Journal of Engg. Research Vol. 11 No 3 pp.259-268 **DOI:10.36909/jer.16871**

Fuzzy-logic-based bi-objective approach for multi-period technician routing and scheduling problems

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Submitted **:** 24-12-2021

Revised **:** 08-07-2022

Accepted **:** 16-07-2022

ABSTRACT

In this study, a multi-period technician routing and scheduling problem is addressed. The problem involves performing tasks at various locations by dividing them into teams of differently skilled technicians. Additionally, a bi-objective mixed-integer programming method is provided to model the problem as the goals of the model are to optimize the travel cost while simultaneously minimizing the overtime and waiting time. Furthermore, a fuzzy logic approach is introduced to solve the problem by offering a single Pareto solution to satisfy both objectives rather than providing efficient solutions, as in classical multi-objective models. Finally, computational experiments and analyses are presented to evaluate the efficiency of the proposed mathematical formulation and solution approach. The results demonstrate that the proposed model performed satisfactorily.

Keywords: Bi-objective Optimization; Fuzzy Logic Approach; Multi-period; Technician Routing and Scheduling.

INTRODUCTION

The technician routing and scheduling problem (TRSP) is a fundamental challenge for many assistance providers, such as telecommunications, security personnel routing, home healthcare, and airline catering providers. These providers must effectively manage their limited workforce resources to address with this issue. The services provided by firms comprise different types of complicated tasks performed by technicians with various skills. In addition, technicians must visit diverse geographic areas to fulfill customer demands. The TRSP can be described as a branch of the vehicle routing problem, including time windows (Moradi, 2020). Therefore, it is an NP-hard problem (Pourjavad and Almehdawe, 2022).

The primary aim of the TRSP is to separate technicians with different skills into teams, assign tasks with varying skill requirements to groups, and specify the routing for each team to optimize the sum of costs. However, tasks assigned to groups with different skill requirements must fulfill various constraints related to skill compatibility. Technicians with different individual skills should be incorporated with the scheduling and routing to accomplish a reasonable workload distribution, increase customer satisfaction, and diminish operational costs (Mathlouthi et al., 2021a). Accordingly, this study focuses on determining, routing, and assigning groups to satisfy customer demands for a given set of tasks that require different skills and a given set of technicians with varying skills over multiple periods or days. The TRSP addressed in this study considers a bi-objective mixed-integer programming (MIP) approach that optimizes travel costs, overtime, and waiting time.

In addition, this study considers a multi-period TRSP within a specific period, and overtime occurs when this time interval is exceeded. To solve this problem, a fuzzy logic approach that offers a single Pareto solution to satisfy both objectives is proposed, rather than providing Pareto-efficient solutions as in classical multi-objective models.

Regarding the TRSP, Tsang and Voudouris (1997) were the first to research the technician workforce scheduling problem. Additionally, some authors have explored the technician scheduling problem in the telecommunications services offered by France Telecom (Dutot et al., 2006). While some authors considered a single period and time window (Cordeau et al., 2010), others considered a multi-period TRSP in different areas (Punyakum et al., 2022). The solution models can be categorized as exact methods (Mathlouthi et al., 2021b), heuristic models (Graf, 2022), metaheuristic methods (Pekel, 2022), and hybrid models (Xie et al., 2017), where the authors proposed a multi-period TRSP as an MIP model (Zamorano and Stolletz, 2017). Furthermore, the TRSP has been addressed via a metaheuristic-based approach using more than one team. To the best of our knowledge, a fuzzy logic method has not been investigated in the existing bi-objective TRSP with multi-period.

The main motivation of this study was to conduct the planning process more effectively by modeling situations in which service times are uncertain in real life using fuzzy logic.

The main contributions of this study can be summarized as follows:

1. A bi-objective MIP approach is presented for the TRSP with multiple periods and team building as a bi-objective model.
2. A fuzzy-logic-based approach is proposed by obtaining a single Pareto solution to satisfy the travel cost, overtime, and waiting time requirements to determine the discussed problem.
3. In this study, more than one team interaction is considered.

