A Framework using an Evolutionary Algorithm for On-call Doctor Scheduling

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Abstract: In this paper, a framework is presented to outline the steps of automating doctor scheduling process using an evolutionary algorithm. Particle Swarm Optimization (PSO) is applied within the framework to generate optimum work schedule for on-call doctors in emergency department at a public hospital in Malaysia. Currently, the doctor schedules are prepared by a head staff called captain who performs this tedious task manually where a lot of time is spent to perform this task. The main purpose of this research is to generate an optimum doctor schedule where the number of staff on duty is sufficed, individual preferences is fulfilled and all doctors are treated fairly. A systematic framework is established which can be applied to any automated on-call doctor scheduling system of emergency department in a Malaysian hospital.

Keywords: Scheduling, On-call doctors scheduling, Rostering, Particle Swarm Optimization, Malaysian Hospital.

1. Introduction

The scheduling problem exists in many industries especially in the healthcare industry. The need for a good schedule is due to the small number of staffs in a specific medical centre to manage large resources and to serve large number of patients. Scheduling is concerned with the determination of appropriate requirements, allocation and duty assignments for an organization in order to meet specific constraints. This involves the allocation of human resources to timeslots and possible locations. This problem is often extremely complicated to solve [1]. Silvestro and Silvestro [2] stated that self-scheduling is created for convenience of the staff. The authors also added that there are no formal procedures for problem solving. As an addition, Hung [3] mentioned that self-scheduling leads to greater staff-satisfaction and improves co-operation. Silvestro and Silvestro also concluded that the benefits of self-scheduling rely on the size and complexity of a specific problem. It can work well in smaller wards where the constraints remain relatively simple.

Previous work on scheduling problem has been done using many approaches which include soft computing techniques as summarized in Table 1 [3-32] for year 2000 until 2012. An early approach to solve scheduling problems is using mathematical programming [33]. Bard *et al*. [10], proposed a review of staff scheduling and rostering problems. The authors present a very specific application area, models and algorithms that have been reported in the literature and the methods to solve them. Different categories of methods on personnel scheduling problems had been highlighted by Bard *et al*. [11] which include constructive heuristic, expert system, integer programming, genetic algorithm, simple local search, simulated annealing and constraint logic programming. Genetic algorithm as an optimization tool is one of the techniques that is able to evolve near-optimal solutions for non-linear optimization problems in different fields of the research operations [33].

Burke *et al.* [34] have mentioned approaches used by different authors in nurse scheduling problem. The authors also described that finding the optimal solution is largely meaningless, when most hospital administrators want to get high quality results in a short amount of time.

Aickelin *et al.* [37] solved the nurse scheduling problem using a hybrid technique that combines an integer programming formulation with evolutionary algorithms. They also proposed a statistical method to compare different scheduling algorithms. Aickelin *et al.* [37] proposed a new memetic evolutionary algorithm to solve the rule-based nurse scheduling. These approaches are able to provide solutions for the scheduling problems. Briefly, Table 1 identifies different categories of methods that have been used in personnel scheduling problems. These methods include optimization approaches (i.e. mathematical programming), constraint logic programming, constructive heuristic, expert systems, genetic algorithms, simple local search, simulated annealing, tabu search, knowledge based systems, artificial neural networks and hybrid systems.

2. General Background of the Case Study

Scheduling an on-call doctor is different from a routine-job doctor. In this research, scheduling an on-call doctor refers to scheduling doctors for emergency cases that occurred after working hours. The scheduling process in Malaysian public hospitals is done manually by one of the medical staff called captain. The captain will generate a duty roster based on specific criteria such as number of available doctors, wards in the department which has to be covered and number of public holidays. The captain will prepare the duty roster, and if there are objections about it, the captain will re-schedule the duty-roster. After that, the new schedule will get approval from the hospital board director. Finally, the schedule will be handed over to the hospital staff to be placed on the notice board.

The cycle length for one schedule for on-call doctor heavily depends on the number of available doctors on duty. If many doctors work at the hospital, then the cycle length for on-call will be longer. For example if a doctor is on-call on Monday, then he or she will be on-call again Monday of the following week. If the cycle length is shorter, then the doctor will be probably on-call again, on Thursday, the same week.

