Maximax&Maximin and 2FBlockwise Operators: Enhancement in the Evolutionary Algorithm for a Nurse Scheduling Problem

Razamin Ramli, Lim Huai Tein
School of Quantitative Sciences, Universiti Utara Malaysia, 06010 Sintok, Kedah, Malaysia.
razamin@uum.edu.my

***Abstract*—An effective and efficient nurse work schedule could fulfill nurses' work satisfaction. It certainly could provide a better coverage with appropriate staffing levels in managing nurse workforce, thus improves hospital operations. Hence, the aim of this paper is to construct the best nurse work schedule based on the rules and requirements of the nurse scheduling problem (NSP). In doing so, an improved selection operator and crossover operator in an Evolutionary Algorithm (EA) strategy for an NSP is developed as an enhanced algorithm. The smart and efficient scheduling procedures were revealed in this strategy. Computation of the performance of each potential solution or schedule was done through a fitness evaluation. The best solution so far was obtained via special Maximax&Maximin (MM) parent selection and 2FBlockwise crossover operators embedded in the EA, which fulfilled all constraints being considered in the NSP as much as possible. This proposed EA has shown that it provides the highest success rate in achieving feasible solutions when comparing with other similar variants of the algorithm.**

***Index Terms*—Evolutionary Algorithm; Crossover Operator; Healthcare Application; Nurse Scheduling Problem; Selection Operator.**

I. INTRODUCTION

Managing change can be classified as one of the important challenges faced by a hospital management. In relation to the healthcare environment, hospitals are experiencing significant change in response to the ever-increasing costs, technology advances, recruitment and retention matters. In order to be in a high competitive position, hospital organizations must retain and utilize competent workforce to ensurea quality care and organizational viability in tandem with the changes. This can be achieved by having efficient nurse work schedules and implementing them in daily routines. High quality nurse schedules are able to support possible improvements in certain aspects, such as in hospital resource efficiency, staff and patient safety, staff and patient satisfaction and administrative workload [1]. This shows that a perfect personnel scheduling program is able to support a hospital management in providing quality health care services. The notion is supported by [2] and [3], who further emphasized that managing a team of healthcare providers via scheduling their work duties would result in delivering a quality patient care, while trying to use the best of whatever available at hand, in order to operate economically and sufficiently.

As has been suggested much earlier, a good work schedule can improve operations by providing better coverage with identical or reduced staffing levels for the management of nursing personnel [4]. It is also an important aid to manage nurses efficiently, in which each nurse shall be fully utilized based on his/her skill and category. In essence, constructing a schedule that involves tasks delegation and allocation of nurses to work shifts has become the major medical economic issues to surmount nurse shortage challenges faced by most of the hospitals [3].Typically, constructing a schedule may differ from one hospital or country to another. For instance, some hospitals still used manual strategies in their nurse scheduling process [5], while automoted nurse scheduling models may have replaced conventional scheduling process in some other developed regions of the globe (e.g., [6]). Automated scheduling process can save a considerable amount of time, hence reducing much administrative work involved.

Furthermore, manual nurse scheduling strategies are prone to mistakes by the head nurse in charge who often overlook details about individual nurses [7]. These mistakes may affect the head nurse in making an effective decision on the nurses' assignments or allocations, which may be construed as being unfair among the nurses. On the flipside, automated models are commonly linked to intelligent models, which are able to alert the head nurse when a particular nurse is overly allocated, for example being assigned to perform two or more tasks at the same time. Therefore, carelessness or bias issues are effectively avoided and not permitted in this variant of model.

Hence, the importance of automated nurse scheduling or an intelligent system is obvious, which could also provide much ease in generating a schedule. Also, the capability of the intelligent model is to overcome challenges as the result of nurse shortages and nurse preferences. Therefore, many studies have attempted to develop an efficient schedule, which include works by [8], [9] and [10]. Hence, this paper continues the effort by proposing an Evolutionary Algorithm (EA) with an improved selection operator in the strategy for a nurse scheduling problem (NSP). The smart and efficient scheduling procedures as suggested by [11], [12] and [13] are further explored and expanded. The improvement in the approach is in the elaboration of the EA as recommended by [10].

Subsequently, the organization of the rest of the paper is as follows. The next section continues with related literature reviews emphasizing the nurse management strategy and several relevant nurse scheduling techniques, especially the hybrid techniques. The following section presents the proposed evolutionary algorithm (EA) in solving a highly complex nurse scheduling problem (NSP) including its data collection, model formulation, objective function, decision variables and constraints involved. Results and discussions are presented in the following section. The final section concludes our work on the proposed EA along with some potential future works.

