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Robust Operating Room Scheduling: A Two Stage Advanced Ant System

Abstract. *In this paper, we address the multiobjective surgical case scheduling (MOSCS) problem in a multioperating theatre environment with uncertain service times in order to minimise the makespan, the number of the nonscheduled surgical cases, robustness, stability, and nervousness. The planning contains two stages; in the first stage, the elective patients are scheduled considering two former criteria using a Pareto ant system and then in the second stage, after arriving emergency patients online, the plan is rescheduled considering three later objectives addition to makespan using a new max-min ant system. On the other hand, we take into account fuzzy numbers for processing times of all stages, and hereafter the problem called multiobjective fuzzy SCS. This problem is strongly an NP-hard optimisation problem; hence we employ a two-stage algorithm including a fuzzy Pareto envelope-based selection ant system so as to tackle the first stage of problem and a new multiobjective Max-Min ant system for solving the second stage of the problem. Moreover, this proposed approach is illustrated by providing three test cases. Therefore, the performance of the proposed algorithm on all test instances is compared to a basic multiobjective ant system under the fuzzy condition, namely Pareto strength ant colony optimisation. Consequently, computational experiments state that our proposed approach outperforms another algorithm, and the results indicate the efficiency and effectiveness of the proposed algorithm in comparison with the traditional algorithm for solving the problem.*

Keywords: *surgical case scheduling, robust operating room, rescheduling, makespan, robustness, stability, nervousness.*

JEL Classification: C61.

1. Introduction

Since more than 40% of the costs of the hospitals related to the operating rooms (ORs) (Denton et al., 2007), these parts are considered as the engine of a hospital. The planning and scheduling play a crucial role in decreasing the costs of ORs since the optimisation of the resources assigned to the patients, as well as the sequences of the patients for surgery can reduce the costs of ORs. In this paper, a flow of elective and nonelective surgical patients through a multistage multiresource constrained is studied. All the stages in an operating theatre including preoperative, perioperative, and postoperative, are taken into account for all patients. Also, the fuzzy processing time is provided in various stages of an operating theatre to indicate the uncertainty of the environment. This problem is the extension of bi-objective SCS studied by (Behmanesh and Zandieh, 2019) to represent robust scheduling. Our problem in

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extended version is divided into two stages: (i) offline multiobjective SCS for elective patients with the fuzzy processing time and (ii) online multiobjective SCS for inserted nonelective patients with the fuzzy processing time and the fuzzy release date. Rescheduling the new emergency patients is done in the second stage of the problem in order to present robust scheduling. We also consider two relevant objective functions for offline scheduling: (i) minimisation of makespan and (ii) minimisation of unscheduled patients. In addition to previous classic functions, three novel objective functions are taken into account for the model of online scheduling: (i) optimisation of robustness, (ii) optimisation of stability, and (iii) optimisation of nervousness. We call this problem robust multiobjective surgical case scheduling (RMOSCS).

