A bi-objective approach based on fuzzy logic for multi-period technician routing and scheduling problems

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ABSTRACT

This paper deals with a multi-period technician routing and scheduling problem. The problem carries out the tasks at various locations by being divided into teams considering differently skilled technicians. This paper provides a bi-objective mixed integer programming method to model the problem since the goals of the performed model are to optimize the travel cost while simultaneously minimizing the overtime and the waiting time. The paper introduces a fuzzy logic approach to solving the problem by offering a single Pareto solution to satisfy both objectives, rather than providing efficient solutions as in the case of classical multi-objective models. Finally, the paper presents the computational experiments and analyses to evaluate the efficiency of the suggested mathematical formulation and solution approach. The results demonstrate that the performed model accomplishes an acceptable satisfaction level.

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 telecommunication, security personnel routing, home health care, and airline catering. These companies must manage limited workforce resources effectively to cope with this issue. The services provided by firms comprise complicated different types of tasks to be performed by technicians with other skills. Besides, technicians require visiting diverse geographic areas to fulfill customer demands. TRSP can be described as a branch of the vehicle routing problem, including time windows (Moradi, 2020). Therefore, it is an NP-Hard (Pourjavad and Almehdawe, 2022).

The primary aim of the TRSP is to separate the technicians of different skills into teams, assign the tasks with varying requirements of skill to groups, and specify the routing for each team, to optimize the sum of cost. On the other hand, the tasks assigned groups with different skill requirements must be fulfilled the various constraints related to skill compatibility. The 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). This paper focuses on determining, routing, and assigning groups to satisfy customer demands for a given set of tasks that required different skills and a given set of technicians with varying skills over multiple periods or days. The problem addressed in this study considers a bi-objective Mixed Integer Programming (MIP) approach by optimizing the travel costs, overtime and waiting time.

Besides, this paper considers the Multi-period TRSP within a specific period, and overtime occurs when this time interval is exceeded. To accomplish this problem, this paper suggests a fuzzy logic approach that offers a single Pareto solution to satisfy both objectives, rather than to provide Pareto efficient solutions as in the case of classical multi-objective models.

Regarding TRSP, the first research is presented by (Tsang and Voudouris, 1997) for the technician workforce scheduling problem. Additionally, some authors explore the technician scheduling problem in the telecommunications services offered by France Telecom (Dutot et al., 2006). While some authors consider a single period and time windows (Cordeau et al., 2010), some authors consider 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). The authors propose the multi-period TRSP considered as a MIP model (Zamorano and Stolletz, 2017). This fuzzy logic method has not been investigated in the existing bi-objective TRSP with multi-period literature to the best of our knowledge. Besides, another study addressed a metaheuristic-based approach for the TRSP with more than one team.

The main motivation of the study is to carry out the planning process more effectively by modeling the situations where service times are uncertain in real life with fuzzy logic.

The main contribution of this research is threefold:

1. A bi-objective MIP approach is presented for the TRSP with multi-period and team building as a bi-objective model.
2. A fuzzy logic approach is proposed by obtaining a single Pareto solution to equally satisfy the travel cost, overtime, and waiting time to figure out the discussed problem.
3. More than one team interaction is considered in this study.

The remainder of this research is categorized as follows. Section 2 introduces the definition and mathematical approach of the problem. Section 3 indicates the proposed solution approach and an implementation sample. In Section 4, the case study and consequences are provided in detail. Finally, Section 5 contains the conclusion and future research.

MATHEMATICAL MODEL

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, and A denotes the arc set. A team $k \in K$ chooses teams of technicians $m, n \in M$ and completes tasks. Each team k begins to complete jobs and returns at 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 a visiting cost c_{ij} that includes the service time p_i related to each task $i \in I'$. In our model, tasks i and j are not equal. The mastership level $l \in L$ exists in skill requirement $q \in Q$. Next, a solution provides a service plan for completing whole tasks during the planning horizon. Each of the routes begins and terminates at the central depot, and it includes a flow of jobs fulfilled by a group in a period. Each group utilizes precisely δ technicians, and $\delta = 2$ is chosen considering the research performed by (Zamorano and Stolletz, 2017). However, the mathematical model enables different values for δ. A team of technicians with other individual skills has to meet the talent needs of each task per day. If teams are overqualified, then the task required, no cost comes out. Team arrangements are not allowed within the working day. However, diverse team configurations on various days are allowed. A technician can only be in a group on the same day, but can also be on different days. Table 1 displays all the notations of the mathematical model. The proposed mathematical model consists of two phases. Firstly, Phase I is presented and shows the deterministic model below. Later, Phase II belongs to the fuzzy model.