II. Nurse Management Strategy

Healthcare industry is one of the most regulated industries and it is a major employing establishment in the service sector ([2], [14]). The healthcare industry is very diverse, including organizations that provide medical care, residential care and treatment, and various forms of the therapies and health services. With various challenges [10] faced especially by a hospital management, it is crucial that the management team must be well organized with their manpower databases to meet those demands and challenges. Hence, an efficient nurse management system is much needed in order to utilize and tackle nurse personnel problems; and thus, it may increase the hospital performance. In strategizing and optimizing the available nurse workforce, an effective effort in managing the workforce is through efficient scheduling techniques being recommended for various nurse environments or working situations. We suggest that the efficient nurse management system can be achieved through the adoption of an efficient scheduling technique. However, we surveyed several relevant nurse scheduling techniques as in the following subsections (see also [11]), in order to identify the most suitable technique for a particular nurse working situation.

A. Nurse Scheduling Techniques

In this era with powerful computing tools, there are some effective nurse scheduling techniques that have been utilized as part of the solution in the nurse management system. [15] and [16] have identified 28 different categories of techniques that have been used on personnel scheduling problems, which include the NSP. These methods include optimization approaches (i.e. mathematical programming), constraint logic programming, constructive heuristic, expert systems, genetic algorithms, set covering/partitioning, simple local search, simulated annealing, tabu search, knowledge based systems, artificial neural networks and hybrid systems. Based on [7], these wide range of approaches and techniques have been investigated and performed in nurse scheduling. The techniques can be classified into four categories, which are optimization, search, constructive heuristics, and hybrid techniques. Among these techniques, the hybrid one has shown potential performance ([6],[17],[18]).

B. Hybrid Scheduling Techniques

As commonly known, metaheuristic techniques consist of tabu search, simulated annealing, genetic algorithms, problem space search, greedy random adaptive search procedure (GRASP), neural networks, machine learning, reinforcement learning and ant colony optimization, among others. The more recent metaheuristics have been used extensively to solve various scheduling problems. However, [19] reported that tabu search (TS), genetic algorithm (GA) and simulated annealing (SA) are very sufficient in obtaining near optimal solutions for the NSP. These techniques can be somehow combined to breed into a hybrid technique, which could further improve the scheduling outcomes.

Some of the hybrid techniques are actually combined or integrated with other types of techniques, such as with the search technique. Search techniques, like the GA has expanded its knowledge horizon. The hybrid of GA with classical heuristic such as the local search and variable neighborhood search (VNS) ([20], [21]) has opened up to another technique known as the evolutionary algorithm (EA). It has shown much potential [7] and proven to provide effective and efficient solutions for the NSP ([4],[22]). Exploring three simple operators is the key to the GA and EA development ([23], [24],[25], [26]). Further, [24] are able to introduce two new crossover (i.e., matrix binary crossover (MBX), and whole arithmetical crossover) schemes and two new mutation (i.e., interchange between two rows, and interchange two sites along a row) schemes. The different methods used in the crossover and mutation operators of the GA clearly portrayed the element of hybridization. This has motivated us to explore the issues related to the operators. Thus, we proposed an EA with the enhancement in the selection and crossover operators, which is the main discussion of this paper.

III. Proposed Evolutionary Algorithm

A. Data Collection

We employed two methods of data collection, which include a series of interviews and document analyses. The data from interviews consists of direct descriptions from nurses about their experiences, opinions, preferences and organizational processes. The respondents were the nurses and head nurse of a Special Care Nursery (SCN) ward at a Malaysian general hospital. The SCN isconsidered as large ward or unit which is able to represent a typical scheduling or rostering problem in many large hospitals [7], including privately operated and teaching hospitals throughout Malaysia. In addition, some information was obtained directly via analyzing the ward's records and annual reports.

B. Model Formulation

We proposed an EA model for a particular NSP, which investigates the potentiality of the EA. Figure 1 exhibits the proposed EA model with a special operator, highlighted as the Maximax&Maximin parent selection, which is elaborated from the model by [10]. Generally, EA is designed with multiple phases or operators, each having its own functions. The parent selection operator was constructed with the capability to choose potential schedules as parents based on the concept of maximum of the maximum and maximum of the minimum in the decision theory.