The remainder of this paper is organized as follows. Section 2 introduces the definition and mathematical approach of the problem being addressed. Section 3 describes the proposed solution approach and an implementation sample. Section 4 presents a case study and its consequences in detail. Finally, Section 5 concludes the paper and presents future research directions.

MATHEMATICAL MODEL

The TRSP is a graph that consists of I and A sets and is defined as $G(I, A)$. Vertex set I includes I' spread jobs and one dummy node (o) designating the station; A denotes the arc set. Team $k \in K$ chooses teams of technicians $m, n \in M$ and completes the tasks. Each team k begins to complete jobs and returns to the depot within the opening hours $[e, f]$ on each day $d \in D$. Each arc $(i, j) \in A$ relates a transportation time t_{ij} and visiting cost c_{ij} that includes the service time p_i related to each task $i \in I'$. In the proposed model, tasks i and j are not equal. Mastership level $l \in L$ exists in skill requirement $q \in Q$. Next, a solution provides a service plan for completing all tasks during the planning horizon. Each route begins and terminates at the central depot and includes the flow of jobs fulfilled by a group in a period.

Each group utilizes precisely δ technicians, and $\delta = 2$ is chosen considering the findings of Zamorano and Stolletz (2017). However, the mathematical model enables different values for δ. Teams of technicians with other individual skills must meet the daily talent requirements of each task. If teams are overqualified, then the task is required and no cost is incurred. Team arrangements are not permitted during workdays. However, diverse team configurations are allowed on different days. A technician can only be in a group on the same day but can also be on different days. Table 1 displays the notation used in the mathematical model. The proposed mathematical model consists of two phases. Phase I describes the deterministic model, while Phase II represents the fuzzy model.

Table 1 Mathematical model notation.

Sets	
I'	Tasks
I	Tasks and central depot
D	Days
A	Arcs $A \subseteq (i,j)\|i,j \in I$
$\underline{D_i} \subseteq D$	Authorized travel days of task i
$A_d \subset A$	Arcs $A_d \subseteq (i,j)\|i,j \in I$ and $\underline{D_i} \cap \underline{D_j}$
K	Teams
M	Technicians
Q	Skills
Parameters	
$[a_{id}, b_{id}]$	The earliest and latest starting time window for task i on day d
c_{ij}	Visiting cost between the locations of tasks i and j
t_{ij}	Time distance between the locations of tasks i and j
$[e, f]$	Daily work hours
δ	Allowed number of technicians per team
v_{iq}	1 if task i needs a mastership {0 or 1} on skill q; 0 otherwise
p_i	Service time of task i
g_{mq}	1 if technician m has a mastership {0 or 1} on skill q; 0 otherwise
ω^{cost}	A customer waiting time cost unit
ot^{cost}	An overtime cost unit
ω^{max}	Waiting time upper bound
ot^{max}	Overtime upper bound
Decision variables	
x_{ijkd}	1 if team k completes task i and visits task j on day d; 0 otherwise
y_{ikd}	1 if team k performs task i on day d; 0 otherwise
z_{mkd}	1 if technician m performs the task for team k on day d; 0 otherwise
S_{ikd}	Starting time of task i performed by team k on day d
ω_i	Waiting time of task i
ot_{kd}	Overtime of team k on day d

$$Min \quad z_1 \cong \sum_{(i,j)\in A} \sum_{k\in K} \sum_{d\in D} c_{ij} x_{ijkd} \tag{1}$$

$$Min \quad z_2 \cong \omega^{cost} \sum_{i\in I'} \omega_i + ot^{cost} \sum_{k\in K} \sum_{d\in D} ot_{kd} \tag{2}$$

