applied system innovation

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A Novel Hybrid Simulated Annealing for No-Wait Open-Shop Surgical Case Scheduling Problems

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Abstract: In this paper, the problem of finding an assignment of "*n*" surgeries to be presented in one of "*m*" identical operating rooms (ORs) or machines as the surgical case scheduling problem (SCSP) is proposed. Since ORs are among NP-hard optimization problems, mathematical and metaheuristic methods to address OR optimization problems are used. The job or surgical operation ordering in any OR is a permanent part of all sequencing and scheduling problems. The transportation times between ORs are defined based on the type of surgical operations and do not depend on distance, so there is no surgical operation waiting time for transferring. These problems are called no-wait open-shop scheduling problems (NWOSP) with transportation times. The transportation system for the problems is considered a multi-transportation system with no limitation on the number of transportation devices. Accordingly, this study modeled a novel combined no-wait open-shop surgical case scheduling problem (NWOSP-SCSP) with multi-transportation times for the first time to minimize the maximum percentile of makespan for OR as a single objective model. A mixed-integer linear program (MILP) with small-sized instances is solved. In addition to the small-sized model, a novel metaheuristic based on a hybrid simulated annealing (SA) algorithm to solve large-sized problems in an acceptable computational time is suggested, considering the comparison of the SA algorithm and a new recommended heuristic algorithm. Then, the proposed hybrid SA and SA algorithms are compared based on their performance measurement. After reaching the results with a numerical analysis in Nova Scotia health authority hospitals and health centers, the hybrid SA algorithm has generated significantly higher performance than the SA algorithm.

Keywords: hybrid meta-heuristic simulated annealing algorithms; operating rooms; no-wait open-shop surgical case scheduling problem; makespan; transportation time; mixed integer linear programming; heuristic algorithm

Citation: Rahimi, A.; Hejazi, S.M.; Zandieh, M.; Mirmozaffari, M. A Novel Hybrid Simulated Annealing for No-Wait Open-Shop Surgical Case Scheduling Problems. *Appl. Syst. Innov.* **2023**, *6*, 15. https://doi.org/10.3390/asi6010015

Academic Editor: Christos Douligeris

Received: 30 November 2022
Revised: 15 January 2023
Accepted: 16 January 2023
Published: 17 January 2023

1. Introduction

There are various decision stages in OR scheduling and planning. These decision stages can be classified as strategic, tactical, or operational.

The strategic stage contains long-term decisions such as capacity planning and allocation, which usually takes a long time. A problem within the strategic level is called a "case mix problem (CMP)", in which the amount of time in OR devoted to a surgical department is defined to optimize profit/cost over a long period. Decisions such as the number and departments of surgeries to be developed and the number of resources involved could be classified into the strategic stage. The time frame of these decisions usually takes from several months to 1 year or longer.

Problems with cyclic OR schedules, such as master surgical scheduling, are classified at the tactical stage. In tactical stage problems or "master surgery scheduling (MSS) problems", surgical specialties over the scheduling window (medium time horizon) are designated to the OR's time slot to optimize and level resource utilization. The tactical stage (cyclic timetable) output as training is applied for decision-making in operational problems. MSS is recognized as a cyclic schedule, and it is usually monthly or quarterly. MSS allocates OR time to specialties corresponding to their specific conditions.

The last decision stage considered in this study, the operational stage, is recognized as the SCSP. In SCSP, scheduling resources and patients are usually planned, and surgical cases are scheduled for specific days and times. It is the shortest and involves resource allocation, surgical cases, and advanced scheduling decisions.

Production scheduling is a key to structural productivity, which organizes a calendar for making components/products. The scheduling problems are categorized into single machine scheduling problems (SMSP), flow shop scheduling problems (FSSP), job shop scheduling problems (JSSP), open shop scheduling problems (OSSP), and hybrid scheduling problems (HSP). In this paper, the OSSP problem is considered. The OSSP is also called moderated-JSSP between the FSSP and JSSP. The FSSP contains "n" jobs, each with "m" operations. The process sequences of these jobs are the same for this problem. The OSSP consists of n jobs, each with at most m operations. The operations of each job can be managed in any sequence. If a job consists of three operations of 1, 2, and 3, then this job can be controlled by employing any one of the following six sequences, which is n: Sequence 1: 1–2–3; Sequence 2: 1–3–2; Sequence 3: 2–1–3; Sequence 4: 2–3–1; Sequence 5: 3–1–2; and Sequence 6: 3–2–1.

This study considers the OSSP with transportation times to minimize the makespan. The number of machines or ORs is described by the parameter m, and the subscripts related to the ORs are i and l, in such a way $i \in (1, 2, \ldots, m)$. Given that in an open shop scheduling problem, sequencing is not simple, and each operation can be processed on any OR, the subscript l is used to express the arrangement of ORs in parameters and decision variables. Thus, $l \in (0, 1, 2, \ldots, m)$, in which zero-OR is a virtual OR. Figure 1 shows the suggested approach.

		Start Machine	Destination Machine	Jobs 1	2	3	....	n
		1	2	T_{121}	T_{221}	T_{321}	T_{j21}	T_{n21}
		1	3	T_{131}	T_{231}	T_{331}	T_{j31}	T_{n31}
	m-1	1	. . . .	T_{1i1}	T_{2i1}	T_{3i1}	T_{ji1}	T_{ni1}
		1	m	T_{1m1}	T_{2m1}	T_{3m1}	T_{jm1}	T_{nm1}
		2	1	T_{112}	T_{212}	T_{312}	T_{j12}	T_{n12}
		2	3	T_{132}	T_{232}	T_{332}	T_{j32}	T_{n32}
m	m-1	2	. . . .	T_{1i2}	T_{2i2}	T_{3i2}	T_{ji2}	T_{ni2}
		2	m	T_{1m2}	T_{2m2}	T_{3m2}	T_{jm2}	T_{nm2}
		. . . .	. . . .	T_{1il}	T_{2il}	T_{3il}	T_{jil}	T_{nil}
		m	1	T_{11m}	T_{21m}	T_{31m}	T_{j1m}	T_{n1m}
		m	2	T_{12m}	T_{22m}	T_{32m}	T_{j2m}	T_{n2m}
	m-1	m	. . . .	T_{1im}	T_{2im}	T_{3im}	T_{jim}	T_{nim}
		m	m-1	$T_{1(m-1)m}$	$T_{2(m-1)m}$	$T_{3(m-1)m}$	$T_{j(m-1)m}$	$T_{n(m-1)m}$

Figure 1. Parameter T_{jil}.

The n parameter exemplifies the number of jobs or surgical operations, and the subscript of the surgical operations are j and k, in such a way that $j \in (1, 2, \ldots, n)$. Given that in the OSSP, the scheduling of surgical operations on ORs is still being defined, the planner's responsibility, subscript k, is to express surgical operations' chronology in the parameters and decision variables. Therefore, $k \in (0, 1, 2, \ldots, n)$, in which zero-surgical operation is a simulated surgical operation for the model.

One of the primary conditions of the scheduling problem is the parameter of processing time that is characterized by P_{ji} and is the concept of processing time of j on OR i; it is designed by O_{ji}. In this research, it is believed that the number of operations is equal to the number of $m \times n$; this means that all surgical operations on all ORs perform just one operation, with the processing time of $P_{ji} \neq 0$.

T_{jil} parameter identifies the transportation time of surgical operation j from OR one to OR i, and the amount of data in each problem is $(m-1) \times m \times n$.

The structure of this paper is as follows.

The literature review is provided in Section 2. A flowchart of the proposed heuristic algorithm and problem assumptions are presented in Section 3. The scheduling problem modeling with the multi-transportation system is discussed in Section 4. The comparison of SA metaheuristic algorithm and the heuristic algorithm in this study is considered in Section 5. The hybrid SA algorithm is presented in Section 6. Numerical analysis in Nova Scotia health centers is considered in Section 7. The comparison of the hybrid SA algorithm and the SA algorithm is discussed in Section 8. Finally, the conclusion is given in Section 9.

