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RESEARCH ARTICLE

An Intelligent Optimization Strategy for Medical Doctor Rostering Using Hybrid Genetic Algorithm-Particle Swarm Optimization in Malaysian Public Hospital

Zanariah Zainudin[a]*, Shafaatunnur Hasan[b], Nurfazrina Mohd Zamry[c], Nor 'Afifah Sabri[d], Nurul Syafidah Jamil[a], Norliana Muslim[d], Nur Amalina Mat Jan[e], Noraini Ibrahim[f]

[a]Department of Digital Economy Technology, Faculty of Information and Communication Technology, Universiti Tunku Abdul Rahman, 31900, Kampar, Perak, Malaysia; [b]Department of Emergent Computing, Faculty of Computing, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia; [c]Department of Computer Science, Faculty of Computing, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia; [d]Department of Computer and Communication Technology, Faculty of Information and Communication Technology, Universiti Tunku Abdul Rahman, 31900, Kampar, Perak, Malaysia; [e]Department of Physical and Mathematical Science, Faculty of Science, Universiti Tunku Abdul Rahman, 31900, Kampar, Perak, Malaysia; [f]Centre for Mathematical Sciences, Universiti Malaysia Pahang Al-Sultan Abdullah, 26300 Kuantan, Pahang, Malaysia

***For correspondence:** zanariah@utar.edu.my

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Abstract Comparing manual rostering to automated rostering reveals that manual rostering is typically more challenging, time-consuming, and exhausting for doctors, particularly due to shifting business regulations, a shortage of healthcare professionals, and heavy workloads. During rostering, it is essential to consider both hard and soft constraints to minimize constraint violations, maximize medical doctor satisfaction, and meet all requirements for hard constraints. To address these challenges, this paper proposes Hybrid Genetic Algorithm and Particle Swarm Optimization (Hybrid GA-PSO) to model rostering. In this approach, one set population of working days represents the rostering structure, which is determined using evolutionary-inspired operators, search, and update procedures. Additionally, the paper conducts observations and interviews with relevant personnel in a Malaysian hospital to gather insights and highlight constraints associated with medical doctors rostering. Rostering requirements determine the relative importance of the hard and soft constraints. The results of the research indicate that the Hybrid GA-PSO approach can produce workable rosters that reduce the workload of physicians and shorten the time needed to create rosters by the total violation of both soft and hard constraints and accuracy. It also ensures compliance with both hard and soft criteria and improves rostering accuracy.

Keywords: Rostering problem, medical doctor roster, optimalization problem, Hybrid GA-PSO.

Introduction

A roster is a structured list or record of individuals or items created for a particular purpose. It is frequently utilized in settings such as workplaces, schools, sports teams, and event planning. A typical roster includes names, roles, schedules, or assignments, aiding in organization, task management, and accountability. Organizations such as healthcare have tried to create effective rosters through a variety of methods in order to improve their resource utilization and achieve greater organizational efficiency [1-

10]. For example, [1] introduces a neutrality-based Iterated Local Search (ILS) approach to tackle shift scheduling optimization. The method utilizes neutrality in the solution space to explore alternatives and improve outcomes. Meanwhile, Adams, O'Sullivan, and Walker explore innovative strategies for achieving workload balance in physician scheduling [2]. Although certain organizations use mathematical methods like linear programming, most things are still done manually. In order to maintain employee satisfaction and maximize available resources, a healthcare facility's roster coordinator often works 10 to 20 hours per week [1, 11]. However, if the roster does not meet the standards at any given time, a new roster is constructed, which disrupts the previously created roster [12–14]. Due to these limitations and the numerous decisions involved, assessing the quality of the roster becomes a challenging task. Consequently, designing an efficient medical doctor roster can significantly reduce the time required for adjustments. This, in turn, enables the staff responsible for re-rostering to focus on other managerial responsibilities.

Numerous meta-heuristic approaches, such as Genetic Algorithms [5, 15, 16],Tabu Search [17] and Hyper-Heuristics [18-20],have been investigated. Ngoo *et al*. [21], employed mathematical programming techniques to create nurse rosters optimized for staffing costs, understaffing costs, and shift patterns based on constraint violations. The lack of a detailed analysis of performance for large-scale, real-world nurse rostering scenarios limits the practical applicability of the proposed method (Genetic Algorithm), even though it may work well for small to medium-sized problems [5]. While, Tabu Search can be computationally expensive due to the repeated generation and evaluation of neighboring solutions. The paper does not address the runtime implications of this in detail, especially when embedding preferences [17]. Similarly, Hyper-heuristics often require fine-tuning of meta-parameters, yet. The authors failed to sufficiently explore the sensitivity of the results to these parameters, which can affect usability in various scheduling contexts [18]. Rostering medical professionals poses unique challenges, requiring a balance of fairness, efficiency, and compliance with intricate rules. Recently, Samah *et al*. [15] proposed a hybrid heuristic and search method to optimize rostering solutions. Additionally, another study introduced an innovative Memetic Evolutionary Algorithm that integrates explicit learning into rule-based scheduling to address rostering challenges for medical doctors [21]. These advancements highlight the potential of hybrid approaches and evolutionary algorithms in improving the quality and adaptability of medical staff rosters.