Table 1 Notations of the mathematical model.

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 $A_d \subseteq (i,j) \| i,j \in I \text{ and } \underline{D_i} \cap \underline{D_j}$
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 location of task i and location of task j
t_{ij}	Time distance between location of task i and location of task 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 unit of time cost of customer waiting time
ot^{cost}	A unit of time cost of overtime
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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Equations (3) and (4) guarantee that each task is assigned once to one team on any feasible day concerning 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 a task placed in a team and on a day. Equation (8) enables us to begin a task only if its former task is fulfilled. This constraint also avoids sub-tours. Equations (9) and (10) provide that a task can only begin the range of its time window. When a team does not initiate a task until its latest starting time, a cost comes out on customer waiting. Equations (8)- (12) are non-linear constraints. However, a big M formulation can linearize constraints (8)- (12).

Equations (11) and (12) determine the first starting and the last fulfilment time. Equation (13) guarantees that one team can employ a technician at most per day, and the number of technicians of each team is denoted in equation (14). Equation (15) guarantees that a team composed of technicians with different skills must meet the proficiency of a task. Equations (16) and (17) define the lower and upper bound of waiting time and overtime. Equation (18) provides the positive variable, and Equation (19) provides the binary variables.

METHODOLOGY

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

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

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

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

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

w_1, w_2, and w_3 show the corresponding weight of the most pessimistic, most likely, and most optimistic values, respectively, and their sum equals 1. In general, the experience and knowledge of decision-makers determine the weights. Considering the study presented by Liang and Cheng, 2009, this paper chooses the values of the weights $w_2 = 4/6$ and $w_1 = w_3 = 1/6$ for all fuzzy restrictions. It is stated that the most probable value commonly is the most significant one and thus should get a greater weight. Conversely, the most pessimistic and optimistic values should get smaller weights (Liang and Cheng, 2009).

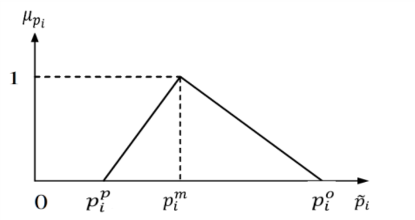

Figure 1 The distribution of TFN $\tilde{p}_i$

Liang and Cheng, 2009 state the continuous linear membership functions for each fuzzy objective as follows:

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

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

Where z_g^{PIS} and z_g^{NIS}state the positive ideal solutions (PIS) and negative ideal solutions (NIS), respectively, for the gth objective function z_g. PIS and NIS provide lower and upper bound$[\, z_g^{PIS},\, z_g^{NIS}]$ for the solutions. Phase II of the proposed mathematical model is shown below.

$$Max\ L$$

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

$$0 \leq L \leq 1 \tag{25}$$

Constraints (3)-(19) added to the above mathematical model then model run for 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 and five days are generated in this paper. Twenty-five tasks are routed and carried out by possible eight technicians. Different team configurations ($k = 1,2$) exist in a day. Team arrangements are not allowed within the working day. However, different team configurations on other days are allowed. A technician works for at most one team per day. The members of a qualified team and all tasks have a given proficiency level (0 and 1). A team of technicians with different individual skills has to meet the talent needs of each task. A unit of time cost of customer waiting time and a unit of time cost of overtime equals 1. ot^{max} is chosen as 0 since teams do not require the extra time to complete the tasks in the case studies. The generated case studies have four different waiting times ($\omega^{max} = 60, 120, 150, 180$).