Subject to

$$\sum_{k\in K}\sum_{d\in D} y_{ikd} = 1 \quad \forall i \in I' \tag{3}$$

$$\sum_{ji,j)\in A_d} x_{ijkd} = y_{ikd} \quad \forall i \in I', \forall k \in K, \forall d \in D \tag{4}$$

$$\sum_{j:(o,j)\in A_d} x_{ojkd} = 1 \quad \forall k \in K, \forall d \in D \tag{5}$$

$$\sum_{i:(i,o)\in A_d} x_{iokd} = 1 \quad \forall k \in K, \forall d \in D \tag{6}$$

$$\sum_{i:(i,h)\in A_d} x_{ihkd} - \sum_{j:(h,j)\in A_d} x_{hjkd} = 0 \quad \forall h \in I', \forall k \in K, \forall d \in D \tag{7}$$

$$x_{ijkd}\left(S_{ikd} + t_{ij} + \tilde{p}_i - S_{jkd}\right) \le 0 \quad \forall i,j: (i,j) \in A_d, \forall k \in K, \forall d \in D \tag{8}$$

$$y_{ikd}\left(a_{id} - s_{ikd}\right) \le 0 \quad \forall i \in I', \forall k \in K, \forall d \in D \tag{9}$$

$$y_{ikd}\left(S_{ikd} - b_{id} - \omega_i\right) \le 0 \quad \forall i \in I', \forall k \in K, \forall d \in D \tag{10}$$

$$x_{ojkd}\left(S_{jkd} - e - t_{oj} - \tilde{p}_j\right) \ge 0 \quad \forall j \in I', \forall k \in K, \forall d \in D \tag{11}$$

$$x_{iokd}\left(S_{ikd} + t_{io} + \tilde{p}_i - f - ot_{kd}\right) \le 0 \quad \forall i \in I', \forall k \in K, \forall d \in D \tag{12}$$

$$\sum_{k\in K} z_{mkd} \le 1 \quad \forall m \in M, \forall d \in D \tag{13}$$

$$\sum_{m\in M} z_{mkd} = \delta \quad \forall k \in K, \forall d \in D \tag{14}$$

$$v_{iq} y_{ikd} \le \sum_{m\in M} g_{mq} z_{mkd} \quad \forall i \in I', \forall q \in Q, \forall k \in K, \forall d \in D \tag{15}$$

$$0 \le \omega_i \le \omega^{max} \tag{16}$$

$$0 \le ot_{kd} \le ot^{max} \tag{17}$$

$$S_{ikd} \ge 0 \quad \forall i \in I, \forall k \in K, \forall d \in D \tag{18}$$

$$x_{ijkd}, y_{ikd}, z_{mkd} \in \{0,1\} \quad \forall\, (i,j) \in A, \forall m \in M, \forall k \in K, \forall d \in D \tag{19}$$

Equations (3) and (4) guarantee that each task is assigned once to a team on any feasible day of the inquired appointment days. Equations (5) and (6) guarantee that each team begins and completes its route at the depot. Equation (7) guarantees the flow of tasks when travelling on a task placed on a team or on a day. Equation (8) enables us to begin a task only if it is fulfilled. This constraint also avoids sub-tours. Equations (9) and (10) indicate that a task can begin only within its time window. When a team does not initiate a task until its latest starting time, the cost comes from customer waiting. Equations (8)–(12) are the non-linear constraints. However, a large *M* formulation can linearize constraints (8)–(12). Equations (11) and (12) determine the first and last fulfilment times, respectively: Equation (13) guarantees that one team can employ at most one technician per day, and the number of technicians in each team is denoted by equation (14). Equation (15) guarantees that a team composed of technicians with different skills must achieve task proficiency. Equations (16) and (17) define the lower and upper bounds of waiting time and overtime, respectively. Equations (18) and (19) provide the positive and binary variables, respectively.

METHODOLOGY

This study considered a triangular distribution version to describe all fuzzy numbers. The essential benefit of a triangular fuzzy number (TFN) is that it provides plainness and flexibility in the fuzzy processes (Lai and Hwang, 1992; Rommelfanger, 1996). The decision maker can build a triangular distribution with three outstanding data points. The first data point is the most pessimistic value with a low probability related to the set of possible values, and its membership value is zero. The second data point is the most likely value and its membership value is unity. The third data point is the most optimistic value with a low probability related to the set of possible values, and its membership value is zero (Liang and Cheng, 2009). Figure 1 shows the distribution of TFN $\tilde{p}_i = (p_i^p,\ p_i^m,\ p_i^o)$ under constraints (8), (11), and (12).