The objective of the research is to improve the rostering of doctors in a particular department of a public hospital in Malaysia, with a focus on night-morning shift organization. Ensuring the dependability of these duty rosters is essential for all participating doctors to manage accidents and emergencies in an efficient manner. The majority of public hospitals in Malaysia are currently using manual rostering, which has resulted in a number of errors in duty assignments because of insufficient information sharing and poor staff communication. The objective of this research is to enhance the rostering of doctors in a specific department of a public hospital in Malaysia, with a particular focus on organizing night-morning shift schedules. Ensuring the reliability of these duty rosters is crucial for all participating doctors to effectively manage accidents and emergencies. Currently, most public hospitals in Malaysia rely on manual rostering, which has led to several errors in duty assignments due to inadequate information sharing and poor communication among staff. Therefore, this paper aims to improve rostering efficiency by developing effective duty schedules for medical practitioners using optimization techniques such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). A duty roster is deemed feasible if it meets all required conditions under any given circumstances. These conditions are divided into two categories: hard constraints, which represent non-negotiable requirements that must be met, and soft constraints, which accommodate preferences [9, 10, 12, 17, 22-26].

The rationale behind this research is the realization that creating a duty roster is more complex than it initially seems. The creation of a personalized duty roster for medical personnel is a difficult undertaking that defies generalization due to the intricate organizational structure of this kind of department and its various components, including staffing levels, work modes, and split zones. The first step in creating a duty roster is to classify the separated zones into Green, Yellow, and Red zones, with each zone being determined by the patient's condition and the severity of the sickness. Secondly, it is crucial to account for the number of staff available in the hospital; in this case, the department employs twenty-two medical doctors. Finally, the work mode consists of a mix of tasks and shifts. The task that performed by hospital's doctors similar to those comparable departments in every public hospital in Malaysia. A doctor's schedule is influenced by whether a day is a working day or a day off. For instance, most employees are off work on Saturdays and Sundays, as well as public holidays like Hari Raya, Chinese New Year, Deepavali and etc. However, doctors may still be required to work on these days based on their duty schedule. Additionally, the medical professional must enlist a substitute doctor in the event of his or her inability to attend work for whatever reason. In order to create workable rostering, hence; it is necessary to identify the problem and measure the quality of potential solutions. Currently, the hospital prepares its duty roster several days in advance, typically one month ahead. However, the roster lacks historical records and does not consider the implicit needs of medical professionals, such as balancing work-life harmony and fostering a supportive workplace environment.

In order to address the aforementioned issues, subsequent research questions are identified:

I. What constraints have been identified for the rostering of medical doctors for the selected departments?
II. Can the hybrid GA-PSO model produce a feasible rostering system for medical doctors?
III. Can the algorithm produce a feasible outcome given based on identified constraint?

To develop a feasible medical doctor rostering system, this paper proposes a hybrid approach that combines Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The justification for using the Hybrid GA-PSO approach lies in its ability to leverage the compensatory strengths of both GA and PSO, resulting in an efficient and effective solution. Compared to previous methods, such as standalone PSO [16, 20] and Genetic Algorithm (GA) [5]. The results of the proposed approach are presented and analyzed in this paper, with comparisons made to the standard Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). A specific performance measure is employed to evaluate the Hybrid GA-PSO model for each duty roster created, focusing on three key aspects: total constraint violations, computational time, and accuracy. The feasibility of the generated duty roster is assessed based on the total violations of hard and soft constraints, as well as its accuracy, in line with findings from previous investigations.

Methodologies

In general, the research methodology framework is carried out in four stages as elaborated below and illustrated in Figure 1.

Stage 1: Preliminary Investigation
Stage 2: Modelling of the Algorithm
Stage 3: Implementation of Hybrid GA-PSO
Stage 4: Result and Discussion

Stage1: Preliminary Investigation

This sub-section provided brief descriptions of the literature reviews and the interview sessions conducted. These steps are used to obtain a comprehensive picture regarding the problem being studied as it is very important to understand the real scenario in order to find the appropriate solution that is applicable to the case study. From the investigation, information on previously related studies, problems, issues, and related approaches were gathered and give a holistic picture of the related researches previously conducted in 2018 until 2024 about staff rostering problem which include the algorithm that have been used and the possible actions that researchers can take in the future [6, 10, 15].

Stage 2: Modelling of the Algorithm

This stage determines the final result to be obtained. Data analysis from the information gathered during the interview sessions is used to design the Hybrid GA-PSO rostering system based on appropriate constraints. Constraints associated with staff scheduling were categorized into two groups, hard and soft constraints, where all hard constraints should be fulfilled while soft constraints should be catered for as much as possible. In this paper, the constraints differ from those in previous studies, as they were specifically designed to meet the requirements of the person-in-charge at the Emergencies Department of a Malaysian public hospital. The feasibility of the generated duty roster is evaluated based on the total number of violations of the hard and soft constraints. The identified hard and soft constraints are thoroughly discussed in this paper. A duty roster is considered feasible only if the following hard constraints are fully satisfied:

I. Six minimum days off for one doctor in four weeks.
II. Nine doctors must be working on any one day.
III. Requests from staff to attend conferences, meetings, and other related work away from the hospital.