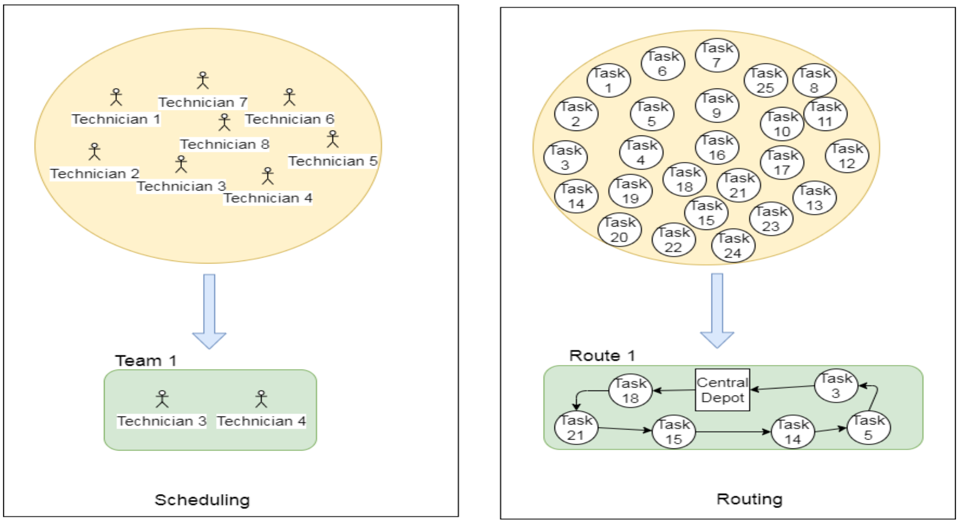

Figure 2 An example of a case study

Figure 2 shows an example of a case study. Earlier, it was declared that three case studies existed. Three case studies consist of pi's pessimistic, mean, and optimistic values. p_i^m equals the crisp value of service time. p_i^p *and* p_i^o equal 90% and 110% of the crisp value of service time, respectively. For example, if the service time is 90 minutes in a deterministic model, $p_i^p = 81, p_i^m = 90, p_i^o = 99$.

Numerical Results

All the procedures introduced in the past sections have been coded in C++, run on a 2.60 GHz workstation with 8 GB RAM, and CPLEX 12.6 is the solver used.

First, the mathematical model is tested with the test data of Zamorano and Stolletz, 2017. Single period and multi-period instances (25a and 25b) are solved and provided solutions according to different team numbers. The performance of the proposed algorithm is tested for the given case study. We solved the problem two times by minimizing z1 and z2, respectively. In this way, the Northwest and Southeast points of objective space are kept, and then the Phase II model is solved by using these bounds. The results show that the proposed algorithm gives considerably decent solutions. To emphasize the performance of the proposed algorithm, an example is presented below:

Table 2 The 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	492.40	66.00	0.977
Min z2	579.30	33.00			

First, the Phase I model is solved by minimizing $z1$ for the $w_{max} = 60$ instance. The solution is $z1 = 490.4$ and $z2 = 1500$ (Northwest point of objective space). Second, the Phase I model is solved by minimizing $z2$; the solution is $z1 = 579.3$ and $z2 = 33$ (Southeast point of objective space). z_1 lower bound is determined by $min\ \{490.4, 579.3\} = 490.4$, z_1 upper bound is determined by $max\{490.4, 579.3\} = 579.3$; and z_2 lower bound is determined by $min\{1500, 33\} = 33$, z_2 upper bound is determined by $max\{1500, 33\} = 1500$. By using these bounds, the Phase II model can be solved by minimizing F value. The solution is $z1 = 492.4$and $z2 = 66$. In this way, the solution satisfies both of two objectives at the same time. For all cases, the obtained decent solutions are presented in Table 3 below.

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	Infeasible			492.40	66.00	0.977
Combination 2				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	Infeasible			487.60	125.60	0.968
Combination 2				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 effect of the w_{max} parameter is provided in Figure 3. z_2 objective is more sensitive in terms of parameter w_{max} in all combinations. The w_{max} value should be lower. Besides, w_{max} value should be positive to avoid infeasible solutions.