2. Literature Review

The constant increase in patients and surgeries requires additional unconventional techniques to develop efficiency, particularly in creating ORs [1,2]. ORs are one of the most significant customer services that require high-cost resources, including human resources, equipment, and medicine [3]. The surgery takes place in a setting of challenging advancements such as vital expenditure on health care [4,5], growing fees in health care costs [6], rising surgery demand caused by aging people, and industrial developments that have increased the range of surgical interventions [7]. OR surgery scheduling deals with characterizing the operation start times of surgeries and allocating the proposed sources to the scheduled surgeries. This allows for several constraints to secure a comprehensive surgery flow, source availability, and specialty supplies of human sources [8,9]. The suggested mission plays an essential role in maintaining timely medications for the patients by maintaining the stability of the hospital's source operation [10]. Current patient scheduling is necessary for operation research, such as multi-objective optimization. Several operation research methods [11–13], such as a discrete-event simulation model [14] and an optimization-based scheduling tool [15], are used to decrease the size of the patient wait list significantly [16]. To simplify the scheduling process, a general method is used to schedule the venesection and clinic visit one day and the infusion the following day [17].

Sequencing and scheduling are critical decision-making processes in developing efficiency in manufacturing and services industries such as healthcare. Scheduling is a decision-making process that allocates resources to activities in given time intervals and optimizes one or more objects [18]. Some researchers detected any scheduling problem as having one of three characteristics: the machine environment, problem conditions, and the objective function of a problem [19–22]. In the first field, the background of the problem is stated [23,24]; in the second field, the acronyms suggest the condition of the problem; and in the third field, the objective function of the scheduling problem is resolved. The second and third fields have numerous modes [25]. A scheduling problem is illustrated with the triple $\alpha|\beta|\gamma$. Field α defines the machine environment and only contains one input. Field β includes details of process types and constraints without input or with one or more inputs. Field γ defines the object which should be minimized and often has one input [26,27]. The initial study [28], which offered a solving algorithm for the open-shop problem, recommended a linear time algorithm to solve open-shop problems with two machines. The objective function is minimizing the makespan. They also created a polynomial algorithm for the case where the shop has more than two machines. Preemptions are not allowed to minimize the makespan, which has been applied in several studies [29–35]. Optimal finish time (OFT) is used in different scheduling problems to find the OFT of open-shop problems and offers a linear time algorithm to see the OFT of open-shop problems with two machines [36–39]. Preemptions were permitted to find the OFT of open-shop problems with more than two machines [40–42]. In these problems, it is believed that the number of operations with a non-zero processing time is more than the number of machines and jobs [43]. Some methods offered a heuristic algorithm for solving the open-shop problem with two machines and transportation times [44–50]. In another suggested model, the transportation time between machines, as a fixed one, was described and associated with a delay time between the completion time of one operation and the start time of the following operation on the same job [51]. The problem of an open shop with two machines and different transportation times was suggested. Two solution methods were provided; a linear time algorithm for a problem case is expected. The transportation times between machines were less than the minimum tasks' processing times. Heuristic algorithms for a problem case in transportation times are process-dependent. They considered transportation times independent of the jobs but dependent on the route. It was believed that the transportation times depended on the distance between the shops and not on the size or weight of the jobs [52–54]. For the first time, transportation problems are divided numerically [55]:

- Problems in which the number of transportation is more than or equal to the number of jobs.
- Problems in which only one transportation can manage the jobs.

They examined complexity and the results of scheduling problems in the flow shop and open shop (limited machine numbers) with transportation times; in their research, the most complex issue of the open shop was finally solved with two machines. In the multi-transportation system, there is no limitation on the number of transportation; in other words, there is no expected time or delay for transferring any halfway job from one machine to the next, and transportation is always available. In scheduling problems, based on the transportation times, there are two modes:

- If transportation times depend only on distance (*JITT*).
- If transportation times depend on the job sequences in addition to distance (*JDTT*). In this case, the job transmitted earlier affects the transportation time of the present job [56]. Since *JITT* is a specific case state of the *JDTT* problem, the complexity hierarchy rule demonstrates that by solving *JDTT*, we have also responded to the *JITT* problem, so verifying the *JDTT* case state is enough [57].

The transportation system in our research is based on Naderi et al. [58]. The transportation times are dependent on jobs. According to the problem's NP-hardness and the development of the above problem in this study, the present problem is also NP-hard. Optimization approaches [59–62], including heuristic and meta-heuristic algorithms [63–67] and recently recommended well-known hybrid methods [68–73], are used to solve the model.

Many resources in OR are used in mathematical modeling. There are two kinds of patient arrival: elective and non-elective. Elective patients can be scheduled, while non-elective patients require surgery instantly. Considering inpatients admitted for an overnight stay, different resources, such as a post-anesthesia care unit (PHU), an OR, and intensive care units, could be applied. Measuring performance could expand to services other than an OR, such as ward, PHU, post-anesthesia care unit (PACU), and intensive care unit (ICU) [74–78]. Figure 2 shows a three-step surgery procedure with the following steps: (1) pre-operative step, in which the required resources are nurses and PHU; (2) intra-operative, which is the step in which surgery will be accomplished. Surgeons, anesthetists, nurses, and ORs are required in this step. (3) Post-operative step, patients are shifted to the PACU and ICU following surgery [78].

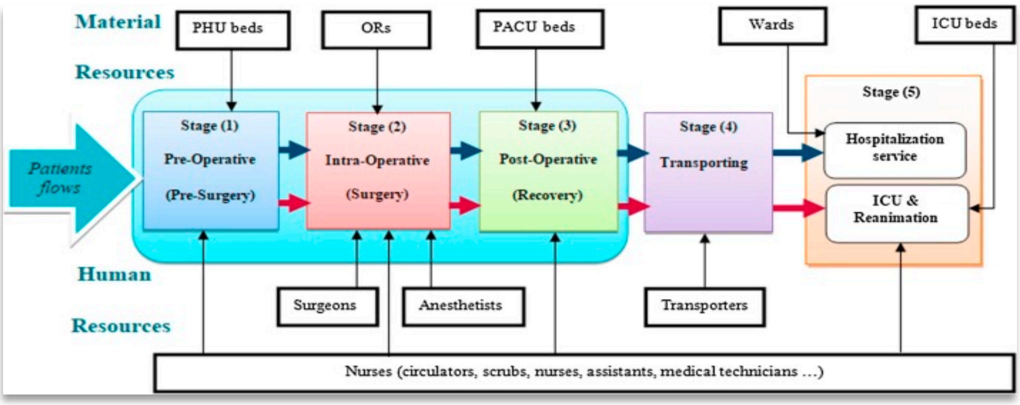

Figure 2. The three stages of the surgical process and its involved resources [78].

This paper considers a single-objective optimization OR problem. Thus, we want to show solution approaches for single-objective optimization OR problems. Figure 3 categorizes optimization approaches that have been applied to OR scheduling problems. For solving OR scheduling problems, exact, evolutionary, and intelligent algorithms (such as mathematical programming, simulation, heuristic, and meta-heuristic), known as NP-hard problems, are used [79]. For example, genetic algorithm (GA), non-dominated sorting GA II, the combination of greedy and novel meta-heuristics, SA, hybrid SA, a single-objective ant colony optimization (ACO), and a hybrid Pareto set ACO under deterministic conditions were previously applied to solve the problem. The lion optimization algorithm (LOA) and Harris hawk optimizer (HHO) are two novel population-based metaheuristics algorithms suggested for future studies. Mathematical programming or exact algorithms usually refer to solutions that always find optimal solutions. These approaches are typically applied to small-size cases unless specific mathematical methods appropriate in large-scale cases are used, such as Bender's decomposition algorithm [17,80].