The soft constraints are as follows:

I. In each shift, the balance in each zone is as follows:
a. The Red Zone equals to 1 person
b. The Yellow Zone equals to 2 persons
c. The Green Zone equals to 3 persons
II. One doctor must not work AM/PM for three consecutive days.

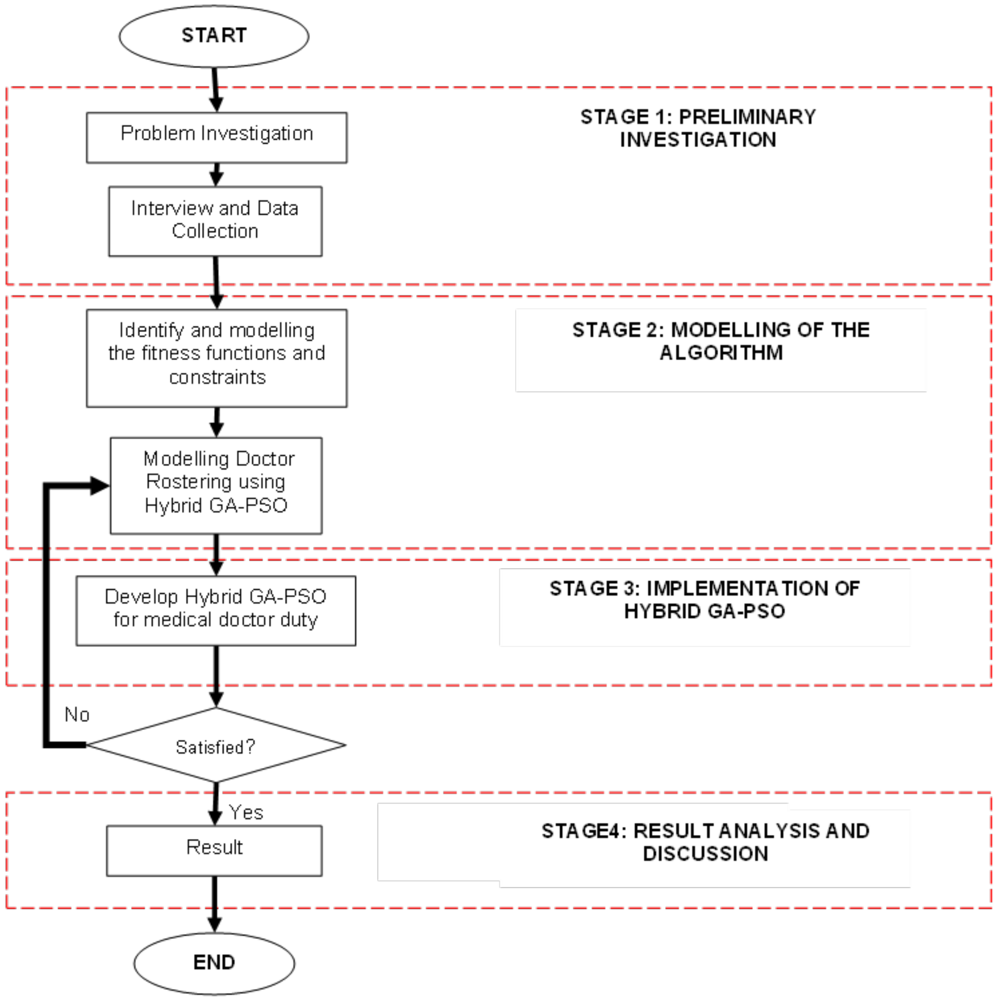

Figure 1. Research methodology for modelling doctor rostering

This section briefly explains the steps used in the Hybrid GA-PSO models to solve the scheduling problem for medical doctors.

Step 1: Set the Parameter

The first step in implementation of the Hybrid GA-PSO is to set all the parameters that are included in the scheduling problem for medical doctor. Each possible shift pattern of a medical doctor is represented by a 30x30 matrix with zero-one vectors; the first seven elements column represent the first week of the month, while the following seven elements column represent the second, third or fourth week of the month “1” in the matrix represents a working day or working night, and “0” represents a day-off or night-off. Depending on the working hours of the doctors, there are a limited number of available shift patterns.

Step 2: Set the Decision Variable

The second step in the implementation of Hybrid GA-PSO model is to set the decision variables that are included in the scheduling problem for medical doctor based on the previous work [10], [23].

$$x_{ij} = \begin{cases} 1 & if\ doctor\ i\ is\ assigned\ to\ shift\ pattern\ j \\ 0 & else \end{cases} \quad (1)$$

where
i = 1, …. n medical doctor index
j = 1, ...m shift pattern index

Step 3: Set the Feasible Shift Patterns

In this step, the feasible shift patterns were established for each medical doctor in the scheduling process. This involves defining how many shifts each doctor is assigned across different time slots (AM, PM, and Night) based on their individual requirements.

