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How to Apply a Metaheuristic Algorithm to Physician Scheduling Problem

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Abstract

Hospitals spend a considerable percentage of their budget on medical personnel. However, proper physician scheduling helps to lower this cost. The emergency department is an area where physicians are available 24/7, so keeping the physicians satisfied is important. According to the scheduler specialist, creating a physician schedule takes a long time. It does not provide physicians with satisfaction and equality in terms of working hours, number of night shifts, and number of days off. This paper uses Random Search Optimization (RSO) to generate physician schedules and guidelines by applying metaheuristics to the physician scheduling problem. The goal is to reduce all overtime work to a minimum. We compared the performance of RSO with mathematical model and manual method. The results showed that RSO reduced total overtime by 50%, distributed the burden effectively, and had a procedure time of less than 12 seconds.

Keywords: Artificial Intelligence, Soft computing, NP-hard problem, Personnel scheduling, Optimization

1. INTRODUCTION

Scheduling problems are the assignment of work to limited resources over a period of time to achieve an objective. Scheduling problems are decisions of resource allocation or task sequencing (Salvendy, 2001). It is the allocation process for the increased effectiveness of activities that plays an important role in the industrial sector (Lenstra and Kan, 1981). It is a large problem with complexity and constraints (Rahimi et al., 2022). The physician scheduling problem is a Non-deterministic Polynomial-time hard (NP-hard) (Ozder et al., 2020). Although the physician scheduling problem is similar to the nurse scheduling problem, there are differences in terms of preferences, requirements, and specialty expertise (Hidri et al., 2020).

Erhard et al. (2018) classified physician scheduling problems into three types according to planning horizon: staffing, rostering, and re-planning problems. Staffing problems focus on strategically solving problems and involves long-term planning - one year. Rostering problems focus on solving tactical or operational level problems, with a planning period ranging from three to twelve months. Re-planning problems focus on the operational level and solving problems in the short-term. These problems are related to unexpected occurrences and can affect regular daily planning.

According to a search for articles on physician scheduling problems in the international database Scopus, the first article was published in 1958 and physician scheduling problems are still being researched today. Figure 1 represents the number of articles published each year on physician scheduling problems. Mathematical model, heuristics, and metaheuristics are used to solve physician scheduling problems, with mathematical model being the most commonly used.

Hidri et al. (2020) published an article on real-world physician scheduling problems in the Intensive Care Unit (ICU), solving this problem using Integer Linear Programming (ILP) with the purpose of minimizing total overtime. The manual method is a physician's allocation of work based on the scheduler's decision. The scheduler makes every effort to arrange it following hospital regulations, physician preferences, and patient demands. ILP decreases the overtime of physicians by 50% compared to manual methods. Furthermore, Hidri et al. compared the answer performance with the Genetic Algorithm (GA) and Simulated Annealing (SA), which reduced the total overtime by 39% and 37%, respectively. However, Hidri et al. did not clarify the physician scheduling procedure of GA and SA.

This paper proposes personnel scheduling and explains how to apply Random Search Optimization (RSO) to solve the physician scheduling problem with the objective of minimizing total overtime. RSO provides comparable results to the mathematical model while taking less time to solve the problem. In addition, establishing a preliminary agreement is also similar to the constraint in Hidri et al (2020). article, guiding other researchers interested in applying metaheuristics to the physician scheduling problem.

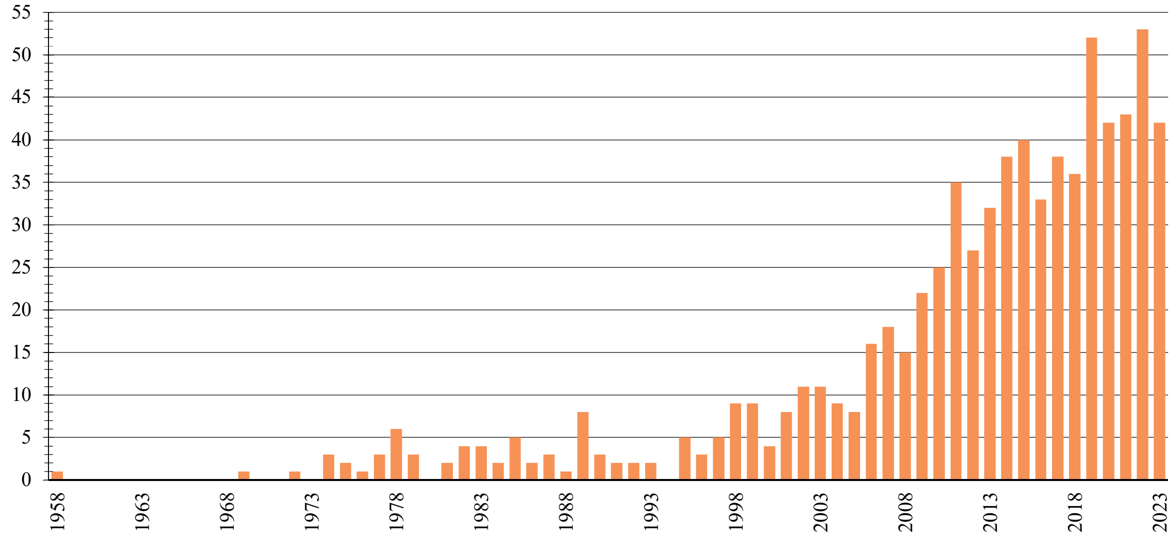

Figure 1 Number of articles published each year on physician scheduling problems

The following section is a literature review on physician scheduling using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA). Section 3 describes the elements of real-world problems from the dataset of Hidri et al. Section 4 depicts the flowchart and explains how to use the personnel scheduling Section 5 presents the results of an experimental study conducted on real data. The last section provides conclusions and suggestions for future research.

2. LITERATURE REVIEW

The researchers used PRISMA in the literature review presented by Liberati et al. (2009). The article collection period is from 2017 to August 2023. Figure 2 depicts the steps of a literature review with the following steps:

1. A search using the keywords "physician" and "schedule*" yielded 18,300 articles.
2. Selecting the desired period (2017 to 2023) yielded 4,779 articles.
3. Select only the subject area of interest and yield 299 articles (Computer science, Engineering, Decision sciences, Business, Mathematics, Economics, and Materials sciences).
4. The researcher made a preliminary selection of 29 articles based on the title and abstract.
5. Read the full-text article, which yielded 25 articles.
6. At last, 23 articles were of quality and related to the keywords.

