500000	18.047	78	73500000	18.054	0.12
			90	62700000	22.515	92	62400000	22.528	0.21
4	20	30	95	96500000	21.608	95	96500000	21.611	0.03
			112	81200000	25.744	112	81200000	25.740	0.02

As shown in Table 17, the proposed algorithms effectively solved problems of various scales and achieved different Pareto front solutions. The last column of the table compares the differences between the solutions obtained using the two approaches. It is evident that both algorithms perform well in producing near-optimal solutions, with the difference between them being less than 1%. The subsequent section describes how the values of the objective functions change based on problem dimensions for both NSGA-II and MOPSO algorithms. Figure 4 illustrates how project completion time varies as the problem size increases. As observed, the project completion time increases with the number of activities, highlighting the effectiveness of the proposed algorithms. Additionally, the NSGA-II technique demonstrated superior performance compared to MOPSO by achieving a shorter project completion time.

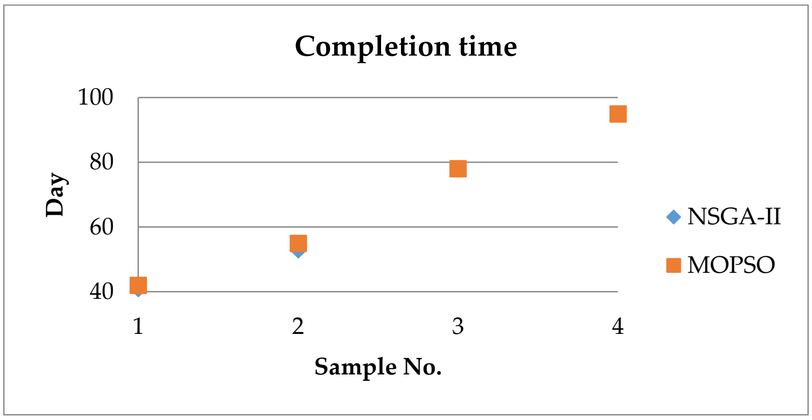

FIGURE 5.Changing project completion time

The process of changing the objective function for minimizing project implementation cost is analyzed next. According to Figure 5, the total project cost increases with both the number of activities and the number of human resources. The results indicate that both algorithms achieved similar values for the cost objective function, as shown in Figure 6.

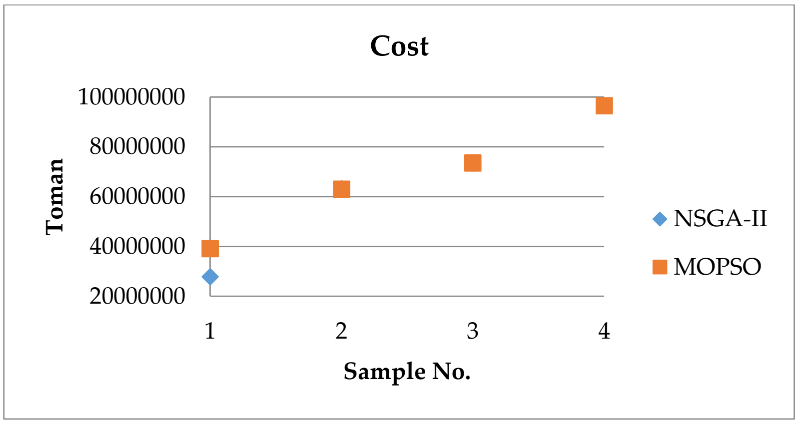

FIGURE 6. Changing project execution cost

The approach to minimizing the gap in predicted skill level was then examined. Figure 7 illustrates that, as the number of human resources and activities increased, it became progressively more challenging to allocate resources effectively to specific tasks. Consequently, the gap between actual and desired competency levels widened over time.