Table 4 The effect 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

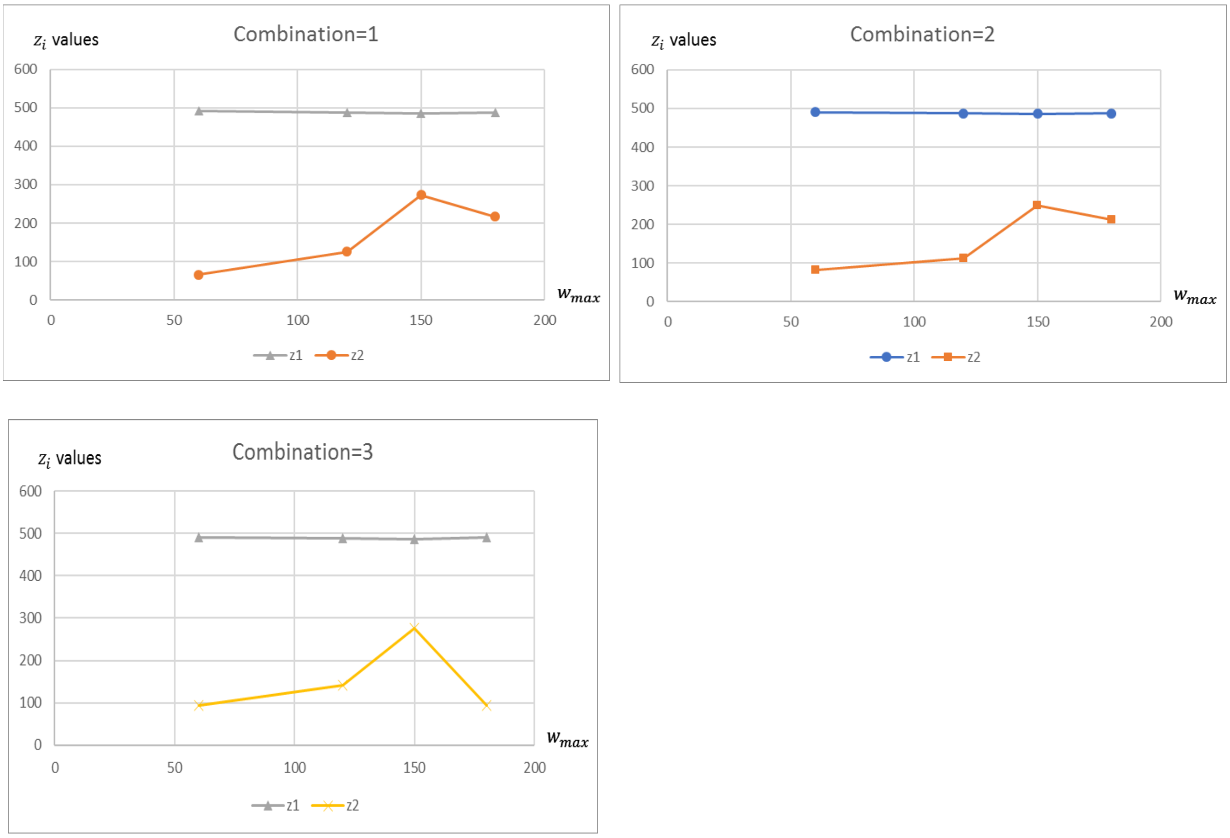

Figure 3 The effect of w_{max} parameter.

The effect of team numbers and the combinations are analyzed, it is noticed that there is no big difference between combinations, but there is a significant difference between team numbers. As can be seen from Table 4, when the number of teams increases, z2 objective values decrease while the objective value of z_1 increases dramatically. If the number of teams is increased from 1 to 2; the average difference in z1 is approximately 31.8%; on the other hand, z_2 decreases about 92.9%.

CONCLUSION

This paper deals with the multi-period TRSP consisting of technicians with different skills and tasks requested by the customer at distinct locations considering a bi-objective MIP approach, which indicates the trade-off between the travel cost and the sum of the overtime and the waiting time and considers a set of particular constraints to TRSP. As a result, the bi-objective model allows us to evaluate the multi-period TRSP from time and cost. Also, the paper proposes a fuzzy logic approach that presents a single Pareto solution to satisfy both objectives to overcome this problem. The bi-objective model introduced for the multi-period TRSP has investigated benchmark cases utilizing the CPLEX solver.

The paper presents the computational tests executed to analyze the performance of the suggested method for the given case study. First, the study evaluates the mathematical model with real-world data, solves the single period instances and the multi-period instances, and presents the solutions according to team numbers. Furthermore, it offers solutions of the case study consisting of the conclusions of Phase I, the deterministic model, and Phase II, which is the fuzzy model, taking into consideration different maximum waiting times and team numbers. The computational results and statistical analyses demonstrate that the proposed algorithm provides decent solutions. The paper examines the computational results of team number and maximum waiting time separately, considering different combinations. The second objective is more sensitive in terms of maximum waiting time in all varieties. It is noticed that the first objective value increased, and the second objective value decreased dramatically by increasing the number of teams. For further research, it would be interesting to study other fuzzy logic models that can be performed to compare the results and to obtain a more effective Pareto solution. Another potential development is to investigate the situation in which the service time changes with the technicians' experience. Since the problem type considered is NP-hard and it is impossible to obtain solutions especially for large-sized customers, researches can be carried out with metaheuristic algorithms such as Genetic and particle swarm optimization.

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