Table 1 summarizes the 23 articles. We divide problem-solving approaches into three categories: 1) Mathematical model in this topic summarizes articles that use the mathematical model to apply the physician scheduling problem and the application area. 2) Heuristic in this topic is a summary of articles that solve problems using heuristics and demonstrate which methodologies are utilized to describe the physician scheduling procedure, and 3) Metaheuristic in this topic is a summary of the articles that used metaheuristics to solve problems. These sectional problems are large and frequently unsolvable using mathematical models.

2.1 Mathematical Model

The most popular mathematical model out of the proportions of solutions are depicted in Figure 3. When compared to other methods, the planning horizon is short (one week to three months). This method, which consists of an objective function and hard-soft constraints, achieves a single best solution value, and does not require parameterization. Mixed Integer Linear Programming (MILP) was used in an article by Gross, Fugener, et al. (2018) that is physician scheduling in university hospitals in Germany takes a time solution of twenty-one seconds, but according to Gross et al. when using a computer system the problem should be solved within ten seconds.

Guler and Gecici (2020) used MILP to create physician scheduling during the COVID-19 outbreak. They established three new departments (COVID-19 ICU, COVID-19 emergency, and COVID-19 service) to accommodate patients. It took one minute to find the answer, but the workload was very unevenly distributed due to different medical specialties.

Camiat et al. (2021) predicted patient demand using ten years of historical data from Sacre-Coeur Montreal Hospital. They use MILP to search for the answer. The solution for physician scheduling in the emergency department can meet demands well, but it cannot meet all the demands.

Schoenfelder and Pfefferlen (2018) used MILP an anesthesiology department physician scheduling in a hospital in Berlin, Germany. They define the penalty coefficient when constraints are violated, and the model takes eighty-five seconds to solve problems. They can reduce almost all the severely punishable violations of the restriction.

Damcı-Kurt et al. (2019) used MILP to create schedule general physicians in United States hospitals and determine the penalty coefficients when violating constraints. Although the answer cannot be quantified in monetary terms, physician schedule improvements benefit both physicians and hospitals.

Fugener and Brunner (2019) used MILP to create physician scheduling in German university hospitals. This model can reduce overtime by 80% but takes up to 12 hours to solve.

Tan et al. (2019) used MILP to reduce physician scheduling time in the emergency room at West China Hospital of Sichuan University by dividing the physician scheduling into two phases: dividing the medical team and allocating work to the physician.

Integer Linear Programming (ILP) was used in an article by Hidri et al. (2020) that physician schedules in the ICU is divided into three buildings, each of which provides a different service, reducing the solution time to two hours.

Cappanera et al. (2022) divided physician scheduling of emergency departments in a European hospital into two phases: holiday determination and physician assignment by use ILP. Because more preferences from physicians complicate the problem, answers can be found within 6 hours.

Sample Average Approximation (SAA and tool) was used in an article by Marchesi et al. (2020) that is physician scheduling in the emergency department with the uncertain demand of patients, the model can reduce queue frequency and the average time door-to-doctor.

Tohidi et al. (2021) used SAA to create physician scheduling in an outpatient polyclinic in Canada, that provides general and specialized examinations to outpatients. It entails relocating some parts out of the hospital into the community to make them more accessible to patients. According to the results, as the problem size increases, the range between the best and worst solution will decrease because the increase in physician preferences making the problem more complex and resulting in fewer solutions and space possibilities. It also takes longer to solve these problems. Although this model reduced costs by 64%, the schedule generation must be updated every two years.

Integer Programming (IP) was used in an article by Liu et al. (2022) during the COVID-19 outbreak in China, physician scheduling generation to screen and treat patients promptly. Though the solution time was appropriate, it was unable to respond to all patient arrivals.

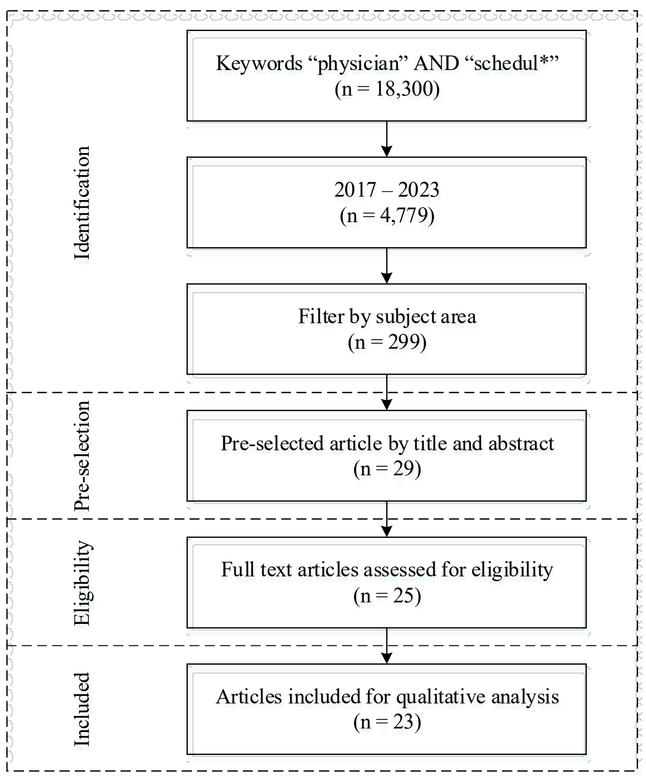

Figure 2 PRISMA flow for this study

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Table 1 Literature review of physician scheduling