Considering constraints (8), (11), and (12) from the original fuzzy mathematical model expressed earlier, we choose service time $\tilde{p}_i$ as a TFN consisting of the maximum and minimum possible values. This study implemented a weighted-average approach to transform $\tilde{p}_i$ into a crisp number (Liang and Cheng, 2009). In the case of the minimum acceptable membership level (∞), the crisp inequalities of constraints (8), (11), and (12) are modified as follows:

$$x_{ijkd}\big(S_{ikd} + c_{ij} + (w_1 p_{i,\propto}^p + w_2 p_{i,\propto}^m + w_3 p_{i,\propto}^o) - S_{jkd}\big) \leq 0 \ \ \forall i, j: (i, j) \in A_d, \forall k \in K, \forall d \in D \quad (20)$$

$$x_{ojkd}\big(S_{jkd} - e - c_{oj} - (w_1 p_{i,\propto}^p + w_2 p_{i,\propto}^m + w_3 p_{i,\propto}^o)\big) \geq 0 \ \ \forall j \in I', \forall k \in K, \forall d \in D \quad (21)$$

$$x_{iokd}\big(S_{ikd} + c_{io} + (w_1 p_{i,\propto}^p + w_2 p_{i,\propto}^m + w_3 p_{i,\propto}^o) - f - ot_{kd}\big) \leq 0 \ \ \forall i \in I', \forall k \in K, \forall d \in D \quad (22)$$

where w_1, w_2, and w_3 show the corresponding weights of the most pessimistic, most likely, and most optimistic values, respectively; their sum is unity. In general, the experience and knowledge of decision makers determine their weights. Considering Liang and Cheng (2009), we chose weight values of $w_2 = 4/6$ and $w_1 = w_3 = 1/6$ for all fuzzy restrictions. It is stated that the most probable value is commonly the most significant one; therefore, it should receive a greater weight. Conversely, the most pessimistic and optimistic values should have lower weights (Liang and Cheng, 2009).

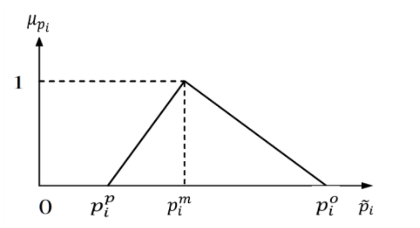

Figure 1 Distribution of TFN $\tilde{p}_i$

Following Liang and Cheng (2009), the continuous linear membership functions for each fuzzy objective are stated as follows:

$$f_g(z_g) = \{1, \qquad z_g \leq z_g^{PIS} \frac{z_g^{NIS} - z_g}{z_g^{NIS} - z_g^{PIS}}, \qquad z_g^{PIS} < z_g < z_g^{NIS} 0,$$

$$\& \qquad z_g \geq z_g^{NIS} \quad g = 1,2 \quad (23)$$

where z_g^{PIS} and z_g^{NIS} are the positive ideal solution (PIS) and negative ideal solution (NIS), respectively, for the gth objective function z_g. PIS and NIS provide the lower and upper bounds $[\ z_g^{PIS},\ z_g^{NIS}]$, respectively, for the solutions. Phase II of the proposed mathematical model is as follows:

$$Max\ L$$

$$L \leq f_g(z_g) \quad \forall g \quad (24)$$

$$0 \leq L \leq 1 \quad (25)$$

Constraints (3)–(19) are added to the mathematical model, and the model runs for the linear membership function (L). The found L provides the values of all other objective functions.