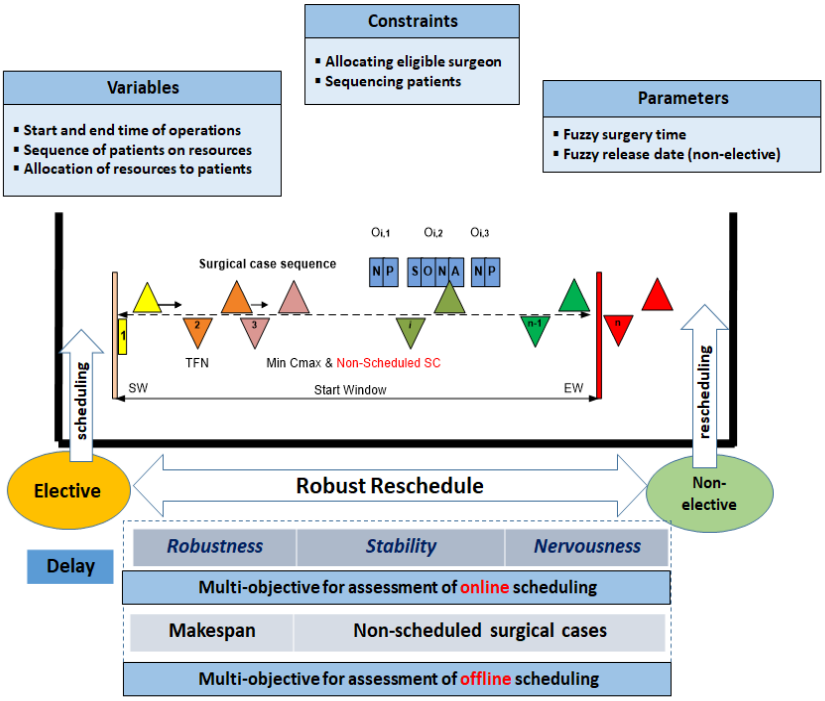

Figure 1. Conceptual framework of robust surgical case scheduling
Source: authors' work.

In the extended model (Fig. 1), the patients are transferred from the ward or ambulatory surgical unit (ASU) to the preoperative holding unit (PHU). Each patient during his/her stay in PHU requires a nurse and a PHU bed, then he/she is moved to the second stage in which an OR, a surgeon, an anaesthetist, and required nurses are allocated to the patient. Lastly, the patient is transported to the Post Anaesthesia Care Unit (PACU) and a nurse and a PACU bed are assigned to the patient. The decisions

making is to determine the optimal resources for each patient and their optimal starting time for each patient. Then some emergency cases enter the OR and the previous schedule (flow of patients) is rescheduled to minimise robustness, stability, and nervousness through the plan in order to obtain a robust schedule. This paper deals with a multiobjective fuzzy surgical case scheduling problem consisting of two stages; in the first stage all patients are elective and are scheduled with fuzzy duration times, and in the second stage, after arriving emergency patients, the previous plan is rescheduled online. We provide a contribution in the field of operations research technique to employ available resources and make surgical case schedule by minimising fuzzy makespan of operating theatre and the number of the nonscheduled surgical cases under open scheduling policy in the first stage, and then in addition to fuzzy makespan, the robustness, stability, and nervousness of primary schedule are minimised. The following contributions to the literature are offered:

- The online SCS as a topic with three novel objective functions for online scheduling: optimisation of robustness, stability, and nervousness is extended. Also, to characterise the problem under uncertain conditions, the fuzzy processing times of all operations in each stage are applied. Therefore, the fuzzy computations are used based on fuzzy logic.
- Also, a novel approach for solving the first stage (FPESAS) and for solving the robust stage (MMAS) is developed.

The next sections are described as follows. In Section 2, we present different research related to surgical case scheduling. In Section 3, the assumptions of the problem are stated and a two-stage advanced ant system, in order to achieve a better algorithm among other algorithms, is proposed. Section 4 provides illustrative data as well as problems and computational experiments, and lastly, we conclude and present our suggestions for future research in Section 5.

2. Background and Related Work

In this section, we focus on the scope of the SCS problem, and the details of SCS are described into three parts that consist of the surgical process and parameters of surgery in the operating room; performance indicators in the operating room; policies of handling the emergency cases. Then, some papers are listed, and the pros and cons are described and, lastly, the general approaches to solving the problem are introduced. The surgical process includes of PHU, surgery, and PACU. Also, the patient as the input of the system is divided into the elective and nonelective cases. An elective case is a patient that is scheduled in advance by determining multiresources as well as the start time of the case, while an emergency case that may arrive randomly on the day of surgery, requires to be performed online on the same day. Also, two stages consisting of surgery and PACU are considered to model the OR problem in some research (Fei et al., 2010; Lee and Yih, 2014; Marques and

Captivo, 2017). In the literature of ORs, upstream units comprise PHUs and wards, while PACUs, and intensive care units (ICUs) are put in downstream units. Multiple operating rooms connect upstream to downstream units (Fügener et al., 2014). Some researchers concentrated on all stages of the surgical processes in ORs (Saremi et al., 2013; Xiang et al., 2015) and among all studies, very few researchers modeled the problem considering elective and nonelective patients during all stages of ORs under uncertain condition (Saremi et al., 2013; Gür et al., 2023), and we focus on optimisation of upstream resources in addition to the second and third stages of surgery taking elective and emergency cases using fuzzy times.