Article	Problem characteristics														Objective	Method		
	Classification	Planning horizon	Real data	Overlapping shifts	No. of shifts	Flexible shifts	No. of physicians	Stochastic demand	Fairness	Preferences	Requirement	Labor law	Breaks	Ergonomic		Mathematics	Heuristics	Metaheuristics
Gross, Fügener, et al. (2018)	Ro	4w	✓		n/a		133		✓	✓		✓			Maximize coverage demand and physicians satisfied	MILP		
Schoenfelder and Pfefferlen (2018)	Ro	1m	✓		7		34		✓	✓	✓	✓			Reduce physician scheduling time and regulation violations	MILP		
Damcı-Kurt et al. (2019)	Ro	3m	✓		n/a		36		✓		✓				Minimize the sum of penalties	MILP		
Fugener and Brunner (2019)	Ro	1w	✓		n/a	✓	17	✓							Minimize the number of assigned physicians	MILP	CG	
Lan et al. (2019)	Ro	1w	✓		4		150		✓	✓				✓	Minimize the dissatisfaction of physicians, cost, and deviation			SCA-VNS
Tan et al. (2019)	Ro	1m	✓	✓	2		25			✓	✓	✓			Minimize the deviation variables	MILP		
Tohidi et al. (2019)	Ro	1w			2		133		✓	✓	✓				Minimize the violation of the soft constraints		IVND	
Guler and Gecici (2020)	Ro	1m	✓		2-3		81		✓	✓		✓			Minimize the deviation variable	MILP		
Hidri et al. (2020)	Ro	1m	✓		2		18		✓	✓	✓	✓			Minimize the total overtime	ILP		
Kraul (2020)	S	1y	✓		n/a		52		✓						Minimize the violation between resource assignment and treatment requirements			GA
Mansini and Zanotti (2020)	Ro	2w			n/a		19		✓			✓			Minimize the total overtime		ALNS	
Marchesi et al. (2020)	Ro	4w	✓	✓	11		85			✓					Minimize the total number of waiting patients	SAA and tool		
Camiat et al. (2021)	Ro	13w	✓		3		35		✓	✓	✓			✓	Minimize the sum of difference between demand and supply	MILP		
Cildoz et al. (2021)	S	1y	✓		19	✓	42		✓	✓				✓	Maximize fairest feasibly		G-NO	
Erhard (2021)	Ro	6w	✓		12	✓	n/a		✓						Minimize the total cost		CG	
Liu and Xie (2021)	Ro	1w	✓		3		n/a	✓							Minimize total waiting time and working time			LS-TS
Tohidi et al. (2021)	Ro	1w	✓		2		147	✓	✓	✓		✓		✓	Maximize the number of visiting patients and minimize the cost of physicians	SAA and tool		

Table 1 (Continued)

Article	Classification	Planning horizon	Real data	Overlapping shifts	No. of shifts	Flexible shifts	No. of physicians	Stochastic demand	Fairness	Preferences	Requirement	Labor law	Breaks	Ergonomic	Objective	Mathematics	Heuristics	Metaheuristics
	Problem characteristics															**Method**		
Wang et al. (2021)	Re	1d	✓		17		n/a		✓						Minimize the risk tolerance level and rescheduling costs		Iterative	
Cappanera et al. (2022)	Ro	1m	✓		4		27		✓	✓					Minimize unfair distribution weekend and workday	ILP		
Li et al. (2022)	Ro	5d	✓		8		7			✓					Minimize average waiting time of patients and respects the physicians preferences			GA
Liu et al. (2022)	Ro	1w	✓		24		14					✓			Minimize the total working time	IP		
Lan et al. (2023)	Ro	1m	✓		6		30					✓			Maximize response to patient demand			PSO-VND
Wang et al. (2023)	Ro	1w	✓	✓	6		n/a	✓							Minimize the total patient waiting time			TS
This paper	Ro	4w	✓		2		18		✓	✓	✓	✓			Minimize the total overtime			RSO

Classification: *S* (Staffing), *Ro* (Rostering), and *Re* (Replanning), **Planning horizon**: *d* (Day), *w* (Week), *m* (Month), and *y* (Year), **Mathematics**: *MILP* (Mixed Integer Linear Programming), *ILP* (Integer Linear Programming), and *SAA* (Sample Average Approximation), *IP* (Integer Programming: branch and price), **Heuristics**: *CG* (Column Generation) and *IVND* (Iterated Variable Neighborhood Descent Algorithm), *ALNS* (Adaptive Large Neighborhood Search), *G-NO* (Hybrid Greedy Randomized Adaptive Search Procedure and Network Flow Optimization), *Iterative* (Exact Iterative Algorithm), **Metaheuristics**: *SCA-VNS* (Hybrid Sine Cosine Algorithm and Variable Neighborhood Search Algorithm), *GA* (Genetic Algorithm), *LS-TS* (Local Search based Tabu Search), *PSO-VND* (Hybrid Particle Swarm Optimization and Variable Neighborhood Descent), *TS* (Tabu Search), *RS* (Random Search).

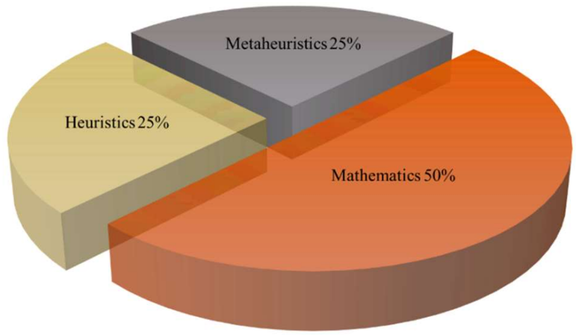

Figure 3 The proportion of methods in 23 articles used in this study

2.2 Heuristics

Heuristics are another technique for solving the physician scheduling problem, with the planning period ranging from one day to one year. Fugener and Brunner (2019) use Column Generation (CG) to create schedule physicians in a German university hospital. With only ten minutes of problem-solving, this method can reduce overtime by 80% as a flexible work shift arrangement.

Erhard (2021) uses CG to create a physician schedule using one to six weeks instances. Although it is not the best solution, it only takes ten minutes instead of a week. Also, use a flowchart to demonstrate how the algorithm works.

Tohidi et al. (2019) considered physician scheduling in ambulatory polyclinics, but the large problem size makes mathematical model unsuitable. As a result, Iterated Variable Neighborhood Descent Algorithm (IVNS) is used, resulting in high-quality solutions with little deviation. And uses pseudocode to explain the algorithm process.