Table 1. Summary of Techniques for Staff Rostering and Rescheduling Problem [2-30]

Year	Authors	Optimization	Construction based	Search	Knowledge based AI	Hybrids
2000	Aicklelin & Dowsland					GA+H
	Downsland & Thompson					TS+IP
	Cai & Li			GA		
2001	Burke *et al.*			MA		
	Brusco & Jacobs	ILP				
2003	Souubeiga			HH		
	Li *et al.*					H+LS+TS
	Dias *et al.*			TS, GA		
2004	Aickelin& White					GA+IP
	Aickelin & Dowsland			IGA		
	Isken	IP				
	Winstanley					CLP+AB
	Moz & Pato	Binary LP				
	Bard (04b)	MIP				
	Bard (04a)	IP				
2005	Bard & Purnomo (05a)	IP(B&P)				
	Azaziez & Al Sharif	0-1 Linear GP				
	Bard & Purnomo (05b)					CGB+IP
	Bard & Purnomo (05c)					CGB+IP+H
	Matthews	LP				
	Bard & Purnomo (05d)	IP				
	Horio		CH			
	Fung et al.					GCS/SS
	Akihiro et al.				NN	
	Brucker et al.		CH			
2006	Beddoe & Petrovic					CBRG+GA
	Suman & Kumar			SA		
	Belien	MIP(B&P), DA				
	Bard &Purnomo	IP(B&P)				
	Belien & Demeulemeester	IP(B&P)				
	Topaloglu	MO-MP				
	Dowsland *et al.*			GA		
2007	Moz & VazPato					GA+CH
	Bard & Purnomo	IP(LR)				
	Burke *et al.* (06a)			EA(SS)		
	Burke *et al.* (06b)					H+VNS
	Punnakitikashem	DA				
	Thompson			LS,SA		
	Bai *et al.*					GA+SA+HH
	Baumelt *et al.*			TS		
	Beddoe & Petrovic					CBE+TS
	Bester *et al.*			TS		
	Majumdar & Bhunia			GA		
2008	Chiaramonte				AB	
	Vanhoucke & Maenhout	IP				

2009	Brucker *et al.*					**CH+LS**
	Goodman *et al.*					**GRASP**
	Javier et al.			**GA**		
	Nissenote & Guther			**PSO**		
	Al-Betar & Khader					**HS+SS**
2010	Bouarab *et al.*	**MP**				
	Altamirano *et al.*			**PSO**		
	Vlah *et al.*			**VNS**		
2011	Ramli & Ahmad			**TS (Enhanced)**		
	T.K. Ho et al.			**PSO**		
	Jaradat & Ayob			**SS**		
	Lo & Lin			**PSO**		
	Constatino *et al.*					**GA+SS**
2012	Naudin *et al.*	**MM**				
	Birgin *et al.* (12a)			**LSN**		
	Birgin *et al.* (12b)			**HH**		
	Wryne & Potts	**LP**				
	A.A Samah *et al.*			**GA (Enhanced)**		

Abbreviations:

GA=Genetic algorithm, **H**=Heuristic, **TS**=Tabu search, **IP**= Integer programming, **LP**=Linear programming, **MO-MP**=Multi-Objective mathematical Programming, **MA**=Memetic algorithm, **ILP**=Integer linear programming, **HH**=Hyper-heuristic, **IGA**=Indirect GA, **CLP**=Constraints logic programming, **AB**=agents-based, **LP**=Linear programming, **MM**= Mathematical Model **MIP**=Mixed integer programming, **B&P**=Branch & Price, **CGB**=Column generation based, **GCS/SS**=Guided complete search/Simplex solver, **NN**=Neural network, **CH**=Constructive heuristics, **CBRG**=Case-based repair generation, **CBR**=Case-based reasoning, **SA**=Simulated annealing, **DA**=Decomposition approach, **SS**=Scatter search, **VNS**=Variable neighborhood search, **LS**=Local search, **LSN**= Local Search Neighbourhood **GRASP**= Greedy random adaptive search procedure, **PSO**=Particle Swarm Optimization

3. Types of Scheduling in Healthcare

According to Pinedo [38], scheduling plays an important role in most manufacturing, production and healthcare systems. Generally, there are two types of scheduling which are cyclical and non-cyclical scheduling.