To measure operating room planning and scheduling, eight main performance indicators have been used in literature; waiting time, utilisation, levelling, throughput, patient deferrals, makespan, preferences, and financial measures Wang et al., 2021). On the other hand, some research considered various objectives in multiobjective SCS. In the model of (Saremi et al., 2013; Xiang et al., 2015), makespan is optimised. We can observe that makespan is considered as a key criterion in more research, but no recent studies have focused on a robust Pareto-based multiobjective SCS considering novel objectives in addition to classic indicators that we study. To the best of our knowledge, the simultaneous optimisation of makespan, robustness, stability, and nervousness for Pareto-based robust scheduling has not been studied in any SCS problem. There are three policies for handling emergency cases in the operating room: the dedicated, flexible, and hybrid strategy (Wang et al., 2023). In the dedicated, one or more ORs are dedicated to some patients who may be emergency cases, while in the flexible, no ORs reserved for patients and also there are two options: (i) an amount of slack is deduced from the total capacity, (ii) emergencies are inserted directly through the primary plan. In the literature, the flexible policy is concentrated more than a dedicated strategy since this incurs more cost to the hospital. The second type of flexible policy is considered in some types of research (Stuart and Kozan, 2012). On the other hand, although there are some papers regarding robust operating room scheduling (Rachuba and Werners, 2017; Marques and Captivo, 2017), only Stuart and Kozan, (2012) concentrated on the robust schedule after rescheduling. Therefore, this research is the first work in which the primary plan is rescheduled considering the flexible policy (option 2) using the fuzzy time to achieve a robust schedule. There are some studies that incorporate fuzzy data in modelling the scheduling problems such as flexible job shop (Lin, 2015) instead of stochastic since the former data reduces the computational difficulties and the latter data increases the complexity of the problem. On the other hand, fuzzy set or the human-originated data can be used in scheduling problem like flexible job shop when we envisage with incomplete/imprecise information or ill-known durations (Gonzalez-Rodriguez et al., 2008a, 2008b; Wang, 2022) it may, in some ORs, there is not a precise dataset

of surgical times, and hence, employing fuzzy data would be better to represent scheduling under uncertain condition.

To tackle the operating room scheduling problem, some exact (Bargetto et al., 2023), heuristic or meta-heuristic algorithms such as Tabu search (Saremi et al., 2013;), NSGA-II from genetic algorithm group (Marques and Captivo, 2015), Monte-Carlo along with genetic algorithm (Lee and Yih, 2014), column generation based heuristic (Fei et al., 2010), artificial bee (Lin & Lee, 2021; Yang et al., 2023), and ant colony optimisation (Xiang et al., 2015, Behmanesh et al., 2020) were developed to achieve optimal or near-optimal solutions. In this paper, we extend the MOSCS (Behmanesh and Zandieh, 2019). The model is extended by arriving the nonelective patients so that this model is rescheduled after inserting the emergency cases into the primary plan in order to present a robust multiobjective schedule. Then the problem is solved by developing the ACO algorithm in two stages; the first problem before rescheduling is tackled by a fuzzy Pareto-envelope based selection ant system, and the second problem after rescheduling is solved by fuzzy Max-Min ant system.