Mansini and Zanotti (2020) used Adaptive Large Neighborhood Search (ALNS) from the destruction and repair processes to improve physician scheduling in general surgery. Although the best solution was not found in small instances, it was found in larger scale instances within an hour. And uses pseudocode to explain the algorithm process.

Cildoz et al. (2021) considered physician scheduling in a hospital compound of Navarre in Spain to determine the number of physicians and generate the initial solution using Hybrid Greedy Randomized Adaptive Search Procedure and Network Flow Optimization (G+NO), which is superior to the mathematical model. The use of flowcharts and pseudocode helps to explain the algorithm process.

Wang et al. (2021) presented a physician rescheduling model in a psychiatric hospital in China. They made an iteration to find the answer. They made an iteration to find the answer, which when entered into a local situation, generated a new solution. A minimized risk tolerance level has also been considered. Physician rescheduling improves resource allocation efficiency and decreases physician workload. This method uses pseudocode to explain the algorithm process.

2.3 Metaheuristics

Metaheuristics is another popular method for solving problems, because it encompasses a wide variety of techniques. Even though it may not be the best solution, it is a solution that can be accepted at the appropriate time. The size of the planning horizon found is five days to one year.

Kraul (2020) studied physician scheduling at a training hospital in Germany, he used GA and found that GA can improve their physician scheduling by more than 110% and have more equality. It uses a pseudocode to explain the algorithm process.

Li et al. (2022) used calibrated waiting time approximated to estimate patient waiting time in the outpatient department. And solving the problem with GA, which can provide good answers in minutes. Increasing physician preferences lengthens patient waiting time.

Lan et al. (2019) divided physician scheduling in the outpatient department into two steps: personnel allocation using an Iterated Hungarian Algorithm and physician scheduling using Hybrid Sine Cosine Algorithm and Variable Neighborhood Search Algorithm (SCA-VNS). The average objective function outperforms other algorithms, has a narrow distribution of answers, and finds answers quickly. It uses a flowchart and pseudocode to explain the algorithm process.

Liu and Xie (2021) physician scheduling in an emergency department using Local Search based Tabu Search (LS-TS). TS generates an initial solution and LS searches for a solution in nearby areas, the answers are highly effective.

Lan et al. (2023) considered physician scheduling in China during the COVID-19 outbreak. They used Hybrid Particle Swarm Optimization and Variable Neighborhood Descent (PSO-VND) to solve the problem. PSO generates the initial solution and then uses VND to improve it. This algorithm outperforms other algorithms, and pseudocode is used to explain the algorithm process.

Wang et al. (2023) physician scheduling in emergency departments in Chinese hospitals, and the forecast service demand is estimated which is close to reality. Although Tabu Search (TS) can reduce patient waiting times, it cannot meet all demands, and flowcharts are used to explain the algorithm process.

According to the literature review, some studies apply the metaheuristic to solve physician scheduling problems. Erhard et al. (2018) conducted a review of physician scheduling from 1985 to 2016 but did not find the application of RSO to the physician scheduling problem, as they did in their analysis of the 2017 to 2023 literature in this study. Some articles, based on heuristics and metaheuristics, use mathematical model equations to explain the physician scheduling process complicated. Flowcharts and pseudocode were used in some articles to explain the physician scheduling process. However, when we reviewed it, we found that these articles still did not explain the process in any detail.

3. Problem Description

In this paper, real-life physician scheduling problems as discussed by Hidri et al. (2020) are used. RSO is used to solve problems to minimize total overtime. This issue is physician scheduling in the emergency department, in which physicians must provide nonstop services 24/7. The ICU department is divided into three sections, each in a different building. These buildings provide dissimilar services as follows:

Building 1: The ICU department's main building.

Building 2: This building provides treatment for burn patients and women with fetal dystocia.

Building 3: Specializes in the treatment of serious car accidents. In this building, there is a specialized team of physicians that is ready to intervene outside the ICU department.

The three buildings have varying workloads, with Building 1 having the most patients and an intensive workload. Buildings 2 and 3 are with a lower workload, respectively.

The working hours in the case ICU department were divided into two shifts, with a day shift beginning at 07:00 a.m. and ending at 19:00 p.m. and a night shift beginning at 19:00 p.m. and ending at 07:00 a.m. Physician scheduling is monthly (four weeks or twenty-eight days). In September, 18 physicians were assigned to the ICU department, the minimum that is required. The existing physicians will be divided into six different teams each month.

We used the hard constraints and specific constraints of Hidri et al. (2020) and transformed them into agreement, which we divided into two categories as follows:

General agreement

1. A team of physicians is appointed to work in the ICU department at the start of each month. During the planning horizon, appointed physicians are not permitted to change teams.
2. A physician must work a minimum of 208 hours per month.
3. Each physician must be appointed to one unique team for one month (four weeks or twenty-eight days). This is to create coordination and understanding between the members of a team.
4. On each team, there should be at three physicians, but no more than six, to ensure that hospital services could be appropriately rendered, but not to exceed hospital capacity.
5. If the team is assigned to work during the night shift, it cannot be assigned to work the next day shift.
6. During a day shift, the team must be allocated to only one building.
7. All physicians on the team must perform the same tasks in the same building at the same time.
8. Each building is handled by a unique team at the same time, therefore, all three buildings would have their own teams.
9. Physicians are able to work overtime for extra money.

Specific agreement

10. A physician assigned to Building 2 and 3 must work only one shift each day, including Saturday and Sunday.
11. A physician assigned to Building 1 must work only one shift per day on weekdays, due to the intensive workload from Monday to Friday.
12. On the night shift, only one team was appointed to serve the three buildings, because the intensive patient demand is reduced at night.
13. If a team is appointed to Building 1, they must work there Monday through Friday to ensure the well-being of the patients.
14. A physician cannot be assigned to work at Building 1 for two consecutive weeks because of the intense workload.
15. On Saturday or Sunday, Building 1 must be ensured by the same team during the day shift and night shift (work 24 hours).
16. The teams working on Saturday or Sunday at Building 1 should have a day off before the weekend and also a day off after the weekend, therefore if a team works Saturday, then they should have Friday and Sunday off. If the team works on Sunday, they should have Saturday and Monday off. Such teams should work only one day on Saturday or Sunday.
17. The team working in Buildings 2 and 3 need to work both Saturday and Sunday and should be of the same team.