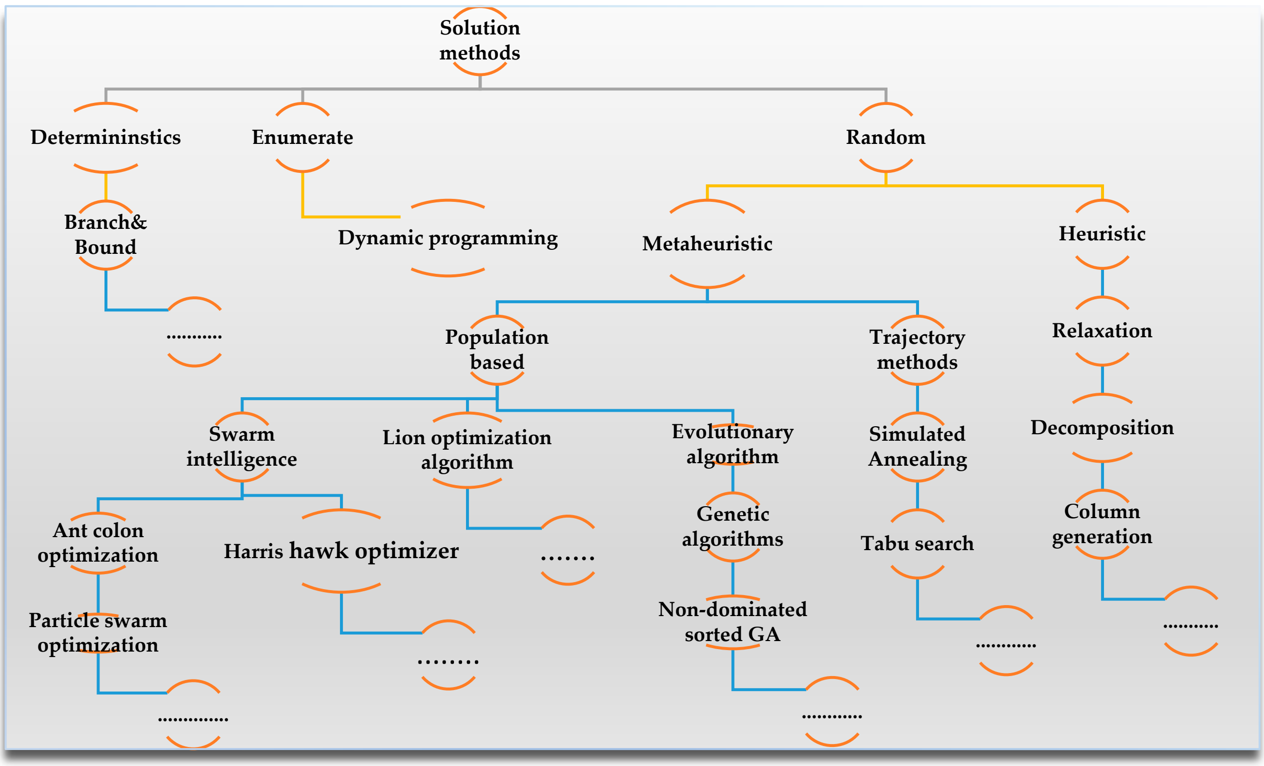

Figure 3. Organizations of different single-objective solution methods for OR scheduling problems [17].

3. Flowchart of the Proposed Heuristic Algorithm and Problem Assumptions

In this research, based on the following 8 steps of Figure 4, a novel heuristic algorithm is proposed to solve a novel NWOSP-SCSP approach based on an $O|TTJD, MT|C_{max}$ problem:

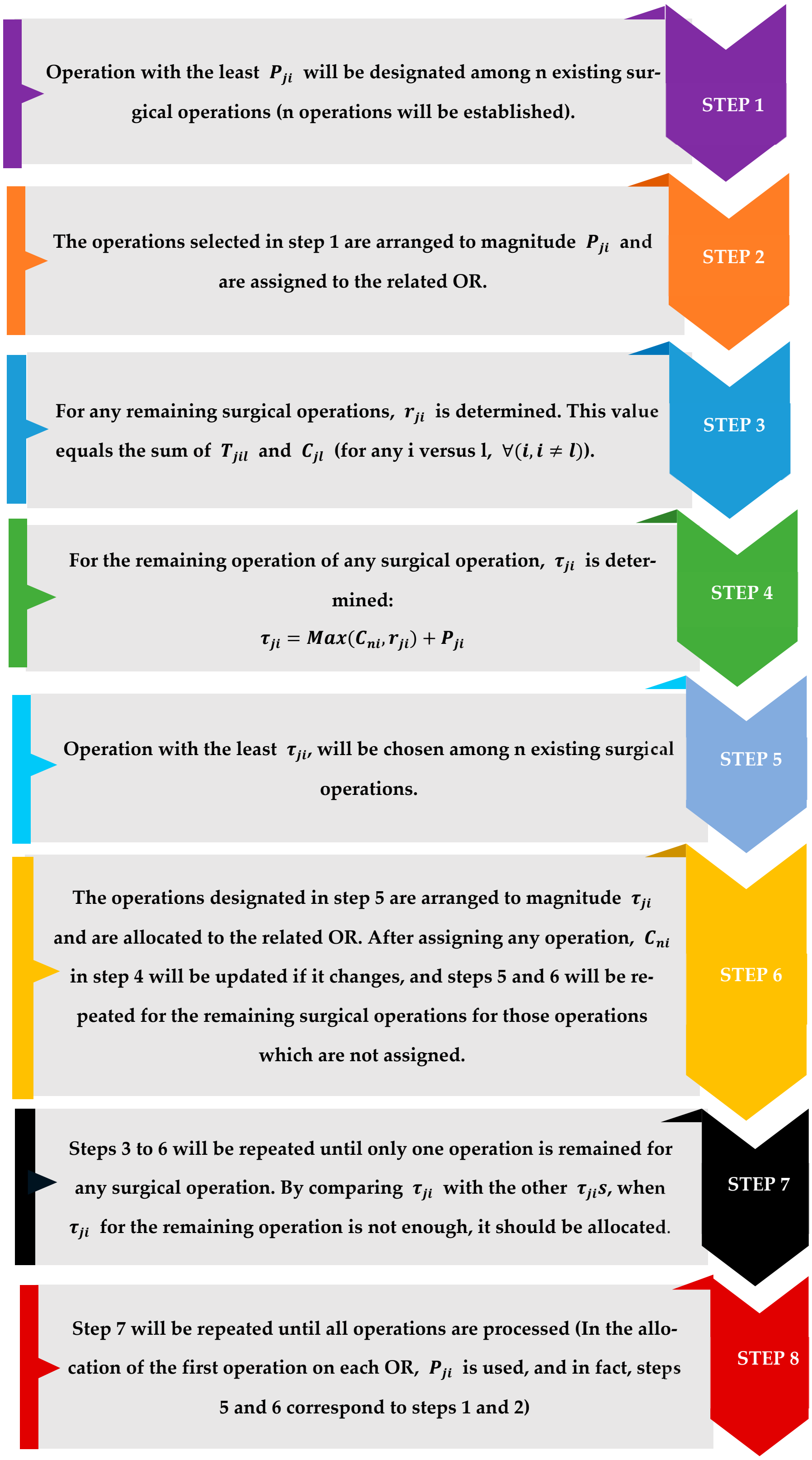

Figure 4. Flowchart for 8 steps of the suggested heuristic algorithm to solve the $O|TTJD, MT|C_{max}$.

It is included in the assumptions that all surgical operations are available for processing at zero time. All ORs are available throughout production. ORs have no breakdown. There is no maintenance activity. Each OR can simultaneously operate at least one surgical operation. Each surgery operation can be processed at a maximum of one OR at a time. All surgery operations are processed precisely once per OR. After the end of each operation, the surgery operations are released and can perform the next operation. All surgery operations are independent (sequencing does not affect processing time). The surgery operations are non-preemptive.

This study applies MILP for the NWOSP-SCSP approach in the suggested model. By presenting the problem in three fields of $\gamma|\beta|\alpha$ is in the form of $O|TTJD, MT|C_{max}$, the concept of $TT\,JD$ in the field β means the transportation time which depends on the type of the surgical operation, and MT represents the multi transportation system. Many researchers have used heuristics to solve OSSP. Some of them have been mentioned in the literature review. The NP-hardness of the open shop scheduling problems has led the researchers to use heuristics to solve problems. Our study solves MILP with small instances using the GAMS BONMIN solver. In addition to the models, a novel metaheuristic hybrid SA algorithm is proposed to solve large-scale problems by applying MATLAB in a good computational time.