3. Fuzzy Two-Stage Advanced Ant System (FTSAS)

In the addressed problem, there is a set of elective surgical cases to be operated on the combination of available required resources, including nurses, anaesthetists, surgeons, and beds in each stage. These cases are scheduled in order to the optimisation of the makespan as well as throughput, and this is called the primary schedule. The duration times of the surgical cases on the required resources are assumed to be the triangular fuzzy number (TFN). To solve the two-stage problem, we clarify our novel method in which, we apply a fuzzy Pareto envelope-based selection ant system (FPESAS) developed by Behmanesh and Zandieh (2019). The FPESAS algorithm is applied to solve the first stage of the problem to optimise the makespan and throughput, before the arrival of the emergency cases. However, to tackle the second stage, we develop another algorithm without domination rule. The proposed algorithm is displayed in Fig. 2.

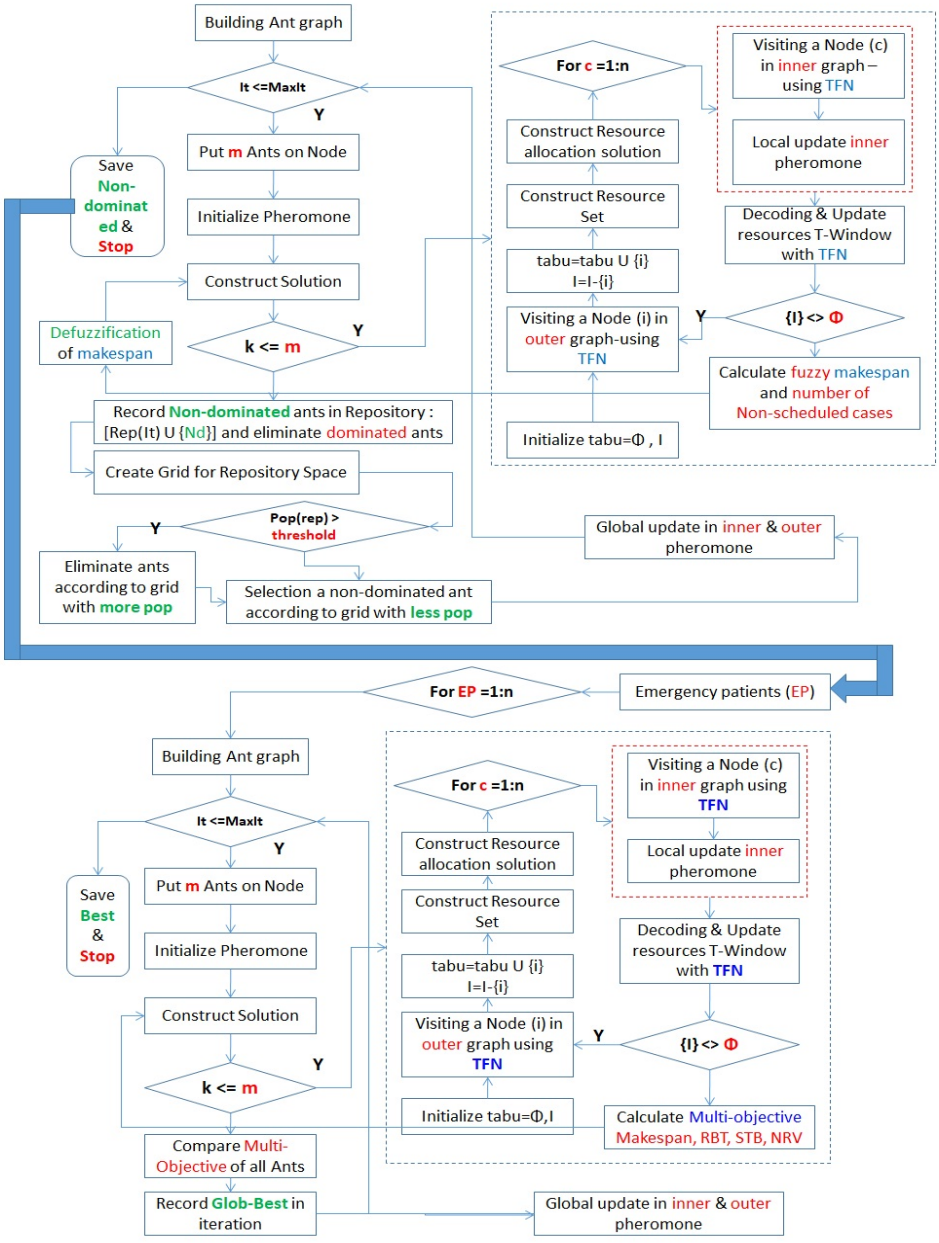

Figure 2. Algorithm of two-stage advanced ant system
Source: authors' work.