We tested the program using the following criteria: “Each physician must have two consecutive days off per week”. Then it was found that the program became unresponsive as it was unable to find a possible solution. As a result, these criteria will not be considered in this paper.

4. Random Search Optimization Personnel Scheduling

The optimization of algorithms applied to Non-deterministic Polynomial-time complete (NP-complete) or NP-hard. This method can solve large and complex problems, and it is classified into two types: Conventional Optimization Algorithms (COAs) and Approximation Optimization Algorithms (AOAs) (Pongcharoen, 2001; Pongcharoen et al., 2001), as shown in Figure 4.

COAs are mathematically based, with procedures, variables, and complex equations. Even if it is the best solution, it takes a long time to solve the problem. Later, various methods were used to solve a wide range of problems. This method is appropriate for small problems because they are too restrictive in terms of finding a fixed solution (Pongcharoen et al., 2004).

AOAs are applied to larger, more complex problems. With many problems today requiring immediate solutions, AOAs will provide answers that are close (Near optimum solution) to or optimum. AOAs require less time to find solutions than COAs (Pongcharoen et al., 2004).

Rastrigin (1963) proposed RSO, which works by iterative move to a better position in the search space. RSO is extremely efficient and necessitates very little modeling time (Schumer and Steiglitz, 1968).

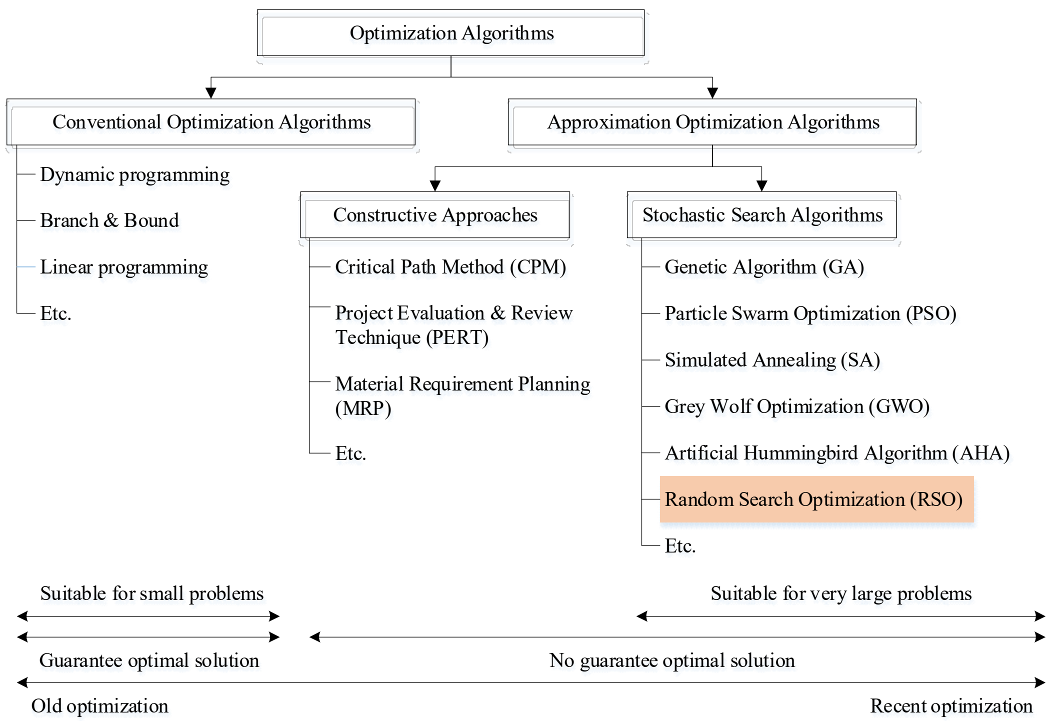

Figure 4 Optimization algorithms

4.1 Flowchart of Random Search Optimization for Physician Scheduling Problem

A personnel scheduling was developed that uses RSO that find the answer using an iterative. The objective was to minimize the overtime. The personnel scheduling was developed in a modular style using the Visual Basic for Applications (VBA) programming language. Figure 5 shows a flowchart that represents the proposed RSO used in the personnel scheduling, which includes the following steps:

1) Started by inputting data from the user-related information.
   a) number of physicians.
   b) number of buildings.
   c) work periods information - number of shifts, planning horizon.
   d) the severity rate is the percentage change in the initial solution (0 - 100).
   e) the step size (s) is round of swaps (Schrack and Choit, 1976).

2) RSO parameters set by the user include.
   a) number of populations (n).
   b) number of iterations (i).
   c) number of replications - an experiment was repeated using 30 different random seed numbers.

3) Problem encoding - a generated initial population (x_1, x_2, x_3, ..., x_n) and generating a representation for an example of a single solution as shown in Table 2.

4) Candidate solutions (x_1, x_2, x_3, ..., x_n) may be unfeasible. A repair process (Pongcharoen et al., 2004) satisfies constraints.

5) The evaluated value for all solutions in the initial population was computed and ranked, which can be calculated from Equation (1).

$$Total\ overtime = \sum_{m=1}^{6} [(NS_m * 12) - 208] * NP_m \quad (1)$$

where
NS_m is the number of shifts in team m (m = 1, ..., 6).
NP_m is the number of physicians in team m (m = 1, …, 6).

