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MODIFIED GENETIC ALGORITHM FOR SOLVING NURSE SCHEDULING PROBLEM

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Abstract: The Nurse scheduling problem (NSP) represents a difficult class of Multi-objective optimization problems consisting of number of interfering objectives between the hospitals and individual nurses. Several constraint-based optimization techniques have been proposed to solve automated nursing scheduling problems in an acceptable computation time but most of these techniques are characterized by premature convergences which inhibit optimal global solution. Thus, a Modified Genetic Algorithm (MGA) was developed to solve Nurse Scheduling Problem. The Modified Genetic Algorithm will be implemented by using Matrix Laboratory (MATLAB) software.
Keywords: Genetic Algorithm; Modified Genetic Algorithm; Nurse Scheduling Problem;

I. INTRODUCTION

The Nurse Scheduling Problem (NSP) is a staff scheduling problem that intends to assign a set of nurses to work shifts to maximize hospital benefit by considering a set of hard and soft constraints like allotment of duty hours, hospital regulations, and so forth.

This nurse scheduling is a delicate task of finding combinatorial solutions by satisfying multiple constraints (Osogami& Imai, 2000). The Nurse Scheduling Problem (NSP) is a combination of optimization problem and important management functions performed by nurses who directly affected the hospital services and the patient care. Staff scheduling is the process of constructing work timetables encoding for staff in order to satisfy the demand for services (Rajeswari*et al.,* 2017). The ability to develop a good staff schedule is a crucial process if the services demand round- the-clock and complicated balancing act between an organization's need and the legal contractual obligations to its staff (Rasip*et al.,* 2014).

Genetic algorithm (GA) is one of the well-known techniques from the area of evolutionary computation that plays a significant role in obtaining meaningful solutions to complex problems with large search space. GAs involves three fundamental operations after creating an initial population, namely selection, crossover, and mutation (Hassanat*et al.,* 2018). Furthermore, GA is powerful search and optimization algorithm, which are computational model based on Darwin's biological evolution theory of genetic selection and natural elimination. The GA, however, takes a long computation time in some specific problems because of its iteratively adaptive process for evolution (Petridis *et al*., 1994). Therefore, it is indispensable to improve GA for reducing the computation time and preventing from local minima efficiently (Kim *et al.,* 2005).

In this paper, a Modified Genetic Algorithm (MGA) will be developed for solving Nurse Scheduling Problem (NSP). The efficiency of MGA technique in scheduling model to solve a particular NSP will be discovered through the evaluation of its performance.

Literature on nurse scheduling problem is very extensive. One may refer to literature reviews on the subject that provide in-depth studies on this problem such as Burke et al (2004). A wide variety of methods have been used to tackle nurse scheduling such as mathematical programming, heuristic technique and artificial intelligence (Hussin *et al.,* 2011). Some of the recent AI techniques include the use of Simulated Annealing, Genetic Algorithm, co-operative Genetic algorithm, Particle Swarm Optimization, Artificial Immune System and different versions of Evolutionary Algorithms to solve NSP (Gonsalves & Kuwata, 2015).

Burke *et al.* (2004) describes different administrative modes where the schedules of nurses are created from a bottom-up approach to a top-down approach.

II. METHODOLOGY

In this paper, modified genetic algorithm (MGA) was used to solve the nurse scheduling problem. The stages involved in the implementation of this research includes; acquisition of data from LAUTECH Teaching Hospital Ogbomoso, Oyo State, Nigeria, definition of Hard and Soft Constraint, formulation of the Nurse Scheduling Problem, application of Modified Genetic Algorithm (MGA) for solving Nurse Scheduling Problem and evaluation of the performance of MGA and GA.

2.1 Modification of Genetic Algorithm

The Standard GA will be modified in this study to improve its performance in solving NSP. The tournament selection method of the standard GA will be modified using the neighborhood concept. At first *k* individuals will be selected randomly from the whole population to define the neighbor kni for the individual *i* (i.e. the first parent). After that, the second parent is selected from this neighbor kni by using binary tournament selection. Finally, the second parent and the individual *i* are recombined and only one offspring is generated. Therefore, the modified GA has two principal differences with a standard GA: the selection operator for mating does not work at population level and all individuals in the population participate in the mating loop as the first parent. The modified Genetic Algorithm is presented in figure 1.