CASE STUDY AND NUMERICAL RESULTS

Case Study

Three fuzzy case studies for 25 tasks over five days were considered in this study. Twenty-five tasks were routed and performed by eight technicians. Different team configurations ($k = 1,2$) exist in a day. Team arrangements were not permitted during workdays. However, different team configurations were permitted on other days. One technician worked on at most one team per day. Members of the qualified team and all tasks had a given proficiency level (zero or unity). Teams of technicians with different skills must meet the talent requirements for each task. A customer waiting time cost unit and an overtime cost unit equal unity. $ot^{max} = 0$ was chosen because teams did not require extra time to complete tasks in the case studies. The generated case studies have four different waiting times, namely, $\omega^{max} = 60, 120, 150, and$ 180 min.

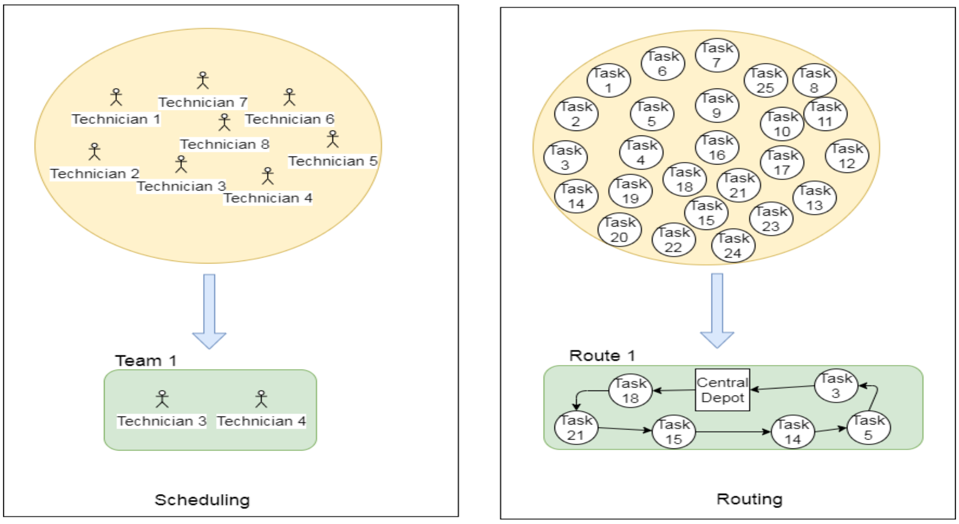

Figure 2 Case study example

Figure 2 shows a case study example. As mentioned earlier, three case studies were considered. The three case studies consist of pessimistic p_i^p, mean p_i^m, and optimistic p_i^o values. p_i^m is the service time crisp value. p_i^p and p_i^o equal 90% and 110% of the service time crisp value, respectively. For example, if the service time in a deterministic model is 90 min, $p_i^p = 81$, $p_i^m = 90$, and $p_i^o = 99$.

Numerical Results

All procedures introduced in the previous sections were coded in C++, run on a 2.60-GHz workstation with 8 GB of RAM, and using the CPLEX 12.6 solver.

First, the mathematical model was tested using data from Zamorano and Stolletz (2017). Single-and multi-period instances (25a and 25b) were solved, and solutions were provided according to different team numbers. The performance of the proposed algorithm was tested in a case study. We solved this problem twice by minimizing z1 and z2. Thus, the northwest and southeast points of the objective space were maintained, and the Phase II model was solved using these bounds. The results show that the proposed algorithm yields satisfactory solutions. To demonstrate the performance of the proposed algorithm, a further example is presented next. Table 2 shows Results of phase I and phase II.