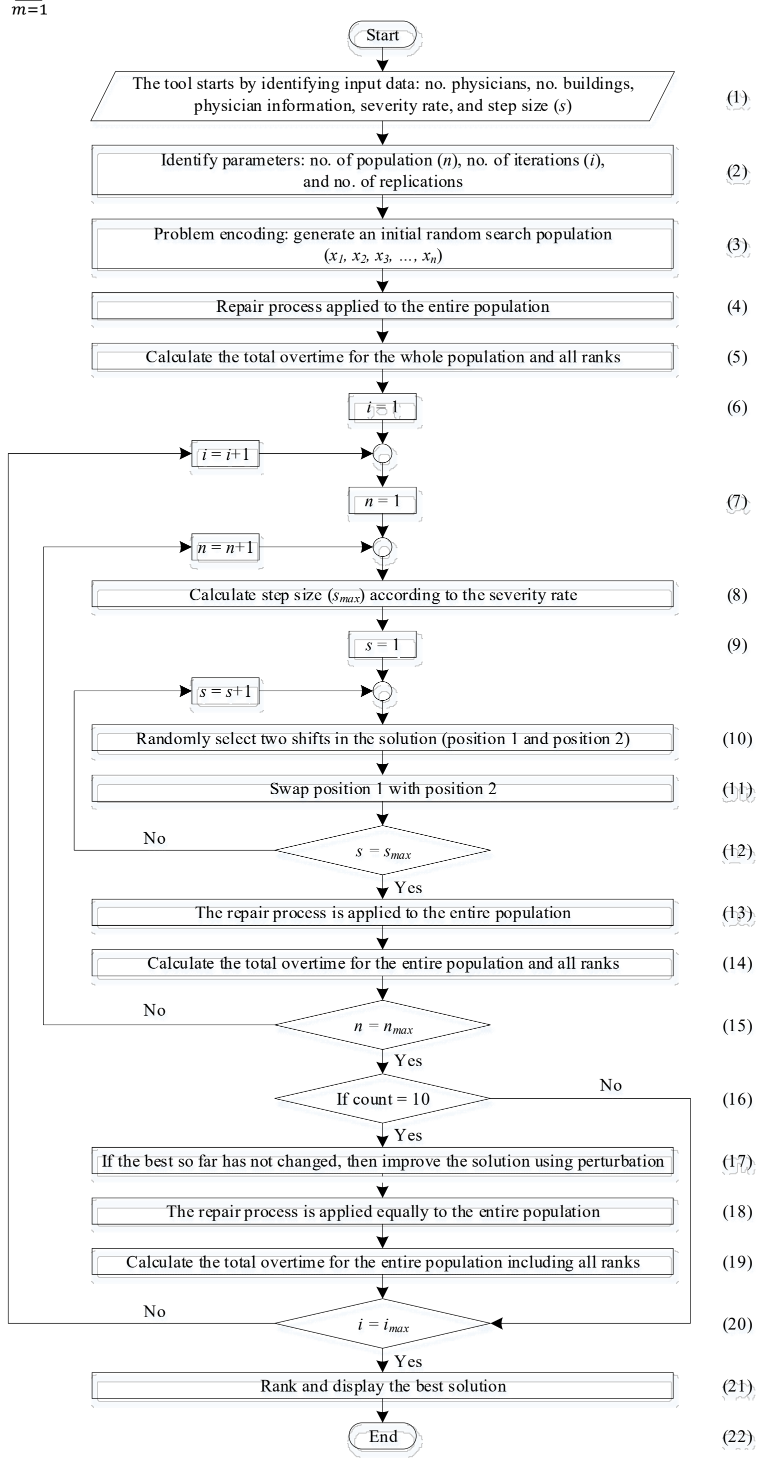

Figure 5 Random search optimization personnel scheduling flowchart

Equation (1) calculates the sum of overtime physicians for six teams, with working hours per shift of 12 hours and a minimum working hours of 208 hours per month.

6) Performs iterations from i: = 1 to i_{max}.
7) Started improving the solution for the first population.
8) Calculate s_{max} to find the round of swaps to improve the solution based on the severity rate, which can be calculated from Equation (2).

$$s_{max} = Rnd * 28 * 6 \quad (2)$$
$$s_{max} \leq \text{Severity rate} * 28 * 6 \quad (3)$$

where
Rnd is random numbers in the interval [0,1].
Equation (2) determines the maximum step size, which must be less than or equal to Equation (3). The number of working days is 28 days (four weeks or one month), and there are 6 teams.

9) Start switching positions for the first round.
10) Randomly select two shifts in the solution (position 1 and position 2).
11) Swap position 1 with position 2 shown in Figure 6.
12) If step size (s) is less than s_{max}, go back to step 9.
13) Apply the same repair procedure to all populations ($x_1, x_2, x_3, \ldots, x_n$).
14) The evaluated value for all solutions in the initial population was computed and ranked.
15) If there are remaining populations go to step 7.
16) If the best so far has not changed after being tested 10 times, then go to step 16, otherwise go to step 19.
17) Improve the solution by perturbation (generate a new initial solution).
18) Apply the same repair procedure to all populations ($x_1, x_2, x_3, \ldots, x_n$).
19) The evaluated value for all solutions in the initial population was computed and ranked.
20) If there are remaining iterations go to step 6.
21) Ranked the individuals and displayed the best solution.
22) End.

Table 2 Representation of a one population candidate solution

Day	Building 1		Building 2		Building 3	
	Day shift	Night shift	Day shift	Night shift	Day shift	Night shift
1	6	1	2	1	5	1
2	6	4	2	4	3	4
3	6	3	5	3	1	3
4	6	1	2	1	5	1
5	6	4	5	4	2	4
6	3	3	2	3	1	3
7	5	5	2	5	1	5
8	4	3	1	3	2	3
9	4	6	5	6	1	6
10	4	2	3	2	1	2
11	4	3	1	3	5	3
12	4	3	5	3	6	3
13	2	2	5	2	6	2
14	3	3	5	3	6	3
15	6	4	5	4	1	4
16	6	3	5	3	2	3
17	6	4	1	4	5	4
18	6	1	3	1	5	1
19	6	2	4	2	5	2
20	3	3	4	3	5	3
21	1	1	4	1	5	1
22	3	5	2	5	6	5
23	3	4	2	4	1	4
24	3	5	2	5	1	5
25	3	1	2	1	4	1
26	3	1	4	1	2	1
27	5	5	6	5	4	5
28	1	1	6	1	4	1