The pseudocode of the proposed two-stage algorithm is displayed as follows:

Algorithm1. Two-stage advanced ant system (fuzzy-PESAS + MMAS)

1. Input: an instance MOSCS

2. First stage : scheduling by fuzzy PESAS algorithm

3. Initialize Pheromone Values (τ_0, in_τ_0, in_λ_0, q_0) and other parameters (*it,m*), *rep-size*, *nGrid,* β', α', γ, β, α, ρ

4. While iteration termination condition not met ($i < it$) **do**

5. Put *m* ants on an arbitrary node (surgical case)

6. Construct an ant solution with a *fuzzy start time of resources (0,0,0)* and *surgeon (blocking strategy)*

7. **While** ant termination condition not met, $k < m$ **do**

8. Initialize tabu:= φ ; surgical cases (SC):= *I*

9. Construct an ant solution by visiting a node *i* in the outer graph according to the transition rule

10. $tabu = tabu \cup \{I_i\}$

11. $I = I \backslash \{I_i\}$

12. Determine *fuzzy start time (ST)* and *end time* (*ET*) of each *SC* according to the no-wait

13. Determine available resources (set *AR*) for surgical case

14. Ant enters into the inner graph and constructs resource set G

15. Construct a resource allocation ant solution

16. **For** each resource type *t* **do**

17. Construct an ant solution by visiting a node *tm* in the inner graph according to the transition rule

18. Local update inner pheromone trial

19. **End for**

20. Update fuzzy time window of occupied resources

21. End while

22. Calculate bi-objectives (*fuzzy makespan, non-scheduled cases*) for an ant solution and defuzzification

23. Determine and record non-dominated ant solutions in Repository according to **FPESAS**

24. Eliminate dominated ant solutions inside the Repository (**FPESAS**)

25. Update grid according to (**FPESAS**)

26. **If** current rep-size > rep-size **then**

27. Delete Pareto point from cell selected with more points

28. **End if**

29. Select Pareto point from cell selected with fewer points in order to update Pheromone (diversification) using rules of Max-Min ant system

30. Global update in both outer and inner pheromone trial

31. End while

32. Return the best Pareto solution found, point solution with more domination (**BestAnt**)

33. Second stage : re-scheduling output of the first stage (BestAnt) by fuzzy MMAS algorithm

34. **Input**: scheduled SCS problem with assigned resources and

Algorithm1. Two-stage advanced ant system (fuzzy-PESAS + MMAS)

sequenced surgical cases (**BestAnt**);
emergency surgical cases with emergency data such as fuzzy inserting time according to Poisson distribution
with poissrnd (lambda, number of emergencies) and fuzzy processing time, and surgeon group
35. **For** *Emergency* = 1 to *n* **do**
36. Discriminate planned and unplanned SCs after inserting emergency SC (**Algorithm2**)
37. Adding emergency to unplanned SCs as new SCS problem
38. Initialize Pheromone Values ($\tau_{min}, in_\tau_{min}, \tau_{max}, in_\tau_{max}$) and parameter (*it,m)*
39. **While** iteration termination condition not met ($i < it$) **do**
40. Run same lines 4 to 22
41. Calculate multiobjectives *Z* (*makespan, RBT, STB, NRV*) for an ant solution
42. Compare iteration based best ant solution, record its tabu as the global best solution
43. Primary update in outer pheromone trial
44. Global update in both outer and inner pheromone trial
45. **End while**
46. Attach rescheduling output {new [URA (Resource allocation for unplanned cases),
US (sequence for unplanned cases)]} on planned SCs {RA, S}
47. **Plot related graphs (**Gantt chart, convergence**)**
48. **Return** the best solution found as new scheduled output for going to line 37 or exit from loop
49. End for
50. Return the best solution found (final best ant solution)