4. Scheduling Problem Modeling with the Multi-Transportation System

For the V_{jik} binary variable, if O_{ji} processes immediately after O_{ki}, it takes 1; otherwise, it will be zero. Suppose on OR i, surgery operation j is processed immediately after surgery operation k. In that case, value is 1. For W_{jil} binary variable, if O_{ji} processes immediately after O_{jl}, it takes 1; otherwise, it will be zero. Suppose surgery operation j, after being processed on OR l, is immediately processed on OR i. In that case, it will take the value of 1. C_{ji} is a continuous variable representing the completion time of j on the OR i.

$$MinC_{max}$$

St.

$$\sum\nolimits_{k=0,k\neq j}^{n} V_{jik} = 1 \;\; \forall_{j,i} \tag{1}$$

$$\sum\nolimits_{l=0,l\neq i}^{n} W_{jik} = 1 \;\; \forall_{j,i} \tag{2}$$

$$\sum\nolimits_{k=1,k\neq j}^{n} V_{jik} \leq 1 \;\; \forall_{j,k>0} \tag{3}$$

$$\sum\nolimits_{l=1,l\neq i}^{n} W_{jik} \leq 1 \;\; \forall_{j,l>0} \tag{4}$$

$$\sum\nolimits_{j=1}^{n} V_{ji0} = 1 \;\; \forall_{i} \tag{5}$$

$$\sum\nolimits_{i=1}^{n} W_{ji0} = 1 \;\; \forall_{i} \tag{6}$$

$$V_{jik} + V_{kij} \leq 1 \;\; \forall_{ij>k,k\in 0,1,2,\ldots,n-1} \tag{7}$$

$$W_{jil} + W_{jli} \leq 1 \;\; \forall_{ij>l,l\in 0,1,2,\ldots,n-1} \tag{8}$$

$$C_{ji} \geq C_{jl} + P_{ji} + T_{jil} - M \times \left(1 - W_{jil}\right) \;\; \forall_{ijl,i\neq l} \tag{9}$$

$$C_{ji} \geq C_{ki} + P_{ji} - M \times \left(1 - V_{jik}\right) \;\; \forall_{ijk,i\neq l,j\neq k} \tag{10}$$

$$C_{max} \geq C_{jl} \;\; \forall_{ij} \tag{11}$$

$$C_{ji} \geq 0 \;\; \forall_{ij} \tag{12}$$

$$C_{j0} = 0 \;\; \forall_{j} \tag{13}$$

$$C_{0i} = 0 \;\; \forall_{i} \tag{14}$$

$$V_{jik} \in 0.1 \;\; \forall_{ijk,j\neq k} \tag{15}$$

$$W_{jil} \in 0.1 \ \forall_{ijl,i \neq l} \tag{16}$$

The object of the model is to minimize the makespan. Constraints set 1 and 2 ensure that each operation is processed once. These two constraints simultaneously refer to the assumption that the number of operations is $m \times n$, and prove that any surgical operation must be processed on any OR once. Constraint set 3 refers to the chronology of operation on OR i and states that any operation on an OR has a maximum of one successor operation that is processed immediately. Constraint set 4 refers to the chronology of surgery operation j on ORs and states that the surgery operation j, after the operation on any OR, has a maximum of one successor operation on another OR that is processed immediately. It should be noted that the term "maximum" has been used since the last operation of any surgical operation in scheduling problems does not follow any successor. Constraints 5 and 6 ensure that after zero virtual surgery operations and zero virtual ORs, exactly one operation is processed immediately. Constraints 7 and 8 ensure that an operation cannot be completed simultaneously before and after another operation. Eventually, one operation can be immediately before or immediately after another operation. Two operations can also have no "immediate" chronology relationships. Constraint set 9 implies that if O_{ji} is immediately processed after O_{jl}, $\left(W_{jil} = 1\right)$, O_{ji} completion time will be more than O_{jl} completion time. In other words, this constraint indicates that the minimum completion time of j on OR i is equal to the total completion time of this surgery operation on the previous OR (l) and the time of being transferred to OR i, and the time of being processed on the OR i. Figure 5 shows the output of constraint 9 (as mentioned before, the machine is the same as OR).

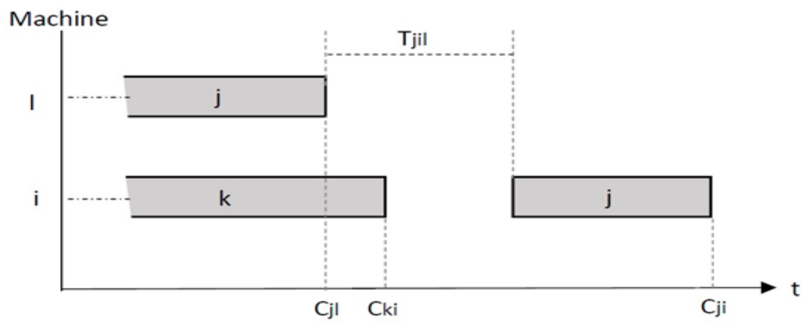

Figure 5. The output of constraint set 9 is acting, $C_{ji} + T_{jil} > C_{ki}$.

Constraint set 10 implies that if the operation O_{ji} is processed immediately after O_{ki} on the OR i, $\left(V_{jik} = 1\right)$, O_{ji} completion time will be more than O_{ki} completion time. In other words, this constraint indicates that the minimum completion time of j on OR i equals the total completion time of its previous surgery operation on the same OR and its processing time on OR i. It should be noted that the existence of these two constraints simultaneously in the model makes C_{ji} obtain the maximum output value of the two constraints. Figure 6 shows the output of constraint 10.

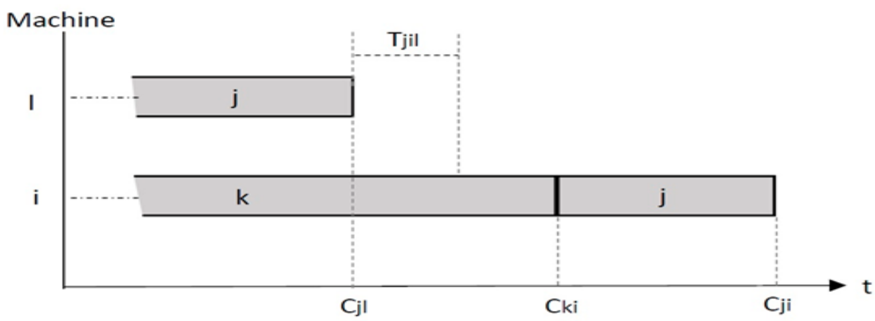

Figure 6. The output of constraint sets 10 is acting, $C_{jl} + T_{jil} < C_{ki}$.

Constraints 11 and 12 define the makespan. Constraints 13 and 14 represent the decision variable of completion time of surgical operation j in OR i, which always has a minimum value of zero. Constraints 15 and 16 are constraints of binary decision variables.

5. Metaheuristic and Heuristic Algorithms in This Study

The SA metaheuristic algorithm and a comparison of SA with the suggested heuristic algorithm are considered in this section.

5.1. Proposed SA Algorithm

A SA algorithm is a simple and effective optimization metaheuristic algorithm to solve optimization problems. The basic information for starting the SA algorithm is as follows.

The initial temperature (T_0) in which the algorithm starts to work must be set up at the beginning of the algorithm, and the Boltzmann probability function generates the value of 1. In other words, at the beginning of the algorithm, the answers of the worst neighbor will be accepted with a probability of 1. They will decline to zero gradually [81]. The temperature reduction rate (α) is considered in the following equation [82].

$$T_h = \alpha \times T_{h-1} \quad h > 2, 0 < \alpha < 1 \tag{17}$$

where T_h and α signify the temperature in the repetition of h and the rate of decrease in temperature, respectively.