For each medical doctor i(i=1, … ,n), we define F(i) as:

$$F(i) = \begin{cases} \sum_{j=1}^{m}\sum_{k=1}^{30} a_{jk} = Di\ \ \forall\, j \in AM\ shifts \\ \sum_{j=1}^{m}\sum_{k=1}^{30} a_{jk} = Bi\ \ \forall\, j \in PM\ shifts \\ \sum_{j=1}^{m}\sum_{k=1}^{30} a_{jk} = Ni\ \ \forall\, j \in N\ shifts \end{cases} \quad \forall\, i = 1, \dots . n \quad (2)$$

where
n = number of medical doctors
m = number of shift patterns

$$a_{jk} = \begin{cases} 1 & if\ shift\ pattern\ j\ covers\ day/night\ k \\ 0 & else \end{cases} \quad (3)$$

Di: Required number of *AM* shifts per week for medical doctor *i*
Bi: Required number of *PM* shifts per week for medical doctor *i*
Ni: Required number of *Night* shifts per week for medical doctor *i*

Step 4: Set the Objective Function

The fourth step is to set the objective function, which is used to minimize the number of working days of a medical doctor in a month in order to give a fair workload distribution to the medical doctors. The function is as follows:

$$ObjectiveFunction_{(x)} = \sum_{i=1}^{n}\sum_{j\in F(i)}^{m} p_{ij}x_{ij} \ \rightarrow min\,! \quad (4)$$

where
p_{ij} = Preference cost for doctor i working in shift pattern j. This cost can represent the doctor's preference or the desirability of assigning a doctor to a particular shift

$$x_{ij} = \begin{cases} 1 & if\ doctor\ i\ is\ assigned\ to\ shift\ pattern\ j \\ 0 & else \end{cases}$$

Subjected to:

1. Every medical doctor works exactly one feasible shift pattern

$$\sum_{j\in F(i)} x_{ij} = 1\ \ \forall i \quad (5)$$

where

$$x_{ij} = \begin{cases} 1 & if\ doctor\ i\ is\ assigned\ to\ shift\ pattern\ j \\ 0 & else \end{cases}$$

F(i) is feasible shift patterns for medical doctor *i*

THEN:
Launch ***Selection***
Launch ***Crossover***
Launch ***Mutation***
IF meet convergence criteria
Go to Step 5
ELSE
LOOP Step 3

Step 5: Set the Update Velocity Function

The fifth step is, firstly, to set the initial velocity of the updated velocity function and generate the initial solution for each particle by adding the S_u where S_u is set of population of each particle in PSO; so that the medical doctors are randomly scheduled to each shift. Secondly, if the initial solution is feasible, then it will continue with the updated Velocity Function in Binary PSO.

$$V_{id} = W_{vid} + c_1 * rand() * (p_{id} - X_{id}) + c_2 * rand() * (p_{gd} - x_{id}) \tag{6}$$

where
v_{id}: velocity of particle
x_{id}: current position of particle
w: weighting function
c_1 and c_2: determine the relative influence of the social and cognitive components
P_{id}: *pbest* of particle *i*
P_{gd} : the *global best position* found by any particle in the swarm

Step 6: Set the Update Position Function

The sixth step is to update the velocity function by calculating the new position's personal and global bests.

$$\boldsymbol{X} = \{X_1, X_2, X_3, \ldots, X_n\} \tag{7}$$

$$\boldsymbol{X_k^{I+1}} = X_{id} + V_{id},\ i = 0,1,\ldots\ldots, M - 1, \tag{8}$$

where
v_{id}: velocity of particle
x_{id}: current position of particle

Step 7: Set the Fitness Function

The seventh step is to set the fitness function that is included in the scheduling problem for the medical doctor. The results of the fitness function would indicate which of the data set generated using GA is the best to be implemented in the following month. In this paper, the fitness function evaluates the result as the summation of violated constraints, where each hard constraint (H1, H2 and H3) is given a weightage of 10, the first three soft constraints (S1, S2, and S3) each has a weightage of 1, and the fourth soft constraint (S4) has a weightage of 0.5.The fitness function values are obtained from the violations of the constraints. The results are then encoded to minimize the number of constraints. The constraints are divided into hard constraints and soft constraints with its mathematical notation given in Equation (9) to Equation (16).

In order to obtain a optimal results, this research selected to minimize the fitness function, which means that the fitness value is small to get a feasible duty roster. When translated into mathematical notation, the constraints become:

$$\forall = (cx, dx, ex, fx, gx, hx, ix)\ \&\&\ (cy, dy, ey.fy, gy, hy, iy) \tag{9}$$
$$\boldsymbol{C1} = sum(cx, cy) > 24\ weighted\ 10 \tag{10}$$
$$\boldsymbol{C2} = sumWorkforOneDay(dx, dy) < 9\ weighted\ 10 \tag{11}$$
$$\boldsymbol{C3} = (ex_1, ey_1 = !0)\ \&\&\ (ex_2, ey_2 = !0)\ \&\&\ (ex_h, ey_h = !0)\ weighted\ 10 \tag{12}$$
$$\boldsymbol{C4} = sumGreenZone(fx, fy) < 3\ weighted\ 1 \tag{13}$$
$$\boldsymbol{C5} = sumYellowZone(gx, gy) < 2\ weighted\ 1 \tag{14}$$
$$\boldsymbol{C6} = sumRedZone(hx, hy) < 1\ weighted\ 1 \tag{15}$$
$$\boldsymbol{C7} = sumConsecutiveDayAM/N(fx, fy) < 3\ weighted\ 0.5 \tag{16}$$

where
x: xth column of a doctor's scheduling.
y: yth row of a doctor's scheduling.