In order to employ the proposed EA, an initial solution or a potential schedule is required and thus, generated at the initialization phase. Each solution in the population is represented as a two-dimensional array of k by m, where n_1, n_2, ... , n_k are the nurses, while d_1, d_2, . . . , d_m are the days in a scheduling period, which is usually two weeks for a government-based general hospital.

The initialization of a population requires a number of different potential solutions to be generated via semi-random heuristics or mechanism in this evolutionary approach. Computation of the performance of each potential solution is done through fitness evaluation. Subsequently, other operators in the model, which are *2FBlockwise* crossover, that is a sequence of directed mutations along with the regeneration and stopping criterion mechanisms is followed as in Figure 1. This action is taken as an attempt to improve the overall performance of a complete nurse-working schedule.

In this study, an optimal schedule is achieved when there are no constraints violations. It means that a schedule, *s* or an individual performance is evaluated by minimizing the penalty function, *F(s)* that relates to the violations of hard and soft constraints. Particularly, greater penalty values are given to constraints which are relatively more important. As given by [27] and [7], the essential objective function is as follows:

$$Min\ F(s) = \sum_{k=1}^{t} P_k\, C_k(s) \qquad (1)$$

In Equation 1, P_k is the penalty value (i.e., weight) of the violated constraint-type *k* in *t* kinds of constraints, $C_k(s)$ is the number of violated constraint-type *k* in *s*. The purpose is to satisfy the constraints as many as posible. Hence, in our EA, a schedule with a large function value is not preferred if compared to the schedule which has a smaller function value.

C. ObjectiveFunction

In the case of NSP, a reactive scheduling component is integrated with a scheduling component. Hence, the penalty function for the whole NSP consists of two main parts representing the two components, which are then structured by several sub-penalty functions. Basically, the first two sub-penalty functions, i.e., $f_1(s)$ and $f_2(s)$ are for the scheduling component, while $f_3(s)$ and $f_4(s)$ are for the reactive scheduling component. The $f_1(s)$ stresses on the violation computation of hard constraint and $f_2(s)$ computes the violation related to the soft constraints. The rationale is to ensure the quality of shift arrangements as part of the scheduling performance. On the other hand, $f_3(s)$ and $f_4(s)$ are used to evaluate the rescheduling performance. Generally, the fitness of the EA represents the sum of all penalties due to the violation of all constraints; hence, the objective function for the EA is to:

$$\text{Minimize } Z_s \text{ or } F(s) = \text{Minimize } (f_1(s) + f_2(s) + f_3(s) + f_4(s)) \qquad (2)$$