In this study, the initial temperature is considered 70 $^{\circ}$C and the temperature decrease rate is 0.98.

How to display the answer applied in this paper is in the form of a matrix with a row and $m \times n$ column. The elements of this matrix are members of the set $1, 2, 3, \ldots, m \times n$; each indicating a scheduling operation.

Based on the recommended answer description, each problem can have $(m \times n)!$ answer modes; the SA algorithm will reach an optimized answer by searching the neighborhood based on initial response. To search for neighbors, we need operators to obtain the final solution by modifying the answers.

In this algorithm, to accelerate the search for finding a better answer, three operators of swap, reversion, and insertion are employed to select the neighborhood.

5.2. Solving the Problem Using the Suggested Heuristic Algorithm and SA Algorithm

In this section, problems with different values have been created to evaluate heuristic and metaheuristic algorithms, and their solution will be presented by coding in MATLAB software. Each problem has been run five times, and the best results are offered.

The SA algorithm acts by the use of a point-based system. It generates a random answer and, by analyzing the neighborhood of that answer, seeks an optimal answer. As shown in Table 1 and Figure 7, the SA algorithm reaches the response of the heuristic algorithm after passing a considerable time on any scale of the problem. For example, on a scale of 5×10, the SA algorithm reaches the answer of the heuristic algorithm after approximately 24,000 s, while the heuristic algorithm finds the same result after about 0.2 s.

Table 1. Results of executing the SA and heuristic algorithms on various test data (10 ORs).

Problem	Best Answer	Time (s)	
		SA	Heuristic
4×10	**294**	**1492.30**	**0.17**
5×10	**290**	**2379.98**	**0.22**
6×10	**270**	**3874.64**	**0.31**
7×10	**359**	**4960.46**	**0.38**
8×10	**337**	**6837.92**	**0.53**

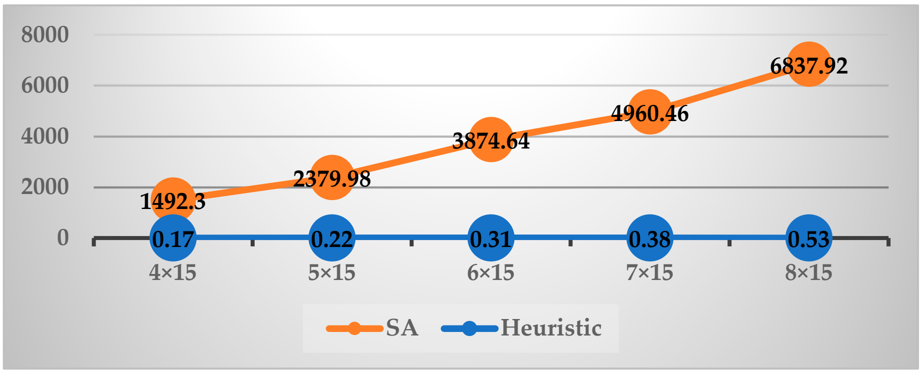

Figure 7. Time-comparison diagram of the SA and heuristic algorithms for different test problems (10 ORs).

As shown in Table 2 and Figure 8, the SA algorithm reaches the response of the heuristic algorithm after passing a considerable time on any scale of the problem. For example, on a scale of 5×15, the SA algorithm reaches the answer of the heuristic algorithm after approximately 14,000 seconds, while the heuristic algorithm finds the same result after about 1 second. In this regard, introducing a hybrid SA algorithm and a comparison of SA and hybrid SA algorithms are presented in the following sections, respectively.

Table 2. Results of executing the SA and heuristic algorithms on various test data (15 ORs).

Problem	Best Answer	Time (s)	
		SA	Heuristic
4×15	421	9990.43	0.81
5×15	375	14,596.08	1.07
6×15	362	22,564.55	1.37
7×15	421	28,596.16	1.80
8×15	388	37,549.58	1.84

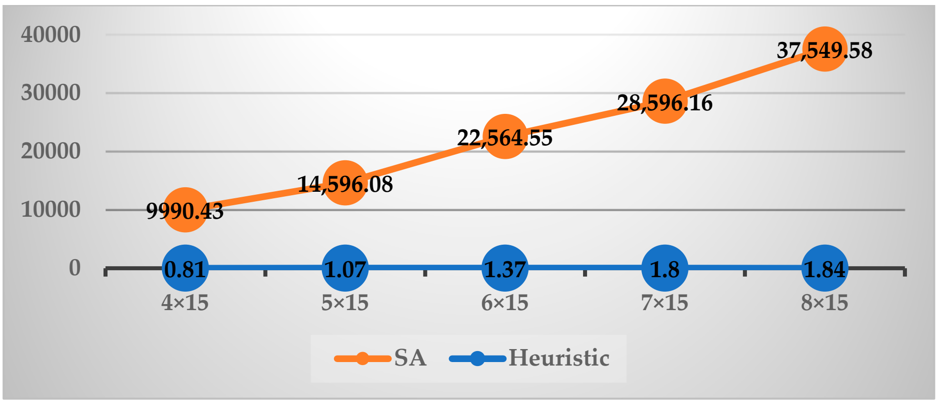

Figure 8. Time-comparison diagram of the SA and heuristic algorithms for different test problems (15 ORs).

6. Hybrid SA Algorithm

As the previous section explains, the SA algorithm works as a point-based system by generating an initial randomized answer. Figures 7 and 8 show that the heuristic algorithm with a meager time yields an equivalent answer to the SA algorithm, which takes hours to get to the answer (SA algorithm). For this reason, a hybrid SA algorithm is presented. Thus, the SA algorithm takes the final solution of the heuristic algorithm instead of generating a random answer to start. Then, searching in the neighboring space of this answer seeks to improve that solution. The hybrid SA is executed, as shown in Figure 9.

$$Let\ s = output\ of\ the\ heuristic\text{'}s\ algorithm$$

$$For\ k = 0\ through\ \ k_{max}$$

$$T \leftarrow\ \ temperature\ (k \backslash k_{max})$$

$$Pick\ a\ random\ neighbor, s_{new} \leftarrow neighbour(s)$$

$$If\ \ P(E_s, E_{s_{new}}, T) \geq random(0{,}1):$$
$$s \leftarrow s_{new}$$

$$Output: the\ final\ state\ s$$

Figure 9. The hybrid SA algorithm.

7. A Numerical Analysis of Nova Scotia Health Centers

Figure 10 shows a detailed map of Nova Scotia health authority hospitals and health centers.

Figure 10. Hospitals and health centers for Nova Scotia Authority [83].

A set of performance measures from a healthcare organization and the provincial government ministries of health are selected. Performance measurements in the different jurisdictions in Nova Scotia are compared and contrasted [84], assessing which jurisdiction is stronger in specific regards. The second suggested solution provides the care Nova Scotians need and deserve. There are five approaches in the second solution. In this paper, approach number four is selected. The fourth approach is to employ advanced explanations to decrease surgical wait times, deliver safe, quality care, and accomplish standards based on the instructions, such as reducing waits for lists by finalizing 2500 extra surgeries in the next 12 months, determining an integrated reservation procedure to handle waitlists for surgeries, make real efficiencies by defining a method for principal intake, the pooling of medical appointment, and continuing to contribute supplies to develop operational room hours and capability. Figures 11 and 12 examine how many surgeries (or surgery) wait times are within our benchmark for diagnosis (endoscopic) and treatment (non-endoscopic) surgeries. Thus, in this paper, the patient's ordering in any surgery room is considered a fixed part of all sequencing and scheduling problems.