C1: Hard Constraint 1
C2: Hard Constraint 2
C3: Hard Constraint 3
C4: Soft Constraint 1
C5: Soft Constraint 2
C6: Soft Constraint 3
C7: Soft Constraint 4

The notation for the fitness calculation for each constraint over the result is given as follows:

$$\boldsymbol{F}(\boldsymbol{x}) = \begin{cases} 1 \; Violated\ Constraint \\ 0 \; Non-Violated\ Constraint \end{cases} \tag{17}$$

The value of the fitness function, calculated when *H1, H2, H3, S1, S2, S3 or S4* are violated, is given by the following formula:

$$\boldsymbol{fitnessfunction}(\boldsymbol{x}) = \sum_k \sum_i \propto_i f(C_i) \tag{18}$$

where
k = n/2(a+1), where
n = number of working days,
a+1 = summation of first and last comparison
i = number of constraints
α_i = weight attached to Constraint C_i

Step 8: Termination
This step controls the mechanism for the repetition of this algorithm. The algorithm is terminated whenever the stopping criterion was satisfied; otherwise, the process will repeat from Step 3. Once the algorithm was terminated, the output data represented by the global best position is reported as the best result found by this algorithm.

Stage 3: Implementation of Hybrid GA-PSO

Implementing the Hybrid GA-PSO algorithm involves multiple stages, from designing the pseudo-code to actual implementation in a program. Initially, several duty rosters were generated, and the performance of the Hybrid GA-PSO algorithm was recorded. This phase focuses on the development and integration of the Hybrid GA-PSO approach. Once the relevant algorithms were coded into the system, potential results were generated. The initial population, created randomly, may include both feasible and non-feasible solutions, which were then evaluated using a fitness function to refine and improve the outcomes beyond what was achieved with Hybrid GA-PSO alone. Finally, the performance of the Hybrid GA-PSO algorithm was assessed based on its computational time and accuracy.

Stage 4: Results and Discussion

Initially, multiple duty rosters were generated to evaluate the performance of different optimization techniques, including Standard Genetic Algorithm (GA), Standard Particle Swarm Optimization (PSO), and the proposed Hybrid GA-PSO approach. The results of these methods were recorded to compare their effectiveness in generating feasible and high-quality rosters. This phase focuses on establishing the foundational details of the study, with particular emphasis on the development and integration of the Hybrid GA-PSO algorithm. This hybrid approach aims to combine the strengths of GA's exploration capabilities with PSO's efficiency in exploitation, enhancing the overall performance in solving the duty rostering problem.

The performance of the proposed Hybrid GA-PSO algorithm is indicated by the non-violation of the allocated maximum working days for the medical doctor as shown in Table 1. In optimization problems like duty rostering, the number of iterations directly impacts the depth of the solution space exploration and the quality of the final result. A rapid approach is to use 200 iterations, which can be useful when computing time is limited or when a good answer is enough but not necessarily the best one. This lower iteration count is often used for less complex problems or when the algorithm converges rapidly to a feasible solution. In contrast, 1000 iterations were selected to conduct comprehensive exploration of the solution space, particularly in cases involving complex constraints or larger datasets. This higher number of iterations allows the algorithm to refine solutions, reduce violations of hard and soft constraints, and escape local optima, thereby improving the quality and robustness of the generated roster. The specific numbers were often determined through empirical testing to find the point where additional iterations result in diminishing returns in solution quality while remaining computationally manageable. Thus, these values represent a trade-off between computational efficiency and the desired precision of the duty roster.

Table 1. Results standard GA, standard PSO and hybrid GA-PSO for Iteration 200 and 1000

Run	Standard GA 200 Iterations			
	Computational Time (seconds)	**Total Constraint Violation (%)**	**Accuracy (%)**	**Maximum Working Days**
1	31.62	10.00	90.00	20
2	17.45	7.50	92.50	19
3	19.31	9.50	90.50	21
4	11.83	7.50	92.50	21
5	20.06	10.00	90.00	20
Average	**20.05**	**8.90**	**91.60**	**20**

Run	Standard GA 1000 Iterations			
	Computational Time (seconds)	**Total Constraint Violation (%)**	**Accuracy (%)**	**Maximum Working Days**
1	196.03	4.00	96.00	20
2	140.52	12.50	87.50	19
3	158.16	11.00	89.00	21
4	211.55	7.00	93.00	22
5	130.24	13.00	87.00	19
Average	**167.30**	**9.50**	**91.00**	**20**