3.1 Cyclical Scheduling

Cyclical refers to the repetition. Cyclical scheduling is a kind of schedule that will recur in cycles for a certain period. This type of schedule is suitable for a company or an organization which has fixed schedule over a long period of time.

	M	T	W	T	F	S	S	M	T	W	T	F	S	S
A	D	D			N	N			D	D		N	N	
B	N	N			D	D			N	N		D	D	
C	D	D			N	N			D	D		N	N	
D	N	N			D	D			N	N		D	D	

Figure 1. Cyclical Scheduling

3.2 Non-Cyclical Scheduling

Non-cyclical scheduling is a kind of schedule that keeps on changing as illustrated in Figure 2. This type of schedule is not suitable for an organization that has a fixed schedule.

	M	T	W	T	F	S	S	M	T	W	T	F	S	S
A	D	D		N	N	N			D	D		N	N	
B	N	N			D	D		N	N	N		D	D	N
C	D	D			N	N			D	D		N	N	
D	N	N	D		D	D	D	D	N	N		D	D	N

Figure 2. Non-Cyclical Scheduling

4. Framework of the Scheduling Problem Using PSO

As shown in Figure 3, An enhanced framework for scheduling problem using PSO is developed based on existing scheduling framework constructed by previous authors [39-40]. Each of the steps is described in the following sections:

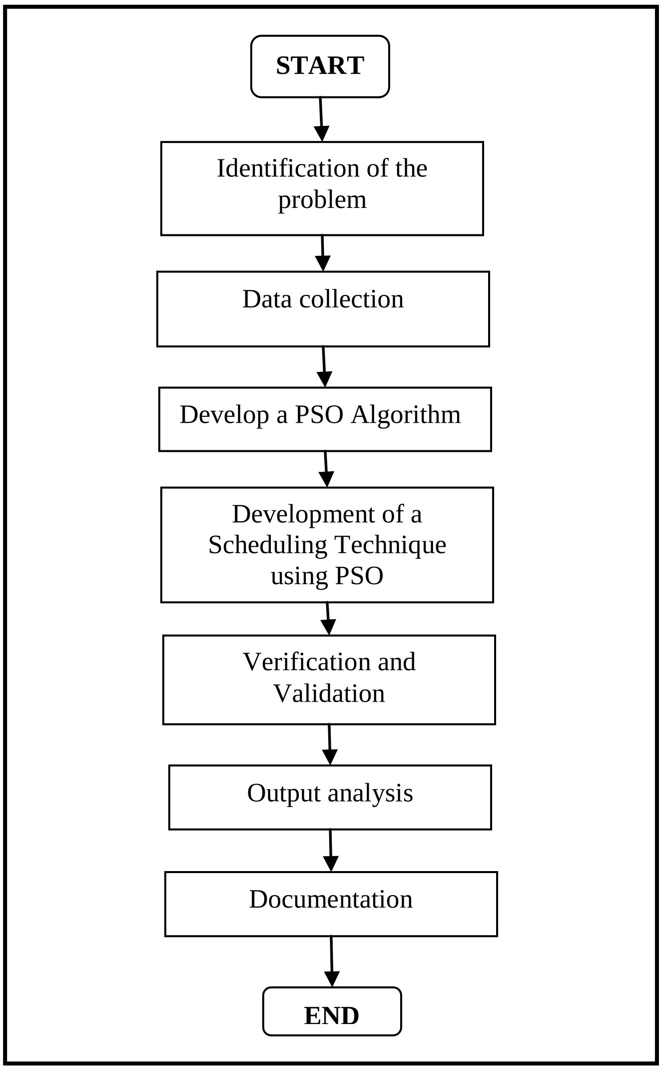

Figure 3. Framework for Scheduling Problem using PSO

4.1 Step 1: Identification of the Problem

Problem identification is the initial step in developing an automated system for on-call doctors. When a problem is studied, it should be clearly understood [40]. At this stage, the main tasks is to review existing PSO methods for effective scheduling which are able to satisfy preferences of the doctors, supporting a fair and non-biased schedule in the hospital [41].