2.2 Mathematical Representation of the Problem

The mathematical model required for hard and soft constraints extensively describes as follows:
The NSP consists of a set of nurses $n = 1, 2, \dots, N$, where each row is specific to particular set of shifts $s = 1, 2, \dots, S$, for the given set day $d = 1, 2, \dots, D$.

The solution schedule X for the 0/1 matrix dimension $N*SD$ is as in equation 2.1.

$$X_{n,d,s} \begin{cases} 1 & if \;\; nurse\; \mathbf{n}\; works\; \mathbf{s}\; for\; day\; \mathbf{d} \\ 0 & otherwise \end{cases} \qquad (2.1)$$

HC1: In this constraint, all demanded shifts are assigned to a nurse.

$$\sum_{n=1}^{N} X_{d,s}^{n} = E_{ds}, \; \forall d \in D, s \in S, \quad (2.2)$$

Where E_{ds} is the number of nurses required for a day (d) at shift (s) and $X^{n}_{d,s}$ is the allocation of nurses in the feasible solution schedule.

HC2: In this constraint, each nurse can work not more than one shift per day:

$$\sum_{s=1}^{S} X^{s}_{n,d} \leq 1, \forall n \in N, d \in D, \quad (2.3)$$

Where $X^{s}_{n,d}$ is the allocation of nurses (n) in solution at shift (s) for a day (d).

HC3: This constraint deals with a minimum number of nurses required for each shift.

$$\sum_{n=1}^{N} X^{n}_{d,s} \geq min^{n}_{d,s}, \forall d \in D, s \in S, \quad (2.4)$$

HC4: In this constraint, the total number of working days for each nurse should range between minimum and maximum range for the given scheduled period.

$$W_{min} \leq \sum_{d=1}^{D} \sum_{s=1}^{S} X^{d,s}_{n} \leq W_{max}, \quad \forall n \in N (2.5)$$

The average working shift for nurse can be determined by using equation (2.

$$W_{avg} = \frac{1}{N} \left(\sum_{d=1}^{D} \sum_{s=1}^{S} X^{d,s}_{n}, \forall n \in N \right) \quad (2.6)$$

Where W_{min} and W_{max} are the minimum and maximum number of days in scheduled period and W_{avg} is the average working shift of the nurse.

HC5: In this constraint, shift 1 followed by shift 3 is not allowed; that is, a morning shift followed by a night shift is not allowed.

$$\sum_{n=1}^{N} \sum_{d=1}^{D} X^{n,d}_{s3} + X^{n,d+1}_{s1} \leq 1, \forall s \in S \quad (2.7)$$

SC1: The maximum number of shifts assigned to each nurse for the given scheduled period is as follows:

$$max \left(\left(\sum_{d=1}^{D} \sum_{s=1}^{S} \quad X^{d,s}_{n} - \alpha^{ub}_{n} \right), 0 \right), \forall n \in N \ (2.8)$$

Where α^{ub}_{n} is the maximum number of shifts assigned to nurse (n).

SC2: The minimum number of shifts assigned to each nurse for the given scheduled period is as follows:

$$max \left(\alpha^{ib}_{n} - \left(\sum_{d=1}^{D} \sum_{s=1}^{S} \quad X^{d,s}_{n} \right), 0 \right), \forall n \in N \ (2.9)$$

Where $\alpha^{ib}_{n} n$ is the minimum number of shifts assigned to nurse (n).

SC3: The maximum number of consecutive working days assigned to each nurse on which a shift is allotted for the scheduled period is as follows:

$$\sum_{k=1}^{\mu_n} max \left(\left(C^{k}_{n} - \phi^{ub}_{n} \right), 0 \right), \forall n \in N \quad (2.10)$$

Where ϕ^{ub}_{n} is the maximum number of consecutive working days of nurse (n), μ_n is the total number of consecutive working spans of nurse (n) in the roster, and C^{k}_{n} is the count of the kth working spans of nurse (n).

SC4: The minimum number of consecutive working days assigned to each nurse on which a shift is allotted for the scheduled period is as follows:

$$\sum_{k=1}^{\mu_n} max \left(\left(\phi^{lb}_{n} - C^{k}_{n} \right), 0 \right), \forall n \in N \quad (2.11)$$

Where ϕ^{lb}_{n} is the minimum number of consecutive working days of nurse (n), μ_n is the total number of consecutive working spans of nurse (n) in the schedule, and C^{k}_{n} is the count of the kth working span of the nurse (n).