Table 2 Results of Phase I and Phase II ($w_{max} = 60$, combination=1)

	Phase I		Phase II		
	z1	z2	z1	z2	F
Min z1	490.40	1500.00			

First, the Phase I model is solved by minimizing $z1$ for the $w_{max} = 60$ instance. The solution is $z1 = 490.4$ and $z2 = 1500$ (the northwest point of the objective space). Second, the Phase I model is solved by minimizing $z2$; the solution is $z1 = 579.3$ and $z2 = 33$ (the southeast point of the objective space). The z_1 lower bound is determined by $min\ \{490.4, 579.3\} = 490.4$, the z_1 upper bound is determined by $max\ \{490.4, 579.3\} = 579.3$, the z_2 lower bound is determined by $min\{1500, 33\} = 33$, and the z_2 upper bound is determined by $max\ \{1500, 33\} = 1500$. Using these bounds, the Phase II model can be solved by minimizing the F value. The solution is $z1 = 492.4$ and $z2 = 66$. Thus, the solution simultaneously satisfies both objectives. The decent solutions obtained for all cases are listed in Table 3.

Table 3 Solutions of the case study for each w_{max} values and team numbers.

	$\boldsymbol{w_{max} = 60}$					
	$team = 1$			$team = 2$		
	$z1$	$z2$	F	$z1$	$z2$	F
Combination 1				492.40	66.00	0.977
Combination 2		Infeasible		490.40	82.70	0.963
Combination 3				490.40	93.90	0.961
	$\boldsymbol{w_{max} = 120}$					
	$team = 1$			$team = 2$		
	$z1$	$z2$	F	$z1$	$z2$	F
Combination 1				487.60	125.60	0.968
Combination 2		Infeasible		487.00	112.10	0.971
Combination 3				487.60	142.50	0.964
	$\boldsymbol{w_{max} = 150}$					
	$team = 1$			$team = 2$		
	$z1$	$z2$	F	$z1$	$z2$	F
Combination 1	332.90	3749.99	0.999	485.70	272.80	0.935
Combination 2	327.70	3750.00	1.000	485.70	248.49	0.940
Combination 3	333.10	3750.00	1.000	485.70	275.00	0.936
	$\boldsymbol{w_{max} = 180}$					
	$team = 1$			$team = 2$		
	$z1$	$z2$	F	$z1$	$z2$	F
Combination 1	327.70	4496.98	0.999	487.00	216.97	0.958
Combination 2	327.70	4496.94	0.999	487.00	212.66	0.958
Combination 3	332.90	4499.99	0.999	490.40	93.90	0.889

The effects of the w_{max} parameter is shown in Figure 3. The z_2 objective is more sensitive in terms of parameter w_{max} for all combinations. The w_{max} value should be low. In addition, w_{max} should also be positive to avoid unfeasible solutions.

Table 4 Effects of team numbers and combinations.

	z_1		z_2	
	team=1	team=2	team=1	team=2
Combination 1	332.9	485.7	3750.0	272.8
Combination 2	327.7	485.7	3750.0	248.5
Combination 3	333.1	485.7	3750.0	275.0