Run	Standard PSO 200 Iterations			
	Computational Time (seconds)	**Total Constraint Violation (%)**	**Accuracy (%)**	**Maximum Working Days**
1	11.53	7.00	93.00	22
2	19.35	6.50	93.50	23
3	7.48	5.00	95.00	22
4	17.13	8.00	92.00	21
5	5.44	10.50	89.50	23
Average	**12.19**	**7.40**	**91.60**	**22**

Run	Standard PSO 1000 Iterations			
	Computational Time (seconds)	**Total Constraint Violation (%)**	**Accuracy (%)**	**Maximum Working Days**
1	22.94	6.00	94.00	23
2	66.46	6.50	93.50	23
3	9.73	6.60	91.00	23
4	33.38	8.00	92.50	23
5	31.10	13.00	89.50	23
Average	**32.72**	**7.6**	**94.00**	**23**

Run	Hybrid GA-PSO 200 Iterations			
	Computational Time (seconds)	**Total Constraint Violation (%)**	**Accuracy (%)**	**Maximum Working Days**
1	23.54	6.00	94.00	19
2	54.38	9.50	90.50	22
3	50.18	9.00	91.00	20
4	21.10	8.00	92.00	21
5	24.56	12.00	88.00	19
Average	**34.75**	**8.40**	**91.60**	**20**

Run	Hybrid GA-PSO 1000 Iterations			
	Computational Time (seconds)	**Total Constraint Violation (%)**	**Accuracy (%)**	**Maximum Working Days**
1	140.04	6.00	94.00	21
2	131.10	7.50	92.50	22
3	198.92	8.00	92.00	21
4	157.61	7.00	93.00	22
5	194.49	4.00	96.00	19
Average	**164.43**	**6.50**	**94.00**	**21**

Figures 2 and 3 illustrate the duty rosters showing different allocations for 22 medical doctors generated by Hybrid GA-PSO at 200 and 1000 iterations. The duty roster is generated through coding that incorporates both hard and soft constraints. Each time the code is executed, the total violations are recorded, and the resulting duty roster was produced. The Hybrid GA-PSO algorithm demonstrates a balanced performance compared to Standard GA and Standard PSO, leveraging the strengths of both approaches. For 200 iterations from Figure 2, Hybrid GA-PSO achieves an average accuracy of 91.60%, matching Standard GA and slightly below Standard PSO (94.00%), with moderate computational time (34.75 seconds) and constraint violations (8.40%). The result at 1000 iterations, as depicted in Figure 3, proven that Hybrid GA-PSO outperforms Standard GA in accuracy (94.00% vs. 91.00%) and achieves lower total constraint violations (6.50% vs. 9.50%) while requiring slightly less computational time on average (164.43 seconds vs. 167.30 seconds). However, compared to Standard PSO at 1000 iterations, Hybrid GA-PSO has comparable accuracy (94.00%) but requires significantly more computational time (164.43 seconds vs. 32.72 seconds). These results highlight Hybrid GA-PSO's ability to combine GA's exploration capabilities and PSO's exploitation strengths to produce robust solutions, albeit with higher computational overhead than PSO.

The primary drawback of using Standard GA and Standard PSO for solving medical doctor duty rostering problems is that each algorithm has inherent weaknesses that hinder their ability to consistently generate feasible duty rosters. These limitations affect their efficiency in meeting the complex constraints and requirements of medical scheduling. The weakness of Standard GA is that certain optimization problems (called variant problems) cannot be solved by means of genetic algorithms due to the poorly known fitness functions that generate bad chromosome blocks [27]. Consequently, there is no absolute assurance that a genetic algorithm will find a global optimum, especially when the populations have a lot of subjects. On the contrary, the weakness of Standard PSO is that it tends to maximize, instead of minimize, the working days for the medical doctors [27]. However, when the two algorithms are used in combination, it successfully solves the medical doctor rostering problem by incorporating the advantages of the two algorithms. This can be seen in Table 1 where the Hybrid GA-PSO demonstrated better accuracy and can create a feasible duty roster for the medical doctors compared to Standard GA and Standard PSO.