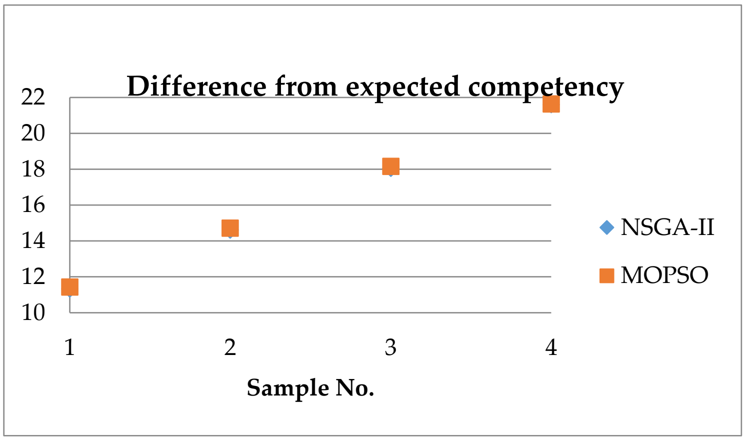

FIGURE 7. Changing difference from expected competency

To validate the proposed method and its ability to locate the ideal Pareto front more thoroughly, four criteria unique to multi-objective algorithms are used: mean ideal distance (MID), diversity metric (DM), space metric (SM), and number of Pareto solutions (NPS). These criteria are computed to assess the performance of the proposed algorithms. An algorithm is considered to perform better if it achieves a higher DM, a lower MID, a lower SM, and a higher NPS [54 and 55]. Table 22 presents the results of these criteria for the various problems.

Table 22. The average value of criteria for the two algorithms

Criteria	DM		MID		SM		NPS	
Problem/ Method	MOPSO	NSGA-II	MOPSO	NSGA-II	MOPSO	NSGA-II	MOPSO	NSGA-II
1	1.06	1.18	0.88	0.98	1.02	0.96	3	5
2	1.2	1.17	1.1	1.03	1.17	1.03	3	12
3	0.92	0.96	0.92	0.88	0.88	0.76	4	19
4	-	1.12	-	1.45	-	1.39	-	24

Table 22 shows that the NSGA-II algorithm significantly outperforms the MOPSO algorithm in terms of the Diversity Metric (DM). This suggests that the NSGA-II algorithm can provide a Pareto front with a greater variety of potential solutions. Additionally, the NSGA-II algorithm performs better in terms of Mean Ideal Distance (MID), indicating that the distance from the ideal point for any solution is smaller compared to the MOPSO approach. The NSGA-II algorithm also excels in Space Metric (SM), generating a more uniform Pareto front than MOPSO. Furthermore, the NSGA-II algorithm consistently identifies more Pareto solutions.

This study developed a three-objective optimization model for the scheduling of construction projects and the allocation of multi-skilled human resources based on competency levels. The Epsilon constraint technique was demonstrated using a meticulously constructed and solved small-scale problem. According to Table 14, various Pareto solutions were obtained with differing levels of manpower. For instance, the option with the smallest deviation from the desired competency level had a high implementation cost due to the reliance on more skilled human resources to meet competency expectations.

Thus, project cost directly correlates with the deviation from the competency level, as supported by the Pareto results. Conversely, these two factors are inversely proportional to the execution time. Clearly, faster completion times are associated with higher skill levels. Given that the problem is NP-hard, two meta-heuristic algorithms were developed to handle large-scale instances. These algorithms were tested on a small-scale problem, and their results were compared with those from the exact solution. As shown in Table 15, the results indicate that both proposed algorithms performed well, with the worst-case average deviation from the exact solution being less than 1%.

The efficiency of the proposed algorithms was further validated by solving medium and large-scale problems. Table 21 demonstrates that while both algorithms produced similar results, the NSGA-II method outperformed MOPSO slightly. To further assess the conclusions, a sensitivity analysis was conducted on the objective functions based on human resource competency levels. This analysis examined the effects of competency levels on outputs such as completion time, implementation cost, and deviation from the target competency level. Figures 8 through 10 illustrate the impact of competency levels, ranging from 6 to 10, on total completion time, total cost, and deviation from the projected competency level.