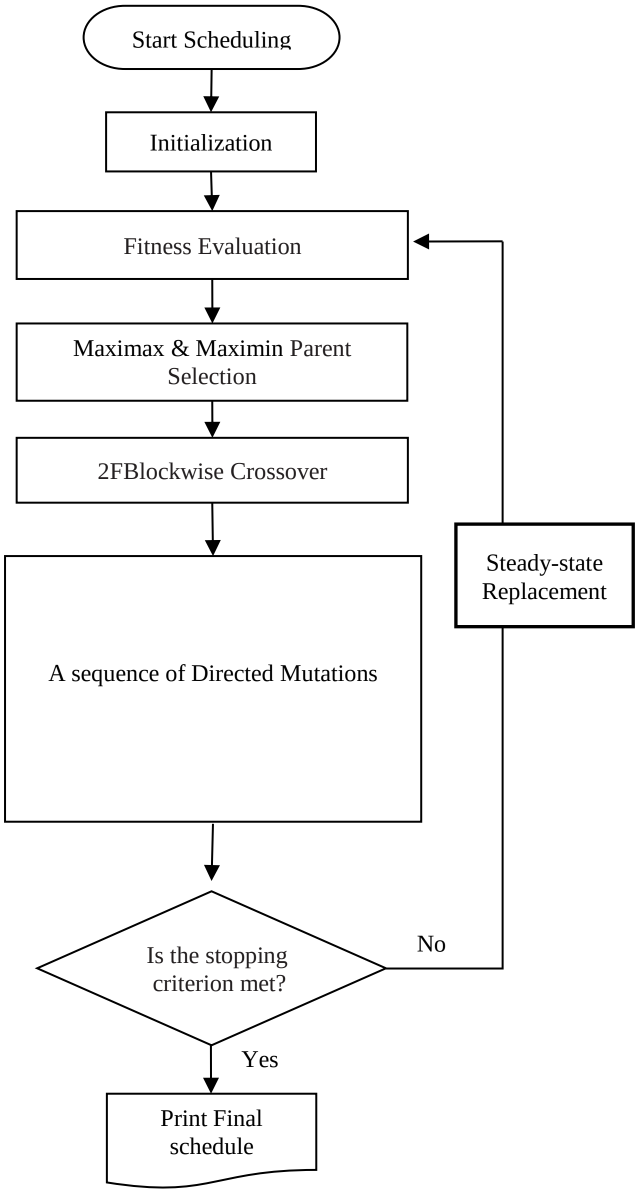

Figure 1: Proposed EA model with enhanced selection and crossover operators

Objective, *$f_1(s)$:* To fulfill nurse regulations (hard constraints), i.e., to minimize the number of nurses assigned to each shift in each skill level.

Objective, *$f_2(s)$:* To fulfill nurse preferences (soft constraints), i.e., to minimize nurse's dislike of the shifts arrangements.

Objective, *$f_3(s)$:* To keep less changes towards the selected schedule without disturbing other nurses' schedule as much as possible, i.e., to minimize the deviation of shift changes after reactive scheduling.

Objective, *$f_4(s)$:* To keep a fair delegation of on-call nurse, i.e., to minimize the deviation of same nurse being assigned to delegate the on-call task during reactive scheduling.

D. Decision Variables

$$X_{vipj} = \begin{cases} 1, & \text{If nurse } i \text{ of skill level } v \text{ is assigned to shift } p \text{ in day } j \\ 0, & \text{Otherwise} \end{cases}$$

$$D_{ijp} = \begin{cases} 1, & \text{If a duty shift type } p \text{ of an already scheduled nurse } i \text{ in day } j \text{ is changed} \\ 0, & \text{Otherwise} \end{cases}$$

$$C_{vjk} = \begin{cases} 1, & \text{If constraint type } k \text{ for skill level } v \text{ in each day } j \text{ is violated} \\ 0, & \text{Otherwise} \end{cases}$$

$$C_{ik} = \begin{cases} 1, & \text{If constraint type } k \text{ exists for each nurse } i \\ 0, & \text{Otherwise} \end{cases}$$

where:
I = number of nurse, i
V = number of skill levels, v
J = number of days, j in scheduling period
P = number of possible shifts patterns, p
K = number of constraint types, k
W_{ijp} = weightage or penalty cost for the relative constraints, D_{ijp}
W_{vjk} = weightage or penalty cost for the relative constraints, C_{vjk}
W_{ik} = weightage or penalty cost for the relative constraints, C_{ik}

$$Z_s = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{v=1}^{V}\sum_{p=1}^{P} W_{ijp} D_{ijp} X_{vipj} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{v=1}^{V}\sum_{p=1}^{P}\sum_{k=1}^{K} W_{vjk}\, C_{vjk} X_{vipj} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{v=1}^{V}\sum_{p=1}^{P}\sum_{k=1}^{K} W_{ik}\, C_{ik} X_{vipj} \quad 3$$

E. Constraints in the NSP

In this NSP, 11 important constraints are being considered. These constraints are related to the basic work rules, nurse workload, overtime, weekend work rule, covering rule, work stretch, off-duty rule, shift arrangement, special requirement, and daily adjustment.

IV. RESULTS

The proposed EA was run and tested with certain assigned parameters, which are the total number of nurses involved in the ward management, crossover probability, number of generations and number of experimental runs. Preliminary results on the size of a population generated in the initialization phase have been done and obtained as reported in [10]. Based on that, the population size of 12 was used in further experiments in this study, as highlighted in Table 1.

In this proposed model of the EA, the Maximax&Maximin parent selection and *2FBlockwise* crossover operators are the focus in the experiments, which is coined as *MM_2FBlockwise* crossover operator. The performance of the EA with Maximax&Maximin (MM) parent selection operator was tested and compared with that of the EA with other established selection operators, which are the Tournament (T) and Rank based (Rk) parent selection operators. The performance of the model are shown in Table 2.