After insertion of emergency patients, two sets of planned cases and unplanned cases should be discriminate for rescheduling and this is displayed in the following Pseudocode:

Algorithm2. Discriminate planned and unplanned SCs after inserting emergency SC

1. Input: scheduled SCS problem (Sequence, Resource allocation($\widetilde{ST}_{ij}$, $\widetilde{ET}_{ij}$, Resource tag),
Emergency data (fuzzy insert time, fuzzy processing time, surgeon group))
2. **Set** URA:= φ, US:= φ, RA:= {Resource allocation}, S:= {Sequence}, SC:= {Number of planned patients}
3. **For** *i*=1 to *SC* **do**
4. **If** fuzzy insert time of emergency <= $\widetilde{ST}_{i1}$ **do**
5. $URA = URA \cup \{RA_i\}$, $RA = RA \backslash \{RA_i\}$
6. $US = US \cup \{S_i\}$, $S = S \backslash \{S_i\}$

Algorithm2. Discriminate planned and unplanned SCs after inserting emergency SC

7. **End if**

8. **End for**

9. Return sets $\{URA\}$, $\{US\}$, $\{RA\}$, $\{S\}$

It must be noted that a single objective (Z) is formulated using the integration of four objectives; new makespan after arrival emergency case (C_{max}), robustness (RBT), stability (STB), and nervousness (NRV) of rescheduled patients. All objectives in model are described as following:

$$RBT = |OC_{max} - C^{S}_{max}| \ , \qquad S = scenario\ of\ reschedule \tag{1}$$

$$STB = \sum_{i=1}^{n}\sum_{j=1}^{3}\left|CT_{ij} - CT^{S}_{ij}\right| \tag{2}$$

$$NRV = \sum_{i=1}^{n}\sum_{j=1}^{3}\left|position(SC_{ij}) - position(SC^{S}_{ij})\right| \tag{3}$$

$$Z = \alpha.C_{max} + \beta.RBT + \gamma.STB + \varphi.NRV \tag{4}$$

$$Z = \alpha\frac{(C_{max} - C^{opt}_{max})}{C^{opt}_{max}} + \beta\frac{(RBT - RBT^{opt})}{RBT^{opt}} + \gamma\frac{(STB - STB^{opt})}{STB^{opt}} + \varphi\frac{(NRV - NRV^{opt})}{NRV^{opt}} \tag{5}$$

where RBT describes the difference between the new makespan after the arrival of the emergency case (C^{S}_{max}) and makespan of old schedule before inserting the emergency case (OC_{max}). STB denotes the difference between the completion time of each surgical case for each stage before (CT_{ij}) and after the insertion of the emergency case (CT^{S}_{ij}). NRV is defined with the difference between positions of each surgical case in the schedule before the arrival of the emergency case and rescheduling after inserting the emergency case. Also, Z in Equations (4) and (5) is the total absolute and relative objective, respectively.

4. Computational Experiments

4.1 Illustrative Examples

To assess the proposed algorithm, the test cases are classified into two parts: the first data for scheduling elective patients; the second data for rescheduling the primary plan after arrival emergency cases. The first data is provided according to the test cases those were applied to evaluate the FPESAS (Behmanesh and Zandieh, 2019), and the second data is simulated as shown in Table 1. As it is displayed, the problems (column 1) are corresponding to nine elective problems, the inserting order (column 2) shows the various insertion of cases in different times, the inserting time (column 3) presents the TFN time of arriving the nonelective patient that is generated by Poisson distribution, the surgical case number (column 4) shows the number of emergency cases that are inserted in plan based on their TFN time, and the number of surgeons in operating room is presented in column 5.