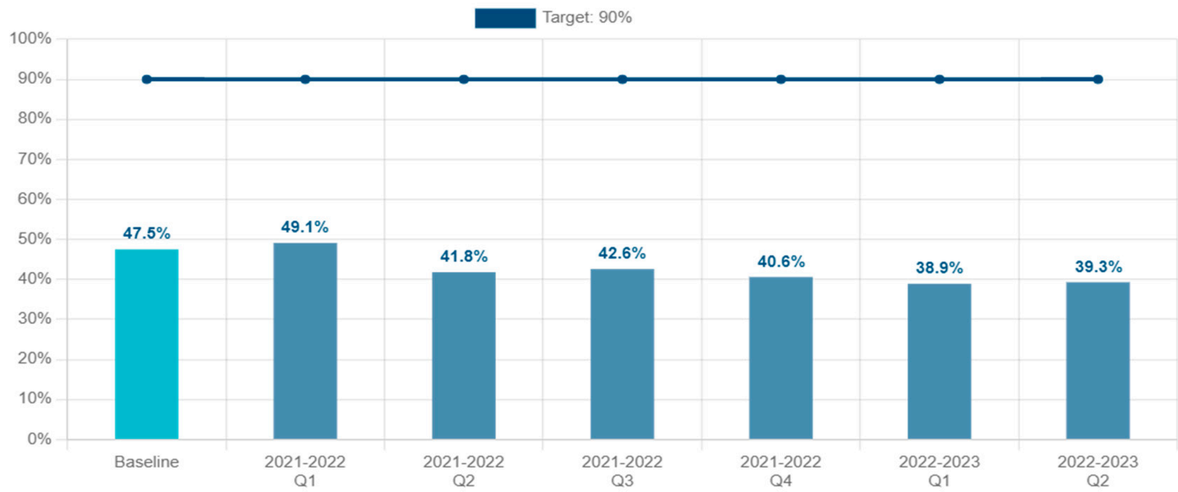

Figure 11. Percentage of endoscopic surgical services completed or wait times within benchmark [84].

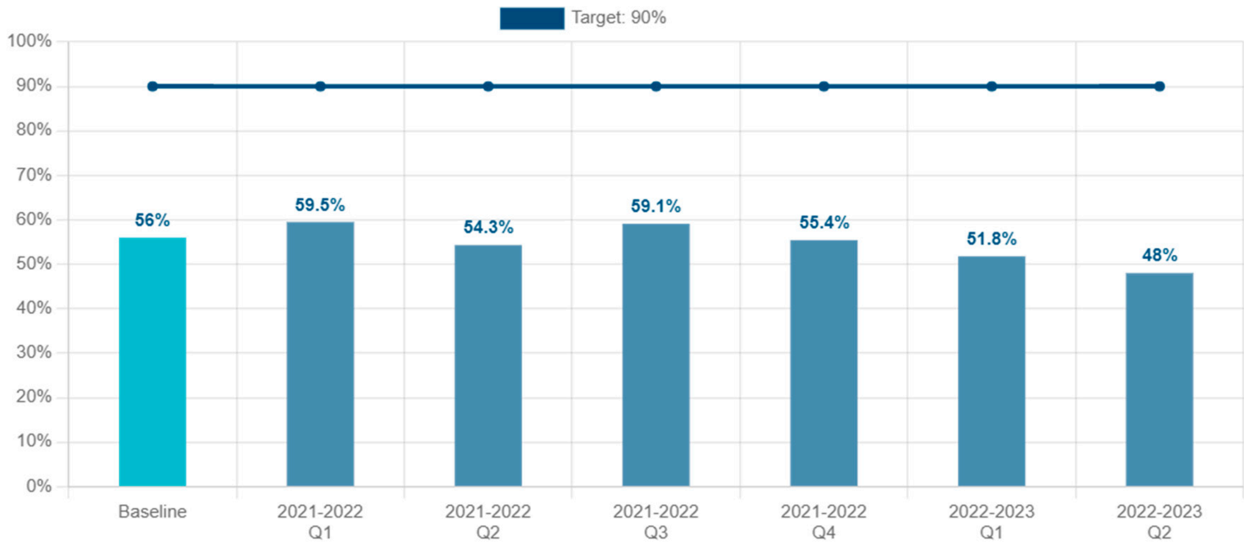

Figure 12. Percentage of non-endoscopic surgical services completed or wait times within benchmark [84].

8. The Comparison of the Hybrid SA Algorithm and SA Algorithm

The hypothesis test is used in four parts (quarters) of the algorithm's performance to evaluate the SA algorithm and hybrid SA algorithm. The first hypothesis test was used in all quarters of the function of the two algorithms, and in this test, the H_0 assumption was rejected. In other words, the two algorithms have a significant difference. The first hypothesis test was considered for the two algorithms by 10 ORs in Table 3, and Figure 13 for the first quarter; by 15 ORs in Table 4, and Figure 14 for the first quarter; 10 ORs in Table 5, and Figure 15 for the second quarter; 15 ORs in Table 6, and Figure 16 for the second quarter; 10 ORs in Table 7, and Figure 17 for the third quarter; 15 ORs in Table 8, and Figure 18 for the third quarter; 10 ORs in Table 9, and Figure 19 for the fourth quarter; and finally 15 ORs in Table 10, and Figure 20 for the fourth quarter. In this test, the H0 assumption is rejected. In other words, the two algorithms have a significant difference. They show that the hybrid SA algorithm performs much better than the SA algorithm for all quarters.

Table 3. Results of executing SA and hybrid SA algorithms in the first quarter (10 ORs).

Problem	First Quarter Performance		Best Answer	Normalization	
	SA	Hybrid		SA	Hybrid
4×10	228	209	200	0.14	0.05
5×10	309	285	228	0.36	0.25
6×10	330	270	232	0.42	0.16
7×10	398	342	282	0.41	0.21
8×10	449	337	298	0.51	0.13

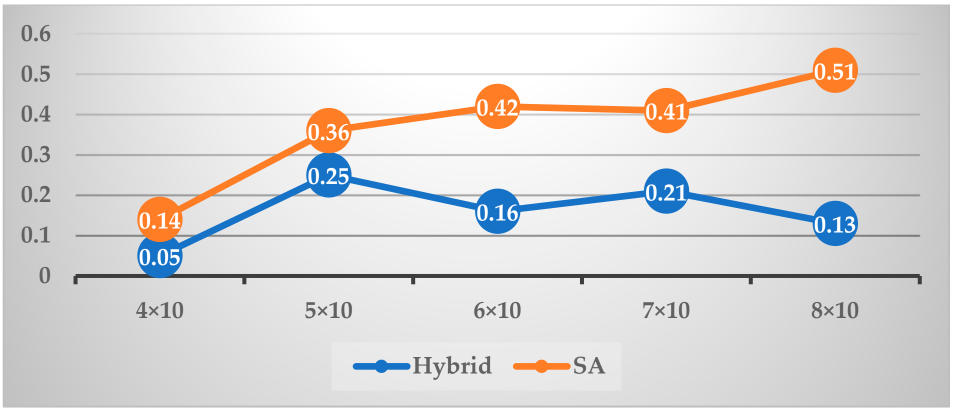

Figure 13. Fitness diagram of SA and hybrid SA in the first quarter (10 ORs).

Table 4. Results of executing the SA and hybrid SA algorithms in the first quarter (15 ORs).

Problem	First Quarter Performance		Best Answer	Normalization	
	SA	Hybrid		SA	Hybrid
4×15	388	387	312	0.24	0.24
5×15	448	375	324	0.38	0.16
6×15	486	362	323	0.50	0.12
7×15	535	421	358	0.49	0.18
8×15	599	388	365	0.64	0.06

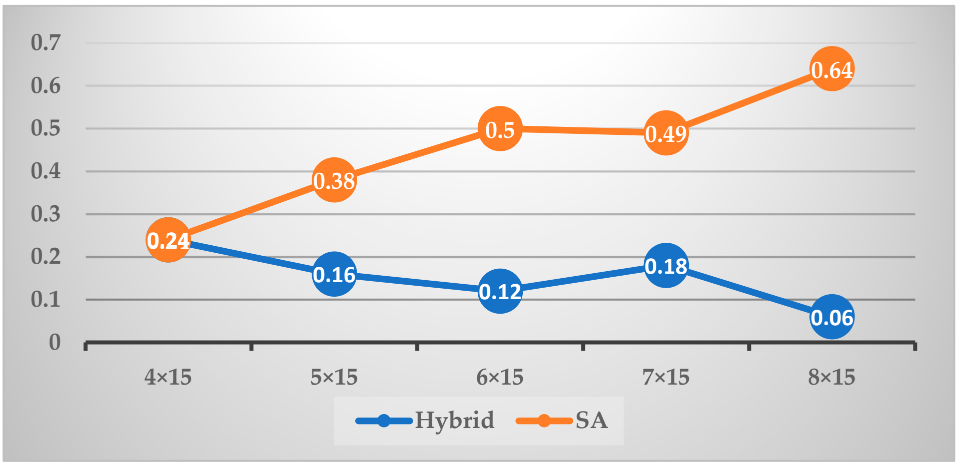

Figure 14. Fitness diagram of SA and hybrid SA in the first quarter (15 ORs).