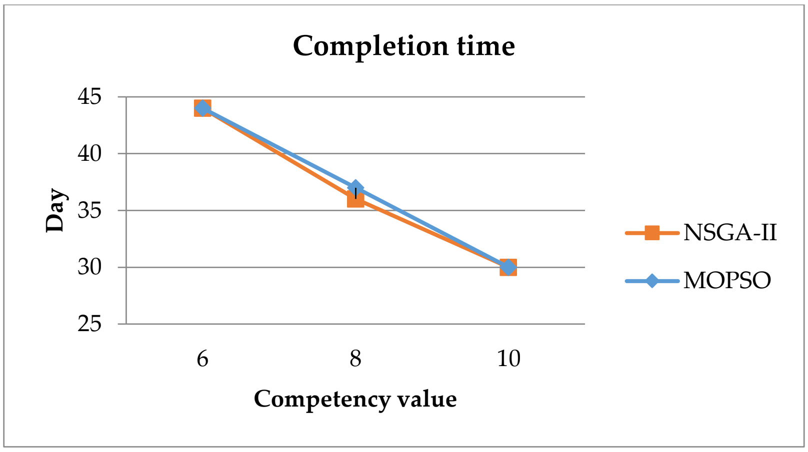

FIGURE 8. Time variation based on competency value

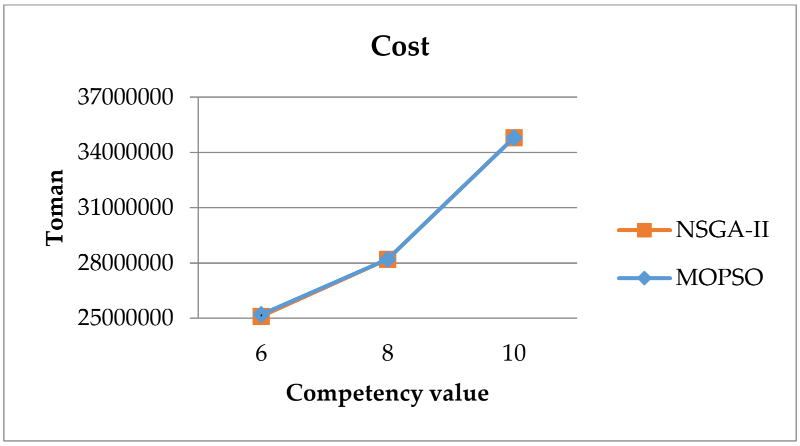

FIGURE 9. Cost variation based on competency value

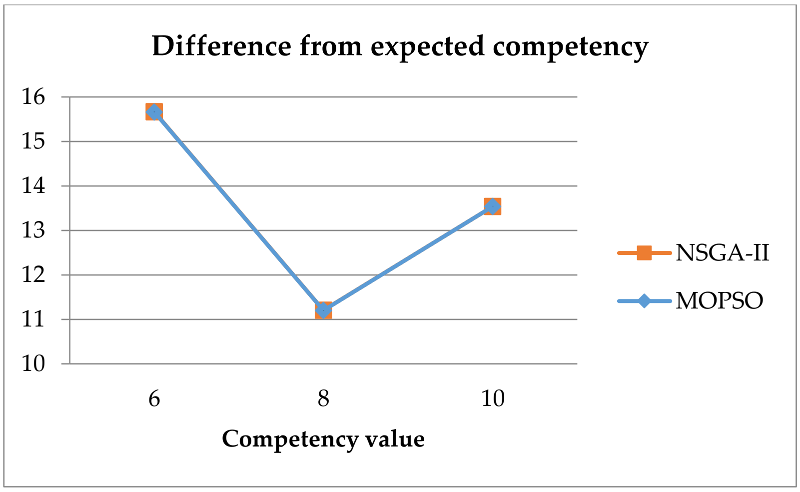

FIGURE 10.Difference from expected competency variation based on competency value

As illustrated in Figure 8, the total completion time decreases as the competency level of human resources increases. This indicates that higher competency levels have a direct impact on reducing project time. Conversely, as shown in Figure 9, there is a direct relationship between competency levels and project cost; specifically, the total cost rises with increasing competency. Finally, Figure 10 reveals that changes in competency levels have a minimal impact on the difference from the expected competency, indicating that the deviation from the desired competency level remains relatively stable regardless of the competency value.

VIII. CONCLUSION

In this study, a mixed-integer mathematical programming model was developed to address human resource allocation in project activities, considering competency levels. The model aims to achieve three objectives: reducing project completion time, minimizing implementation costs, and reducing the deviation from expected competency levels. Initially, a small-scale example problem was precisely solved using GAMS software with the Epsilon constraint technique. Subsequently, two metaheuristic algorithms, NSGA-II and MOPSO, were developed to handle larger-scale problems.

The performance of these algorithms was validated by comparing their results to those obtained from the exact solution provided by GAMS. The algorithms demonstrated their effectiveness in solving both small and large-scale problems accurately. Further, sensitivity analysis revealed the impact of human competency levels on the objective functions.

Given that real-world scenarios often involve uncertainty, future work could incorporate uncertainty management techniques such as fuzzy theory, stochastic optimization, and robust optimization. Additionally, exploring the effects of learning and forgetting on human resource skills and employing goal programming for multi-objective problems could offer further advancements.

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Author contribution

All authors made an equal contribution to the development and planning of the study.

Conflict of Interest

The authors declare no conflicts of interest.

Data availability

All data generated or analyzed during this study are included in this published article.

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