Notes::>

AM/N (G)	Green Zone
AM/N (K)	Yellow Zone
AM/N (M)	Red Zone
DO	Day Off

Doctors\Days	Days 1	Days 2	Days 3	Days 4	Days 5	Days 6	Days 7	Days 8	Days 9	Days 10	Days 11	Days 12	Days 13
Doctor 1	DO	PM(K)	DO	PM(H)	PM(K)	AM/N(M)	AM/N(K)	DO	PM(K)	DO	DO	PM(K)	DO
Doctor 2	DO	DO	DO	DO	DO	DO	DO	PM(H)	DO	DO	PM(H)	PM(K)	DO
Doctor 3	AM/N(K)	DO	DO	DO	DO	PM(H)	PM(K)	DO	AM/N(K)	DO	DO	DO	DO
Doctor 4	DO	DO	DO	DO	AM/N(K)	AM/N(H)	PM(H)	PM(H)	AM/N(H)	AM/N(H)	AM/N(H)	DO	AM/N(M)
Doctor 5	AM/N(K)	PM(M)	DO	PM(K)	PM(M)	AM/N(K)	AM/N(M)	DO	PM(K)	DO	DO	PM(M)	PM(K)
Doctor 6	AM/N(H)	DO	DO	DO	DO	DO	AM/N(K)	AM/N(H)	PM(K)	DO	PM(H)	AM/N(K)	DO
Doctor 7	DO	PM(H)	DO	PM(H)	PM(M)	PM(H)	AM/N(K)	DO	PM(K)	PM(K)	AM/N(M)	AM/N(K)	DO
Doctor 8	PM(H)	AM/N(H)	AM/N(K)	PM(H)	DO	DO	DO	PM(H)	DO	DO	PM(K)	AM/N(H)	AM/N(H)
Doctor 9	PM(H)	DO	PM(K)	AM/N(H)	PM(H)	AM/N(K)	DO	AM/N(H)	DO	PM(H)	DO	PM(M)	DO
Doctor 10	AM/N(K)	PM(H)	AM/N(H)	PM(M)	DO	AM/N(K)	DO	PM(M)	AM/N(H)	DO	AM/N(M)	PM(K)	PM(H)
Doctor 11	PM(H)	DO	PM(H)	DO	DO	PM(K)	DO	DO	AM/N(H)	PM(M)	DO	DO	PM(H)
Doctor 12	AM/N(H)	AM/N(H)	PM(H)	PM(K)	AM/N(K)	AM/N(K)	DO	DO	DO	DO	DO	DO	PM(K)
Doctor 13	PM(K)	DO	DO	DO	DO	DO	DO	PM(K)	DO	DO	DO	PM(K)	DO
Doctor 14	AM/N(M)	DO	DO	PM(M)	DO	DO	AM/N(H)	PM(H)	AM/N(M)	PM(H)	DO	DO	DO
Doctor 15	DO	PM(M)	AM/N(K)	DO	AM/N(K)	AM/N(H)	AM/N(H)	PM(H)	DO	AM/N(M)	DO	PM(H)	DO
Doctor 16	DO	AM/N(H)	PM(H)	DO	DO	PM(K)	PM(M)	DO	DO	DO	DO	PM(M)	AM/N(K)
Doctor 17	PM(H)	AM/N(H)	DO	AM/N(H)	DO	DO	DO	DO	PM(K)	AM/N(M)	DO	DO	DO
Doctor 18	DO	PM(M)	AM/N(K)	DO	AM/N(M)	DO	DO	PM(K)	DO	AM/N(H)	DO	PM(H)	DO
Doctor 19	DO	PM(H)	AM/N(M)	DO	AM/N(H)	PM(H)	PM(H)	PM(K)	DO	PM(M)	DO	DO	AM/N(K)
Doctor 20	AM/N(M)	PM(H)	AM/N(H)	DO	DO	AM/N(H)	DO	DO	DO	PM(M)	AM/N(H)	DO	DO
Doctor 21	DO	DO	DO	DO	DO	DO	AM/N(K)	PM(K)	PM(M)	AM/N(M)	AM/N(K)	DO	DO
Doctor 22	DO	AM/N(K)	AM/N(K)	DO	DO	PM(H)	PM(H)	PM(H)	DO	DO	PM(H)	PM(K)	AM/N(K)