Table 1. Test emergency cases for rescheduling phase

Problem	Inserting Order	Inserting Time	Surgical Case Number	Surgeon Specialty Number
1	0	0	8	5
	1	(89,110,131)	1	
2	0	0	10	6
	1	(23,46,62)	1	
3	0	0	10	6
	1	(12,15,18)	1	
	2	(75,115,158)	1	
4	0	0	15	6
	1	(36,46,57)	1	
	2	(141,166,199)	1	
5	0	0	20	10
	1	(27,40,50)	1	
	2	(106,126,140)	1	
6	0	0	20	10
	1	(49,66,89)	1	
	2	(81,90,100)	1	
	3	(270,300,318)	1	
7	0	0	30	10
	1	(200,220,250)	1	
	2	(250,280,310)	1	
8	0	0	30	12
	1	(210,230,260)	1	
	2	(270,290,320)	2	
9	0	0	30	12
	1	(180,200,215)	1	
	2	(260,280,295)	2	
	3	(300,315,340)	1	

Source: authors' work.

The algorithms were coded in MATLAB language and ran on an Intel Core (TM) Duo CPU T2450, 2.00 GHz computer with 1 GB of RAM.

4.2 Parameter Tuning for the Proposed Algorithm

There are various parameters in general single-objective ACO algorithms that are effective in the performance of the algorithm. The most parameters of FPESAS-MMAS are presented in Table 2.

Table 2. Parameters of algorithms

Description of parameters
the number of the ants (m)
the number of the iteration (*Max-It*)
evaporation rate (ρ)
importance factor of pheromone (α)
importance factor of heuristic information (β)
inner resource-related pheromone (λ_0)
decremented pheromone value (q_0)
the selection pressure of the cell for pheromone updating ($\acute{\beta}$)
the selection pressure of the cell for eliminating (γ)
the number of the grid per each objective (*nGrid*)
inflation rate for the grid ($\acute{\alpha}$)

Source: authors' work.

The parameters of the FPESAS were set based on the values of the algorithm since the same data were provided for the first stage of the problem. Besides, the experiments were designed to set parameters of algorithms for solving the second stage of the problem in each case separately. The final setting parameters of each algorithm for three cases are displayed in Table 3.

Table 3. Setting parameters of algorithms for solving the second stage of the problem

Case no.	Algorithms of Stage #2	(max-it , m)	q_0	λ_0	α	β
1	AS	40-60	0.1	4	0.9	5
	MMAS	40-60	0.4	5	0.9	2
2	AS	50-80	0.1	4	0.9	5
	MMAS	50-80	0.4	5	0.9	2
3	AS	60-100	0.1	4	0.9	5
	MMAS	60-100	0.4	5	0.9	2

Source: authors' work.

4.3 Evaluation of the Proposed Algorithm's Performance

After the parameter tuning for the algorithms, two algorithms are run 10 times for each problem. The computational results corresponding to the robust multiobjective value (Z) obtained by two algorithms for small to large size problems. We designed two-factor factorial experiments for examining the effect of the two

solution algorithms and nine test instances on each of the three performance evaluation metrics, with 10 times runs in order to analyse these results. Table 4 indicates the performance of our proposed algorithm (PESAS-MMAS) in comparison with PSACO-ACO as a traditional method for all problems after rescheduling. The first and second columns display considered test problems and approaches, respectively. The next three columns represent the average, best, and worst of the multiobjective value (Z) for solutions obtained.

Table 4. Comparison of the performance of the algorithms on all instances after rescheduling

Problems	Method	Multiobjective (Z)		
		Average	Best	Worst
Instance1	PESAS	**0**	**0**	**0**
	PSACO	0.0089	0	0.0178
Instance2	PESAS	**0.0253**	**0.0253**	**0.0253**
	PSACO	0.0713	**0.0253**	0.303
Instance3	PESAS	**0.0764**	**0.0614**	**0.1366**
	PSACO	0.2472	0.1724	0.379
Instance4	PESAS	**0.298**	**0.277**	**0.343**
	PSACO	0.76	0.717	0.829
Instance5	PESAS	**0.472**	**0.449**	**0.508**
	PSACO	0.891	0.787	1.047
Instance6	PESAS	**0.127**	**0.123**	**0.134**
	PSACO	0.59	0.562	0.628
Instance7	PESAS	**0.682**	**0.594**	**0.84**
	PSACO	1.12	0.801	1.61
Instance8	PESAS	**0.803**	**0.775**	**0.845**
	PSACO	1.46	1.17	2.36
Instance9	PESAS	**0.934**	**0.806**	**1.02**
	PSACO	1.493	1.06	2.03

Source: authors' work.