Hard and soft constraints must be identified during this stage. The schedule's requirements are constrained by both hard and soft constraints. The hard constraints usually include coverage requirements, while soft constraints concern on the time requirements of the schedules [42]. Normally the constraints differ from one case study to another. The summary of the constraints used by several authors [43-45] is presented in Table 2.

Table 2. Summary of Hard Constraint and Soft Constraint in Various Scheduling Problems

Name of Journal	Constraints
A General Approach to the Physician Rostering Problem.	**Hard Constraints** • Each staff can work only one shift a day • The number of staff allocated to the shift must be at least one per week • Each staff has a day off per week **Soft Constraints** • The shift must be allocated fairly • Maximum working days is 4 • Minimum working days is 5
An Exploration Study of Nurse Rostering Practice at HUKM	**Hard Constraints** • All shifts must have at least 2 days off per two week • All shifts must have the requested number of nurses • All nurse cannot work more than one shift per day • Maximum working days is 4 days • Minimum working day is 1 day **Soft Constraints** • Attempt to give fair number of working days and days off to all staff • Attempt to give each nurse at least one day off in the weekend during the schedule period.
Medical Doctor Rostering Problem in a Hospital Emergency Department by Means of Genetic Algorithms	**Hard Constraints** • A minimum number of doctors must be assigned to each working shift. • Whenever staff get public holiday, there must be at least one staff working on a stand-by mode basis. • Any member of staff who is on 24-h duty or who works a night shift will have day off for the following day **Soft Constraints** • All members of staff should work the same number of Saturdays and Sundays per month • The number of different types of shift should be shared out among staff as fairly and equally as possible

4.2 Step 2: Data Collection

An adequate data set is essential to produce binary codes which are readable by computer program (e.g Matlab). The data collection process should be completed on a step-by-step basis. The collected data set are not ready for further procedures, until it undergoes a series of data design.

The data sets which are in form of binary codes are categorized into work days and off days for the doctors. An example of dataset is shown in Table 3 below. '0' represents *off days* and '1' represents *work days* for on-call doctor.

Each medical doctor must be assigned *off days* and *work days*. In this case study, *off days* for a doctor can be set as one day per week.

Table 3. Example of Dataset

	Days 1	Days 2	Days 3	Days 4
Doctor 1	1	1	1	0
Doctor 2	0	1	1	0
Doctor 3	1	1	1	0
Doctor 4	0	0	0	0
Doctor 5	1	1	1	0

4.3 Step 3: Development of PSO Algorithm

The PSO is an evolutionary computation technique introduced by Kennedy and Eberhart in 1995 [45]. According to Ogier J.M. [45], PSO algorithm is not only a tool for optimization, but also a socio-cognition tool which is based on human and artificial agents of bird flocking and fish swarm.

PSO is quite similar to Genetic Algorithm (GA). In terms of similarity of these two algorithms, PSO initializes population based on an optimized particle; Meanwhile, GA initializes a population based on a chromosome. The difference between the two approaches is that PSO has a particle to update velocity when the particle moves over the search space. Each particle keeps track of its coordinate, which are associated with the solution. On the other hand, GA converts problem in a specific domain into a model by using fitness data structure and evolves the chromosomes using selection, recombination, and mutation operators.

While the generated results of GA may not be efficient as promised, using PSO more recommended [45]. The rate of convergence in PSO is good due to fast information flow among the solution vectors, while its diversity decreases very quickly in the iterations resulting in a suboptimal solution [45].

Figure 4 illustrates basic concept of PSO. The *pbest* refer to personal best while the *gbest* concern on best value obtained so far by any particle in the eighbourhood of that particle location, using a random solution.