Figure 2. The results of Hybrid GA-PSO for 200 iterations

Notes::>

AM/N (G)	Green Zone
AM/N (K)	Yellow Zone
AM/N (M)	Red Zone
DO	Day Off

Doctors\Days	Days 1	Days 2	Days 3	Days 4	Days 5	Days 6	Days 7	Days 8	Days 9	Days 10	Days 11	Days 12	Days 13	Days 14
Doctor 1	DO	AM/N(K)	AM/N(K)	DO	AM/N(H)	AM/N(M)	DO	DO	DO	DO	PM(H)	DO	DO	PM(K)
Doctor 2	DO	PM(K)	DO	DO	DO	DO	AM/N(H)	PM(M)	PM(K)	DO	DO	PM(K)	AM/N(M)	DO
Doctor 3	DO	PM(K)	DO	DO	DO	DO	DO	PM(H)	PM(H)	DO	AM/N(M)	DO	DO	DO
Doctor 4	PM(K)	PM(K)	DO	DO	PM(H)	DO	PM(H)	AM/N(K)	PM(K)	PM(H)	AM/N(K)	AM/N(M)	DO	AM/N(M)
Doctor 5	DO	AM/N(M)	AM/N(H)	AM/N(H)	DO	AM/N(H)	PM(H)	DO	DO	PM(K)	AM/N(H)	AM/N(M)	DO	DO
Doctor 6	AM/N(M)	PM(H)	AM/N(M)	PM(H)	DO	PM(H)	PM(H)	DO	AM/N(M)	DO	DO	AM/N(H)	PM(H)	PM(K)
Doctor 7	DO	DO	DO	DO	DO	AM/N(H)	DO	PM(H)	PM(K)	DO	PM(M)	DO	PM(H)	DO
Doctor 8	AM/N(H)	DO	DO	AM/N(H)	DO	DO	AM/N(H)	DO	AM/N(M)	DO	PM(M)	DO	AM/N(M)	DO
Doctor 9	DO	PM(K)	PM(H)	AM/N(H)	AM/N(H)	AM/N(H)	AM/N(H)	DO	DO	DO	AM/N(H)	PM(H)	DO	AM/N(M)
Doctor 10	DO	AM/N(H)	DO	DO	DO	PM(K)	PM(M)	PM(K)	DO	AM/N(H)	PM(H)	DO	PM(H)	DO
Doctor 11	DO	PM(M)	AM/N(H)	AM/N(M)	AM/N(H)	AM/N(K)	PM(M)	AM/N(M)	DO	DO	AM/N(K)	AM/N(H)	AM/N(H)	DO
Doctor 12	AM/N(H)	PM(H)	DO	AM/N(M)	DO	DO	DO	DO	PM(H)	AM/N(H)	DO	PM(M)	AM/N(K)	DO
Doctor 13	DO	DO	DO	AM/N(H)	AM/N(K)	DO	PM(K)	AM/N(H)	PM(K)	DO	DO	PM(H)	AM/N(K)	AM/N(H)
Doctor 14	PM(K)	AM/N(H)	AM/N(M)	AM/N(K)	DO	PM(M)	DO	DO	AM/N(H)	PM(M)	DO	PM(M)	PM(M)	PM(K)
Doctor 15	DO	AM/N(H)	DO	AM/N(K)	DO	PM(K)	DO	DO	DO	PM(M)	DO	DO	DO	DO
Doctor 16	PM(M)	DO	DO	AM/N(M)	DO	PM(K)	DO	DO	PM(H)	DO	DO	DO	PM(M)	DO
Doctor 17	DO	DO	DO	DO	DO	AM/N(H)	DO	AM/N(K)	DO	AM/N(M)	AM/N(H)	DO	DO	DO
Doctor 18	DO	AM/N(K)	AM/N(H)	DO	DO	AM/N(H)	AM/N(K)	DO	PM(H)	DO	DO	AM/N(H)	DO	PM(K)
Doctor 19	PM(H)	PM(H)	AM/N(K)	DO	PM(M)	DO	DO	AM/N(H)	DO	AM/N(H)	DO	PM(H)	DO	PM(M)
Doctor 20	AM/N(H)	PM(H)	AM/N(H)	DO	PM(H)	PM(K)	AM/N(M)	DO	AM/N(H)	DO	DO	DO	DO	PM(H)
Doctor 21	AM/N(H)	DO	PM(H)	AM/N(H)	AM/N(K)	DO	DO	PM(H)	DO	PM(K)	DO	DO	DO	PM(H)
Doctor 22	DO	DO	DO	AM/N(H)	PM(K)	PM(K)	DO	PM(H)	DO	DO	PM(K)	PM(H)	DO	DO

Figure 3. The results of Hybrid GA-PSO for 1000 iteration

Conclusions

In conclusion, the Hybrid GA-PSO algorithm demonstrated its effectiveness in balancing accuracy and constraint satisfaction by combining the exploration strengths of Genetic Algorithms and the exploitation efficiency of Particle Swarm Optimization. At 200 iterations, it performed comparably to Standard GA and slightly below Standard PSO in accuracy, while maintaining moderate computational time and constraint violations. At 1000 iterations, Hybrid GA-PSO outperformed Standard GA in accuracy and constraint satisfaction while showing comparable accuracy to Standard PSO, though at a higher computational cost. These results indicate that Hybrid GA-PSO is a robust solution for generating high-quality duty rosters, particularly in scenarios where accuracy and constraint satisfaction are prioritized, even if computational time is less critical.

Medical doctor's rostering problems are commonly encountered in the healthcare industry as each department in a hospital has a different set of duty rosters and different kinds of constraints and requirements to fulfil. Furthermore, to create a functional duty roster, both hard and soft constraints must be satisfied [1]. The generated duty rosters frequently exhibit conflicts in requirements and occasionally necessitate modifications to address these discrepancies. Thus, the aim of this research is to generate a feasible rostering result with a minimal computation time while satisfying all the desired hard constraints and minimizing the violations of the soft constraints (fitness function). This research has successfully developed an algorithm that could solve the medical doctor rostering problem. The performance of the approach was tested, and it has proven to generate more feasible duty rosters.

For future work, the proposed Hybrid GA-PSO methods for creating medical doctors' duty rosters are to be used for re-rostering of previously generated shift assignments to respond to absenteeism or unavailability of medical staff by reallocating resources. Rostering and re-rostering of shift assignments in any business are usually challenging, tedious, and tiresome task due to operational problems such as changes in business rules, shortages of resources, unplanned absences and unexpected demands. In order to minimize disruption to the operation while providing suitable cover in a cost-effective way, a real-time re-rostering of shift assignments using Hybrid GA-PSO is proposed to address these operation challenges.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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