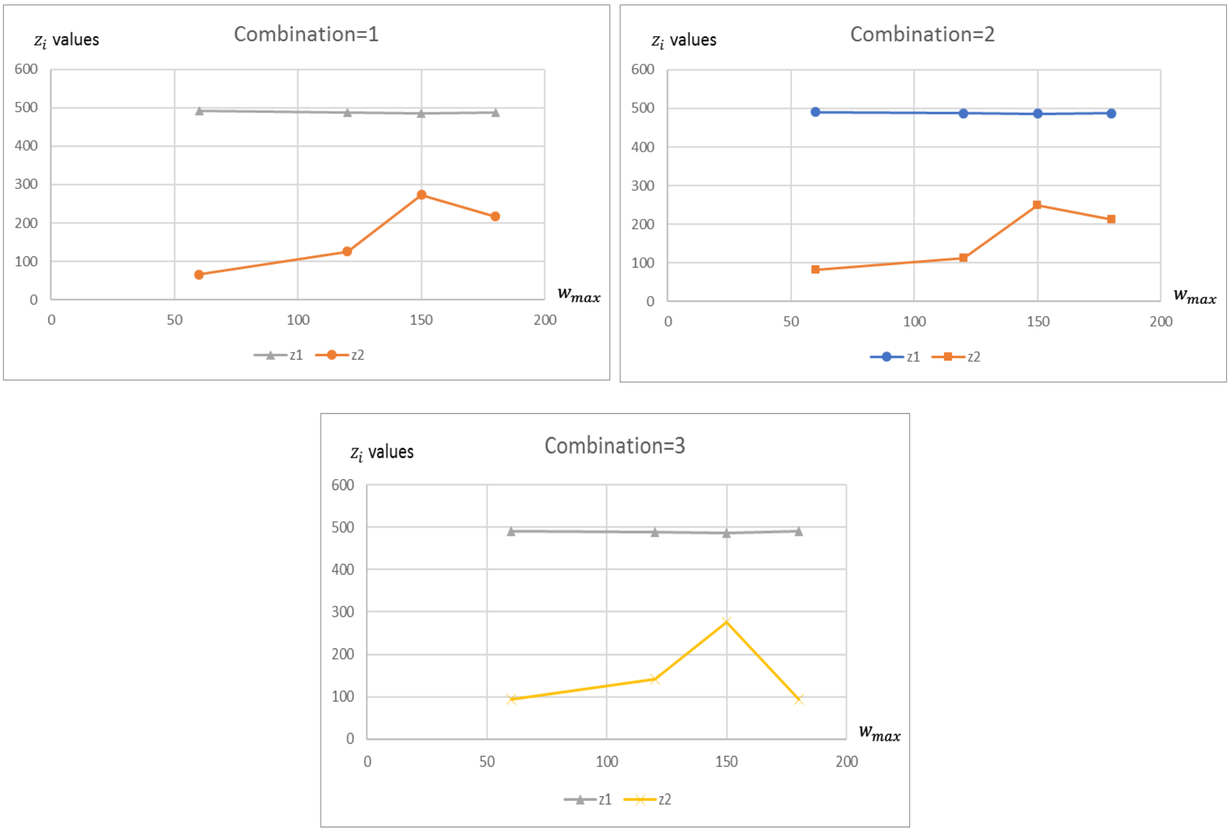

Figure 3 Effects of w_{max} for all combinations.

The effects of team numbers and combinations were also analyzed, and it was observed that there was no significant difference between combinations, but there was a significant difference between team numbers. As shown in Table 4, when the number of teams increased, the z2 objective values decreased, whereas the z_1 objective values increased dramatically. If the number of teams increased from one to two, the average difference in z1 was approximately 31.8%; whereas z_2 decreased by approximately 92.9%.

CONCLUSION

In this study, a multi-period TRSP consisting of technicians with different skills and tasks requested by the customer at distinct locations is addressed by considering a bi-objective MIP approach, which indicates the trade-off between travel cost and the overtime and waiting time sum and considers a set of particular constraints to the TRSP. As a result, the bi-objective model allowed us to evaluate the multi-period TRSP based on time and cost. In addition, a fuzzy logic approach that presents a single Pareto solution to satisfy both objectives is proposed to overcome this problem. The bi-objective model introduced for the multi-period TRSP was used to investigate benchmark cases using the CPLEX solver.

Computational tests were executed to analyze the performance of the proposed method for a given case study. First, the mathematical model was evaluated with real-world data, single- and multi-period instances were solved, and solutions were presented according to team numbers. Furthermore, solutions to a case study consisting of the conclusions of Phase I, the deterministic model, and Phase II, which is a fuzzy model, were offered considering different maximum waiting times and team numbers. The computational results and statistical analyses demonstrate that the proposed algorithm provides acceptable solutions. We examined the computational results for the team number and maximum waiting time separately, considering different combinations. It was found that the second objective is more sensitive to the maximum waiting time for all varieties. The first objective value increased and the second objective value decreased dramatically as the number of teams increased. In future work, it would be interesting to study other fuzzy logic models that could be used for comparison and obtain a more effective Pareto solution. Another potential development is to investigate situations in which the service time changes according to the technician's experience. Because the problem considered is an NP-hard problem and it is impossible to obtain solutions, especially for large-sized customers, research can be carried out with metaheuristic algorithms, such as the genetic algorithm and particle swarm optimization.

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