The ANOVA test results for robust multiobjective (Z) as a response variable are displayed in Table 5. According to the P-value for both the main effect of the algorithm and instance problem, it is observed that these factors affect the response, significantly. Additionally, the interaction effect of algorithms and problems is significant. Fig. 3 indicates that the proposed FPESAS-MMAS outperforms PSACO-ACO on each instance since the proposed method obtains better solutions compared to the traditional algorithm.

Table 5. ANOVA result for multiobjective

Source of variation	DF	SS	MS	F	*P*-value
Algorithm	1	5.7985	5.7985	226.29	0.000
Problem	8	33.2006	4.1501	161.96	0.000

Source of variation	DF	SS	MS	F	*P*-value
Interaction	8	2.092	0.2615	10.21	0.000
Error	162	4.1511	0.0256		
Total	179	45.2422			

Source: authors' work.

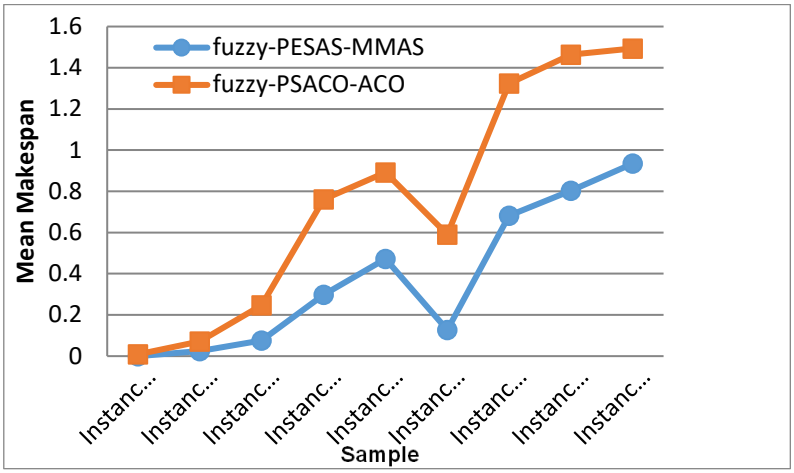

Figure 3. Interaction between the algorithms and test problems for the multiobjective
Source: authors' work.

5. Conclusions

In this paper, we address the robust operating room scheduling so that some emergency cases are inserted into the plan and this is rescheduled under uncertainty using TFNs. There are non-traditional objectives such as robustness, stability, and nervousness in addition to the fuzzy makespan and the throughput in the second stage of the problem. To tackle the NP-Hard multiobjective fuzzy surgical case scheduling problem, a two-stage advanced ant system is developed. Our methodology is based on ACO algorithms, in which the FPESAS is applied to solve the first stage of the problem and the MMAS algorithm is used to solve the second stage of the problem. To illustrate the proposed method, we provided nine instances of data for both elective and nonelective cases. The proposed algorithm is compared with a traditional method in all cases. Consequently, it can be observed that our proposed algorithm outperforms PSACO-ACO in accordance with the results. Lastly, we suggest some directions as opportunities for future research in this scope. Considering constraints such as the priority of the elective cases as well as dual resource-constraint in the operating room are essential for a real-world surgical case schedule. Moreover, the pheromone updating approach in the ACO algorithm can be developed using the fuzzy parameters to improve the diversification mechanism of

the algorithm. For this aim, in future research, a fuzzy ACO is developed in order to solve the MOSCS problem considering the priority with fuzzy durations.

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