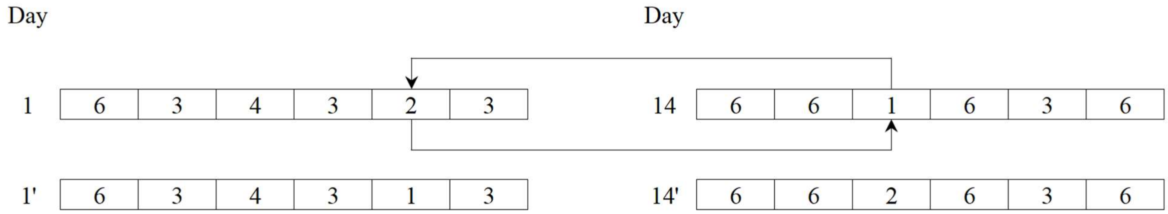

Figure 6 Swapping procedure

5. Computational Experiments and Discussion

In this paper used RSO to solve physician scheduling for the ICU department. To allocate work to physicians, we use the data set from an article of Hidri et al. (2020). We compared our method to manual method and ILP. In September, 18 physicians were assigned to the ICU department, which this month is significant because the number of physicians is limited. At the beginning of every month, physicians will be divided into 6 different teams. The computational experiments were performed on a personal computer with Ryzen 5, 2.10 GHz CPU, and 8 GB RAM

5.1 The Results and Analysis of Random Search Optimization

The article by Sooncharoen et al. (2020) discusses production scheduling for the capital goods industry in a variety of size problems (small, medium, large, and extra-large) by applying gray wolf optimization. It was discovered that the amount of search (N/I) 100/25 produced the best average of answers. As a result, the N/I = 100/25 is utilized in this paper, where N/I is the combination of the population and the iteration.

The RSO physician schedule is presented in Table 3. September is an interesting month because it has the fewest physicians assigned to the ICU department. Table 4 shows an analysis of physician schedules, workload, overtime, underload, and days off. The goal is to minimize total overtime, and the parameters listed below are used to compare to other methods.

NS_m is the number of day shifts in team m (m = 1, ..., 6).
NP_m is the number of physicians in team m (m = 1, …, 6).
OT_m is the overtime of team m (m = 1, …, 6). which can be calculated from Equation (4), if the result is positive it means overtime, but if it is negative, it means underload.

$$OT_m = [(NS_m * 12) - 208] * NP_m \tag{4}$$

UL_m is the under load of team m (m = 1, …, 6).
NNS_m is the number of night shifts in team m (m = 1, …, 6).
NDO_m is the number of days off in team m (m = 1, …, 6).

In this context and according to Table 3, teams 5, 4, 3, and 1 work on weekdays (Monday to Friday) in weeks 1, 2, 3, and 4, respectively, as an agreement (11). An agreement (12) requires that night shift physicians take care of all three buildings, team 6 works on night shift on days 1st, 5th, 7th, 9th, 11st, 13rd, 19th, 25th, and 26th. According to the agreement (15), team 2 working in Building 1 on the 6th, 14th, and 21st must work 24 hours.

Table 4 demonstrates that the total overtime is 288 hours, with no underload. The number of day shifts ranges from 18 to 19, which indicates that the physician scheduling is fair. The number of night shifts varies from 2 to 9 and the number of days off ranges from 9 to 12.

5.2 Comparative Study with Other Methods and Discussion

Hidri et al. (2020) uses mathematical model for presenting physician scheduling in the intensive care unit. The hospital uses half of the cost on medical personnel resource allocations. Their article aims to minimize total overtime, thereby resulting in reduced costs. Currently, physician scheduling is produced by a team of specialized schedulers, is known as a manual physician schedule, that takes more than two weeks to complete. This manual method does not account for the fairness, preferences, and requirements of physicians. So, they used ILP and defined hard constraints and non-classic constraints to produce physician scheduling. The outcome is the best answer and not infringing constraints. The ILP physician schedule can reduce total overtime by 50%, eliminate under-loading, and distribute duty properly. They also use metaheuristics to generate a physician scheduling of GA and SA physicians to compare its performance to that of ILP. However, because we do not know the procedure of the meta-heuristics method, GA and SA are not compared in this paper.

Table 5 shows physician scheduling using ILP and manual methods. The manual physician schedule on days 6th, 13rd, 20th, and 27th by teams 6, 3, 4, and 5 respectively, do not have a day off before work on Saturdays they must work twenty-four hours, which violates the agreement (16). In weeks 2, 3, and 4, teams 4, 5, and 2, respectively, were not allocated to work. It demonstrates that the workload distribution is unfair, even if it takes more than two weeks to complete. However, the ILP physician schedule only takes about two hours to produce, with no infringing constraints, and is still the best solution.

Table 6 shows an analysis of the ILP and manual methods. The manual method has 13 to 25-day shifts, 2 to 7-night shifts, and 5 to 16 days off, which is an unfair distribution of work and days off. Teams 2, 4, and 5 failed to reach their minimum workload, violating the agreement (2), resulting in increased total overtime. The ILP physician schedule has distributions of day shifts and days off that are good and that demonstrate equality, but the number of night shifts ranges from 2 to 8. Because the day shift is a good distribution, eliminates under-loading, and total overtime is less than the manual method.

Table 3 Random Search Optimization physician schedule

Day	Building 1		Building 2		Building 3	
	Day shift	Night shift	Day shift	Night shift	Day shift	Night shift
1	5	6	1	6	2	6
2	5	2	3	2	4	2
3	5	2	4	2	3	2
4	5	1	4	1	6	1
5	5	6	3	6	4	6
6	2	2	3	2	1	2
7	6	6	3	6	1	6
8	4	5	2	5	1	5
9	4	6	1	6	3	6
10	4	5	2	5	1	5
11	4	6	3	6	2	6
12	4	3	5	3	2	3
13	6	6	1	6	5	6
14	2	2	1	2	5	2
15	3	4	5	4	1	4
16	3	5	6	5	2	5
17	3	4	6	4	2	4
18	3	2	6	2	1	2
19	3	6	4	6	5	6
20	1	1	5	1	4	1
21	2	2	5	2	4	2
22	1	4	6	4	3	4
23	1	2	3	2	6	2
24	1	5	6	5	4	5
25	1	6	3	6	4	6
26	1	6	5	6	3	6
27	4	4	2	4	5	4
28	3	3	2	3	5	3