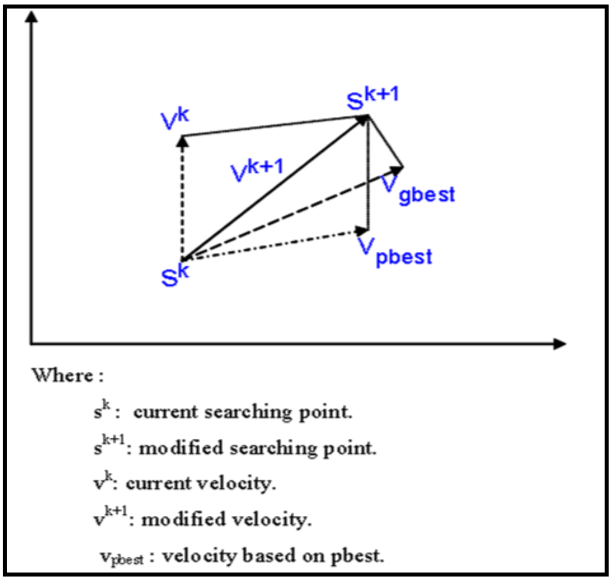

Figure 4. Basic Concept of PSO [17]

The functional statement of the steps in PSO algorithm is embodied in the pseudo code shown in Figure 5, which is adapted from Zainal A. *Et al*. [46]:

Start initialize all the possible positions (represent all possible feature subset bands).
If the feature in *N*, thus, there are 2*N* possible future subsets.
Introduce *m* particles, where each particle will randomly take one position in the future subset space.
Initialize their p*best* for particles. For first round, their p*best* = current position.
Find their g*best*
Loop (exit when *fitness* >*max_fitness*)
Evaluate fitness of each particle's position. Choose *gbest*.
For each particle, check the following:
If *pcurrent*>p*best* then p*best* = p*best*
For each p*best* check the following:
If p*best*>*gbest* then *gbest* = p*best*
Update velocity for each particle according to the following formula :
*vid = wid *C1 rand1 (pid – x id) + C2 rand2 (pgd - x id)*
Update the position for each particle according to the following formula:
x id = x id + v id
End

Figure 5. Psuedo Code for Standard PSO Algorithm

4.4 Step 4: Development of a Scheduling Technique using PSO

One of the systematic ways to generate a good schedule for on-call doctor is using PSO. Scheduling using PSO is implemented based on the steps proposed by Irene [47] as illustrated in Figure 6.

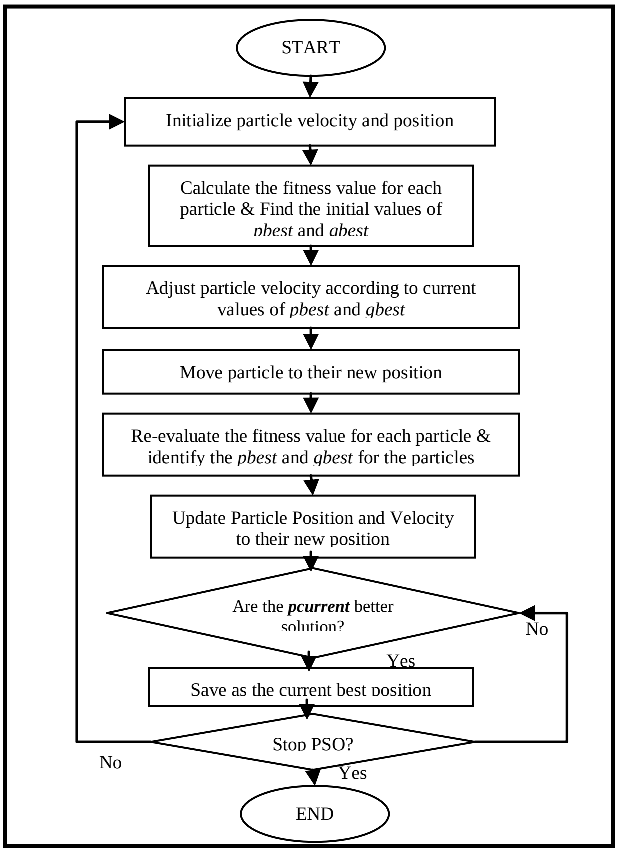

Figure 6. Flowchart of PSO based on the case study

4.5 Step 5: Verification and Validation

For verification purpose, a set of input data are employed in the PSO program and the testing process is to be performed to obtain the specific result. In this process, the schedule is tested several times. Verification process produces complete result that will be validated to perceive accuracy of the schedule. The validation process can be performed using a computer program (e.g Matlab).