Table 5. Results of executing the SA and hybrid SA algorithms in the second quarter (10 ORs).

Problem	Second Quarter Performance		Best Answer	Normalization	
	SA	Hybrid		SA	Hybrid
4×10	202	202	200	0.01	0.01
5×10	268	251	228	0.18	0.10
6×10	303	270	232	0.31	0.16
7×10	398	342	282	0.41	0.21
8×10	438	337	298	0.47	0.13

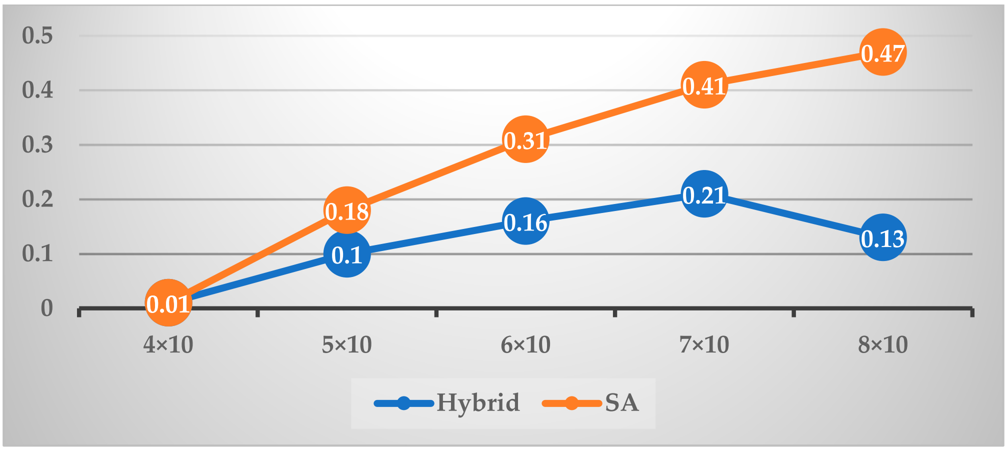

Figure 15. Fitness diagram of SA and hybrid SA in the second quarter (10 ORs).

Table 6. Results of executing the SA and hybrid SA algorithms in the second quarter (15 ORs).

Problem	Second Quarter Performance		Best Answer	Normalization	
	SA	Hybrid		SA	Hybrid
4×15	356	348	312	0.14	0.12
5×15	447	375	324	0.38	0.16
6×15	472	362	323	0.46	0.12
7×15	535	421	358	0.49	0.18
8×15	599	388	365	0.64	0.06

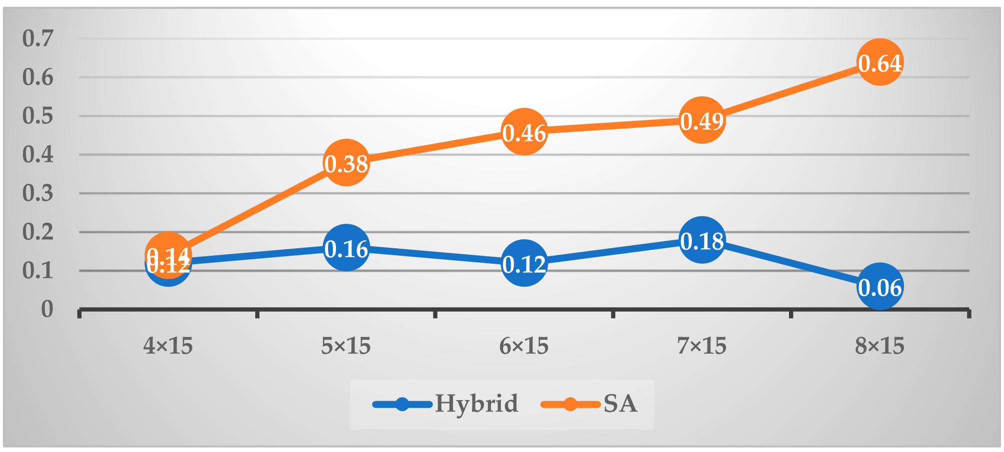

Figure 16. Fitness diagram of SA and hybrid SA in the second quarter (15 ORs).

Table 7. Results of executing the SA and hybrid SA algorithms in the third quarter (10 ORs).

Problem	Third Quarter Performance		Best Answer	Normalization	
	SA	Hybrid		SA	Hybrid
4×10	202	202	200	0.01	0.01
5×10	241	244	228	0.06	0.07
6×10	270	260	232	0.16	0.12
7×10	356	327	282	0.26	0.16
8×10	433	337	298	0.45	0.13

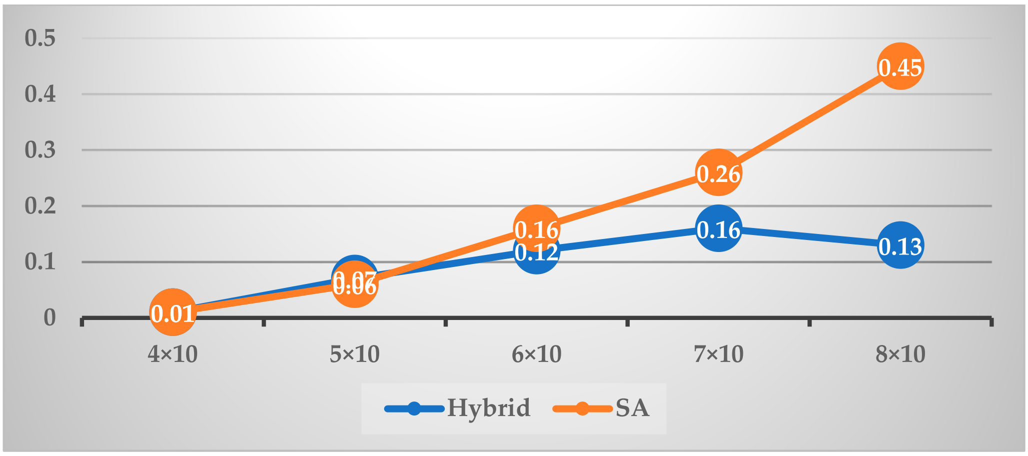

Figure 17. Fitness diagram of SA and hybrid SA in the third quarter (10 ORs).

Table 8. Results of executing the SA and hybrid SA algorithms in the third quarter (15 ORs).

Problem	Third Quarter Performance		Best Answer	Normalization	
	SA	Hybrid		SA	Hybrid
4×15	345	335	312	0.11	0.07
5×15	414	375	324	0.28	0.16
6×15	460	362	323	0.42	0.12
7×15	535	421	358	0.49	0.18
8×15	599	388	365	0.64	0.06

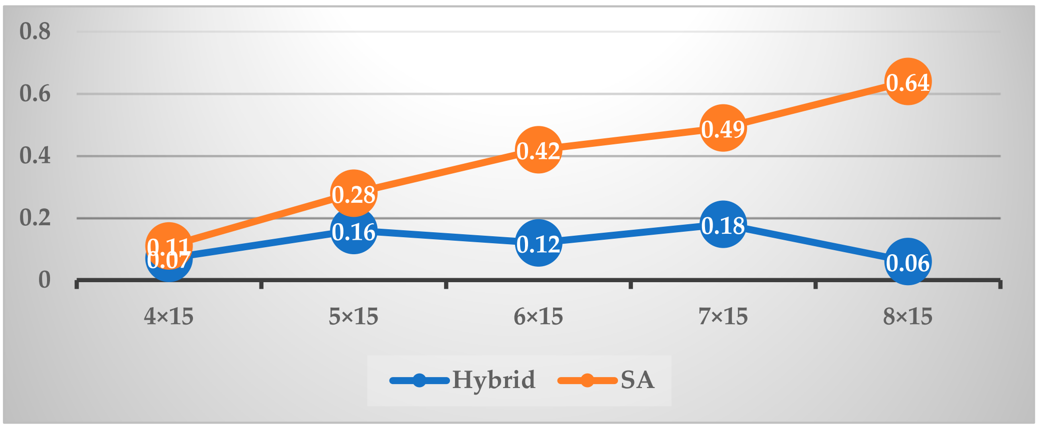

Figure 18. Fitness diagram of SA and hybrid SA in the third quarter (15 ORs).