Table 4 Analysis of the Random Search Optimization physician schedule

Team	NS_m (Shifts)	NP_m (Person)	OT_m (Hours)	UL_m (Hours)	NNS_m (Shifts)	NDO_m (Days)
1	18	3	24	0	2	11
2	19	3	60	0	7	12
3	19	3	60	0	2	10
4	19	3	60	0	4	10
5	19	3	60	0	4	9
6	18	3	24	0	9	12
Total	112	18	288	0	28	64

Table 5 Integer Linear Programming and manual physician schedule

Day	Integer Linear Programming (ILP)						Manual Method					
	Building 1		Building 2		Building 3		Building 1		Building 2		Building 3	
	Day shift	Night shift	Day shift	Night shift	Day shift	Night shift	Day shift	Night shift	Day shift	Night shift	Day shift	Night shift
1	1	4	3	4	6	4	6	1	3	1	4	1
2	1	4	6	4	3	4	6	4	2	4	1	4
3	1	5	3	5	6	5	6	5	2	5	1	5
4	1	3	2	3	4	3	6	5	2	5	1	5
5	1	3	5	3	2	3	6	4	2	4	1	4
6	6	6	2	6	5	6	6	6	5	6	1	6
7	4	4	2	4	5	4	2	2	5	2	1	2
8	3	6	2	6	5	6	3	5	1	5	6	5
9	3	4	2	4	5	4	3	5	1	5	6	5
10	3	2	5	2	1	2	3	2	1	2	6	2
11	3	6	5	6	1	6	3	2	1	2	6	2
12	3	5	4	5	1	5	3	5	1	5	6	5
13	2	2	6	2	4	2	3	3	2	3	6	3
14	1	1	6	1	4	1	1	1	2	1	6	1
15	6	5	4	5	2	5	4	2	6	2	3	2
16	6	5	2	5	3	5	4	2	6	2	3	2
17	6	2	4	2	1	2	4	1	6	1	3	1
18	6	5	4	5	1	5	4	1	6	1	3	1
19	6	5	3	5	1	5	4	2	6	2	3	2
20	2	2	1	2	3	2	4	4	1	4	3	4
21	4	4	1	4	3	4	6	6	1	6	3	6
22	2	5	1	5	6	5	5	1	3	1	4	1
23	2	1	6	1	3	1	5	1	3	1	4	1
24	2	6	5	6	4	6	5	6	3	6	4	6
25	2	6	5	6	4	6	5	6	3	6	4	6
26	2	6	3	6	4	6	5	1	3	1	4	1
27	1	1	3	1	4	1	5	5	6	5	4	5
28	5	5	3	5	4	5	3	3	6	3	4	3

Table 6 Analysis of the Integer Linear Programming and manual physician schedule

Team	Integer Linear Programming (ILP)						Manual Method					
	NS_m (Shifts)	NP_m (Person)	OT_m (Hours)	UL_m (Hours)	NNS_m (Shifts)	NDO_m (Days)	NS_m (Shifts)	NP_m (Person)	OT_m (Hours)	UL_m (Hours)	NNS_m (Shifts)	NDO_m (Days)
1	19	3	60	0	3	11	21	3	132	0	7	8
2	19	3	60	0	4	11	13	3	0	156	6	16
3	18	3	24	0	2	10	22	3	168	0	2	8
4	19	3	60	0	5	11	17	3	0	12	3	12
5	18	3	24	0	8	11	14	3	0	120	6	15
6	19	3	60	0	6	10	25	3	276	0	4	5
Total	112	18	288	0	28	64	112	18	576	288	28	64

Table 7 compares the performance of RSO and ILP utilizing *PRO* (Percent Reduction of Overtime compared to the manual method), *PRU* (Percent Reduction of Underload is compared to the manual method), *ADO* (Average Days Off), and *ANS* (Average Number of Night shifts). As can be shown, both methods can reduce total overtime by 50% while eliminating under-load (100%). The *ADO* is computed by dividing 64 days off every month by the number of teams. On weekdays, two teams cease working (5 days * 2 teams * 4 weeks = 40 times), while three teams stop working on weekends (2 days * 3 teams * 4 weeks = 24 times). The *ANS* is computed using a month with 28-night shifts divided by the number of physician teams.

Table 7 Comparison of RSO and ILP

Method	*PRO* (%)	*PRU* (%)	*ADO* (Days)	*ANS* (Shifts)
RSO	50	100	10.67	4.67
ILP	50	100	10.67	4.67

The ILP and RSO can decrease total overtime in half when compared to the manual method, allowing all physicians to satisfy a minimum workload. Both techniques produce an optimal distribution of day shifts and decrease processing time by more than 99% as shown in Table 8 (*PRP*: Percent Reduce of Processing time compared to the manual method), but RSO is still unable to distribute the number of days off as effectively as ILP. However, both have disadvantages in terms of night shift workload distribution because they have a wider distribution range and a significantly different number of shifts than *ANS*.

Table 8 Processing time for producing a physician schedule using the manual method, ILP, and RSO

Method	*Processing time*	*PRP*
Manual	2 weeks	-
ILP	2 hours	99.16667
RSO	12 seconds	99.99862

6. CONCLUSION

The scheduling problem is an NP-hard problem, with varying properties depending on the area of application. Physician scheduling is the assignment of a work to a medical practitioner. This subject is currently receiving more attention and is frequently solved using a mathematical model approach. This paper uses data from the article of Hidri et al. (2020), which is a real-life situation involving the assignment workload to physicians in the ICU department. The ICU department of this hospital has a unique structure as well as characteristics. This work modified their constraints by adopting the general and specific agreement to provide guidelines for future research. RSO is constantly seeking a better position than its previous position in the search space. We are comparing the performance of ILP with RSO, and it appears that both techniques are very effective, as indicated in Table 7. According to Table 8, the ILP and RSO can reduce processing time by more than 99%. However, as seen in Table 4 and Table 6, both techniques fail to allocate the night shift fairly.

Future work aims to deal with the optimal solution, such as minimizing the total unbalanced workload, minimizing the total cost, or maximizing the total fairness. Thongsamai et al. (2024). discussed the physician scheduling problem but have not yet applied other metaheuristics like the Artificial Hummingbird Algorithm (AHA) to improve the optimal solutions. Statistical parameter tuning, modifying, and hybridizing metaheuristics can also improve the optimal solutions.

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