4.6 Step 6: Output analysis

The previous steps listed in the earlier stage of our research work were still undergoing some phases. Output of the generated schedule is to be analyzed using selected software, (e.g Matlab).

4.7 Step 7: Documentation

The final step in the framework of generating a good schedule is the documentation which is beneficial for future references.

5. Preliminary Analysis

The results presented in the Table 4 show the ability of tge proposed algorithm to construct feasible solutions for on-call doctor at a Malaysian Hospital. At this stage, the generated schedules are produced based on the identified hard and soft constraints where have been identified earlier.

Table 4. Total Working Days for On-Call Doctor in April 2012

Doctor	Working Days/30 days	Doctor	Working Days/30 days
Doctor 1	16	**Doctor 16**	13
Doctor 2	13	**Doctor 17**	13
Doctor 3	13	**Doctor 18**	11
Doctor 4	11	**Doctor 19**	13
Doctor 5	13	**Doctor 20**	12
Doctor 6	11	**Doctor 21**	14
Doctor 7	14	**Doctor 22**	11
Doctor 8	11	**Doctor 23**	13
Doctor 9	13	**Doctor 24**	14
Doctor 10	11	**Doctor 25**	11
Doctor 11	13	**Doctor 26**	13
Doctor 12	13	**Doctor 27**	12
Doctor 13	11	**Doctor 28**	13
Doctor 14	13	**Doctor 29**	12
Doctor 15	16	**Doctor 30**	13

The generated graph in Figure 7 is easy to read and to be compared rather than Table 4. The output were generated through the steps of data generation in programming code, which include the step of updating velocity and also update position based on Figure 7. The PSO output analysis generated in graphical form shows that the on-call doctor was equally distributed in one month. The generated graph refers to the working days for each on-call doctor based on one month. From the graph, it is noted that the utilization of each on-call doctor is nearly equal. The result can further be analyzed using another technique (e.g GA).

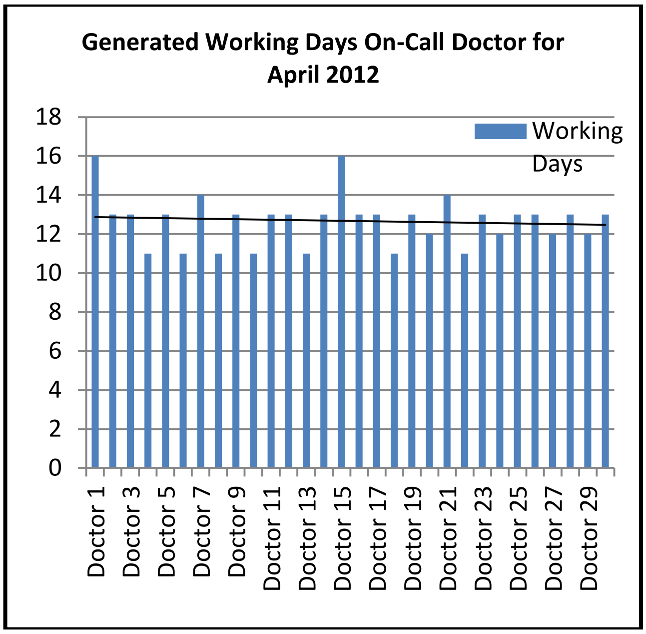

Figure 7. Generated Working Days On-call doctor for one month in April 2012

6. Conclusion

The computational experiments show the ability of the proposed algorithm in constructing a feasible solution for all of the Malaysian Hospitals using hard and soft constraints. In this paper, we present a framework to automate the scheduling of on-call doctor by applying an evolutionary algorithm (i.e PSO approach). The structured framework will help to guide researchers to develop an automated on-call doctor scheduling system of emergency department at any specific hospital. For future work, we are going to apply the GA approach in order to improve the constructed initial solution.

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