Table 1
Comparative analysis of different population size on EA performance

MM_2FBlockCross	popsize 10	popsize 12	popsize 16	popsize 18	popsize 20	popsize 30	popsize 40
Best Fitness	1004037	2046	3046	3063	3049	5051	5048
Average Fitness	1005041	3045	6048	5049	3049	5051	6049
STD	972	1412.1	1646.53	2708.03	0	0	1033.31
Feasible rate	0%	20%	50%	40%	70%	10%	100%

Table 2
Comparative analysis on different parent selection's performance

popSz12	T	MM	Rk
Best Fitness	3037	3038	4040
inTolerableRO	3	1	0
noDisapprovalRO	0	0	0
Time (Sec)	203.876102	129.403649	189.19618
Convergence	63	25	9
Average Fitness	4040	4041	4040
STD	0	1417.7491	0
Feasible rate (%)	7%	13%	7%

When comparing with the Rank based (Rk) and the Tournament parent selection (T), the Maximax&Maximin parent selection (MM) was a more superior operator than the Rank based parent selection, although the Tournament parent selection obtained the best fitness among all. Nevertheless, these three operators were able to perform well in a manner of producing similar efficiency. In order to have a fair comparison between these parent selection operators, the other operators such as the Row-wise Crossover and Directed Mutation were made to remain the same in the algorithms.

Table 3
Comparative analysis of different crossover's performance

popSz12	Row-wise Crossover	2FBlockwise Crossover
Best Fitness	3037	3040
InTolerableRO	3	1
noDisapprovalRO	0	0
Time (Sec)	203.876102	129.769958
Convergence	63	15
Avrg Fitness	3037	5049
STD	0	3459.50363
Feasible rate (%)	7%	20%

On the other hand, the 2FBlockwise Crossoveris was more successful in producing feasible solution within a faster run time when comparing with the Row-wise Crossover, as exhibited in Table 3. It also had a fast convergenc, which was affected by the vertical constraint violation. However, based on the best fitness, Row-wise Crossover had a minimum fitness than the 2FBlockwise Crossover. However, the difference was not too much, merely three penalty for soft constraints (i.e., 3034-3037=3). Therefore, both crossover operators were able to produce similar best fitness. Similarly, for a fair comparison other cooperating operators, such as the Tournament parent selection and the Directed Mutations were made to remain the same for both algorithms.

V. Discussions

We have developed six different strategies within the EA approach. These six strategies are: (i) T_Rowwise: The EA with the Tournament parent selection and Row-wise crossover; (ii) MM_Rowwise: The EA with Maximax&Maximin parent selection and the Row-wise Crossover; (iii) Rk_Rowwise: The EA with the Rank based parent selection and the Row-wise Crossover; (iv) T_2FBlockwise: The EA with the Tournament parent selection and the 2FBlockwise Crossover; (v) MM_2FBlockwise: The EA with the Maximax&Maximin parent selection and the 2FBlockwise Crossover; (vi) Rk_2FBlockwise: The EA with the Rank based parent selection and 2FBlockwise Crossover.

In order to determine the most suitable strategy in the EA approach for this complex NSP, several relevant criteria were used in the evaluation process. The criteria considered for comparison purposes in the experiment are the best fitness value, number of intolerable row operation (inTolerableRO), number of disapproval row operation (noDisapprovalRO), time taken, number of convergence, average fitness after a set of generations, standard deviation (STD) and feasible rate of the solutions obtained.

The proposed Maximax&Maximin parent selection and the 2FBlockwise Crossover operators or strategies were found to be effective and shown to have good performance. As the overall performance, the enhanced EA with MM_2FBlockwise approach was able to produce the best so far solution (with best fitness = 2046) in a range of less than 100 generations. Although the NSP is a really complex workforce problem, this proposed approach could still has the highest success rate to produce feasible solutions,when comparing to the others, which was 20% of the 30 runs.

VI. Conclusions and Future Work

Various testing and experiments have been carried out to obtain feasible and high quality solutions or nurse work schedules, which fulfill all constraints being considered in this highly complex NSP. The proposed enhanced EA with special Maximax&Maximin parent selection and 2FBlockwise Crossoveroperators were developed and evaluated against other variants of the EA models to prove its performance and capability. In the experiments, the directed mutations operator as portrayed in the EA model was also developed accordingly, but their details are not highlighted here since the focus of this paper is to discuss and reveal our new MM_2FBlockwise strategy as part of the proposed EA approach.

Subsequently, further experiments and strategies can be carried out to emphasize the special mutation operators. Hence, other overall similar models can be developed appropriately for the purpose of comparison and evaluation towards their reliability, accuracy, effectiveness and efficiency.

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