Table 9. Results of executing the SA and hybrid SA algorithms in the fourth quarter (10 ORs).

Problem	Fourth Quarter Performance		Best Answer	Normalization	
	SA	Hybrid		SA	Hybrid
4×10	202	202	200	0.01	0.01
5×10	238	240	228	0.04	0.05
6×10	255	252	232	0.1	0.09
7×10	377	320	282	0.20	0.13
8×10	401	337	298	0.35	0.13

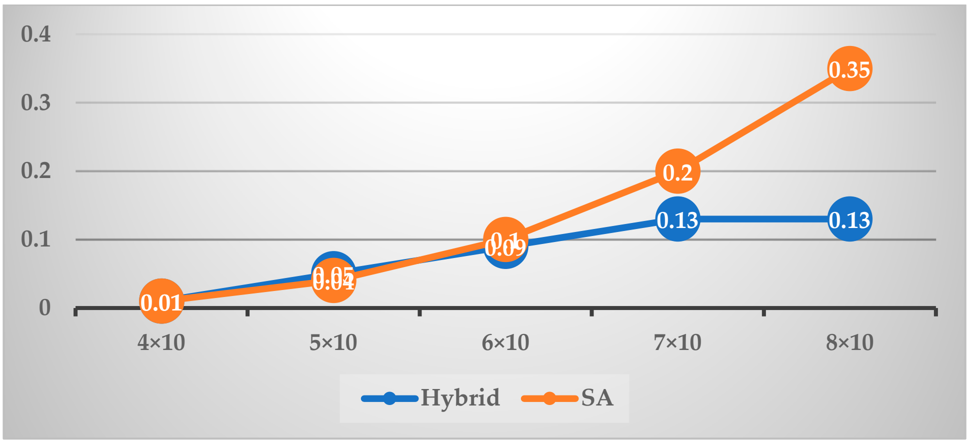

Figure 19. Fitness diagram of SA and hybrid SA in the fourth quarter (10 ORs).

Table 10. Results of executing the SA and hybrid SA algorithms in the fourth quarter (15 ORs).

Problem	Fourth Quarter Performance		Best Answer	Normalization	
	SA	Hybrid		SA	Hybrid
4×15	334	332	312	0.07	0.06
5×15	414	375	324	0.28	0.16
6×15	460	362	323	0.42	0.12
7×15	532	421	358	0.49	0.18
8×15	595	388	365	0.63	0.06

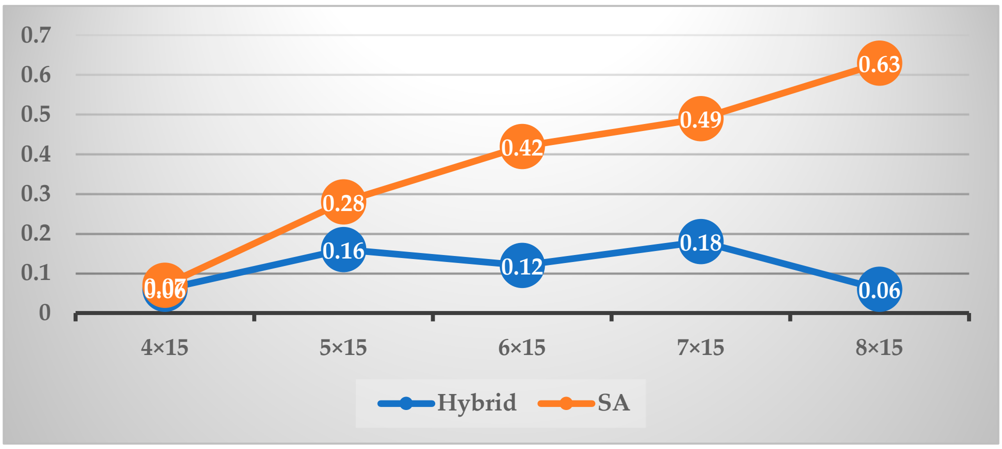

Figure 20. Fitness diagram of SA and hybrid SA in the fourth quarter (15 ORs).

9. Conclusions

This paper dealt with a novel NWOSP-SCSP case of open-shop problems under makespan minimization with the transportation times for OR as a single objective model based on MILP. Since the optimization of OR problems is an NP-hard optimization problem, we assessed mathematical and metaheuristic methods to address OR optimization problems. Problem modeling was described in the context of a multi-transportation system. Two computational experiments were considered to evaluate the performances of MILP, heuristic, SA metaheuristic, and a hybrid algorithm. In the first experiment, we generated small-sized instances by which we compared the mathematical models and evaluated the general performance of the proposed metaheuristics. In the second experiment, the potential of metaheuristics to solve some benchmarks in the literature of pure open shops was further assessed. A heuristic algorithm was created to solve problems of different sizes, and its performance was compared with the SA algorithm. The results of these two algorithms led to the presentation of a novel hybrid SA algorithm. With a hypothesis test in different quarters, its performance was evaluated. The hypothesis test is used in four parts of the algorithm's performance to assess the SA and hybrid SA algorithms. Thus, the first hypothesis test was used in all quarters of the function of the two algorithms, and in this test, the H_0 assumption was rejected. In other words, the two algorithms have a significant difference. After reaching the results with a numerical analysis in Nova Scotia health authority hospitals and health centers, the results of the evaluations show the remarkable superiority of the hybrid SA algorithm. Finally, all the results proved that the models and metaheuristics effectively tackled the NWOSP-SCSP approach, which will be a new perspective in future literature reviews.

Future Study

This research assumes that the number of surgical operations equals the number of ORs. In other words, each surgical operation is processed exactly in each OR. A situation where the number of operations differs from the number of ORs is suggested for consideration in future studies. For example, one or more surgical operations will not be processed in one or more ORs. Solving the problem with other metaheuristic algorithms and comparing them with the SA algorithm results is also suggested. In the present study, a heuristic algorithm was presented for solving $O|TTJD, MT|C_{max}$ problems and was compared with the SA algorithm, and finally, a hybrid SA algorithm was suggested to obtain the best results; some studies to find an algorithm for solving $O|TTJD, ST|C_{max}$ problems are suggested if there is single transportation (ST) between each OR. As interesting future research, one could study a multi-objective no-wait open shop in surgical case scheduling problems. Another exciting research direction is considering branch-and-bound or other exact methods. A comprehensive review of bi-objective and multi-objective OR scheduling is recommended. Finally, further research on developing novel and hybrid strategies for delivering an actual problem is suggested.

Author Contributions: Methodology, A.R., S.M.H., M.Z. and M.M.; conceptualization, A.R., M.Z. and M.M.; software, S.M.H.; validation, A.R.; formal analysis, S.M.H. and M.M.; investigation, M.M.; resources, A.R. and M.M.; data curation, A.R., S.M.H., M.Z. and M.M.; writing—original draft preparation, M.M.; writing—review and editing, M.M.; visualization, A.R., S.M.H. and M.Z.; supervision, M.Z.; project administration, A.R., S.M.H., M.Z. and M.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data used in the study are available from the authors and can be taken upon acceptable requests.

Acknowledgments: The authors would like to thank the reviewers and the editor-in-chief for their helpful comments and recommendations.

Conflicts of Interest: The authors declare no conflict.

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