SC5: The maximum number of consecutive working days assigned to each nurse on which no shift is allotted for the given scheduled period is as follows:

$$\sum_{k=1}^{\lambda_n} max \left(\left(\sigma^{k}_{n} - \omega^{ub}_{n} \right), 0 \right), \forall n \in N \quad (2.12)$$

Where ω^{ub}_{n} is the maximum number of consecutive free days of nurse (n), Γn is the total number of consecutive free working spans of nurse (n) in the roster, and σ^{k}_{n} is the count of the kth working span of the nurse (n).

SC6: The minimum number of consecutive working days assigned to each nurse on which no shift is allotted for the given scheduled period is as follows:

$$\sum_{k=1}^{\lambda_n} max \left(\left(\omega^{lb}_{n} - \sigma^{k}_{n} \right), 0 \right), \forall n \in N \quad (2.13)$$

Where ω^{lb}_{n} is the minimum number of consecutive free days of nurse (n), Γn is the total number of consecutive free working spans of nurse (n) in the schedule, and σ^{k}_{n} is the count of the kth working span of the nurse (n).

SC7: The maximum number of consecutive working weekends with at least one shift assigned to nurse for the given scheduled period is as follows:

$$\sum_{k=1}^{\tau_n} max \left(\left(\eta^{k}_{n} - \Psi^{ub}_{n} \right), 0 \right), \forall n \in N \quad (2.14)$$

Where Ψ_n^{ub} is the maximum number of consecutive working weekends of nurse (n), τ_n is the total number of consecutive working weekend spans of nurse (n) in the schedule, and η_n^k is the count of the kth working weekend span of the nurse (n).

SC8: The minimum number of consecutive working weekends with at least one shift assigned to nurse for the given scheduled period is as follows:

$$\sum_{k=1}^{\tau_n} max\left(\left(\Psi_n^{lb} - \eta_n^k\right), 0\right), \ \forall\, n \in N \qquad (2.15)$$

Where Ψ_n^{lb} is the minimum number of consecutive working weekends of nurse (n), τ_n is the total number of consecutive working weekend spans of nurse (n) in the roster, and η_n^k is the count of the kth working weekend span of the nurse (n).

SC9: The maximum number of weekends with at least one shift assigned to nurse in four weeks is as follows:

$$\sum_{k=1}^{I_n} max\left(\left(\beta_n^k - \gamma_n^{ub}\right), 0\right), \ \forall\, n \in N \quad (2.16)$$

where β_n^k is the number of working days at the kth weekend of nurse (n), γ_n^{ub} is the maximum number of working days for nurse (n), and I_n is the total count of the weekend in the scheduling period of nurse (n).

The objective function of the NSP is to maximize the nurse preferences and minimize the penalty cost from violations of soft constraints in equation (2.17).

$$min\ f\left(X_{n,d,s}\right) = \sum_{SC=1}^{14} P_{SC}\left(\sum_{n=1}^{N}\sum_{s=1}^{S}\sum_{d=1}^{D} X_{n,d,s}\right) * T_{SC}\left(\sum_{n=1}^{N}\sum_{s=1}^{S}\sum_{d=1}^{D} X_{n,d,s}\right) \qquad (2.17)$$

Here SC refers to the set of soft constraints indexed in Table 3.1, $P_{SC}(x)$ refers to the penalty weight violation of the soft constraint, and $T_{SC}(x)$ refers to the total violations of the soft constraints in schedule solution.

2.3 Constraints Definition and Problem Formulation

The NSP problem is a real-world problem at hospitals; the problem is to assign a predefined set of shifts (like S1-Morning shift, S2-Afternoon shift and S3-Night shift, and S4-Free-shift (Day off)) of a scheduled period for a set of nurses of different preferences and skills in each ward. These four shifts, namely, morning shift, afternoon shift, night shift, and free shift (holiday or day off) will be considered in this study. In general, both hard and soft constraints are considered for generating and assessing solutions. Hard constraints are the regulations which must be satisfied to achieve the feasible solution. They cannot be violated since hard constraints are demanded by hospital regulations. The hard constraints HC1 to HC5 must be filled to schedule the nurse schedule. The soft constraints SC1 to SC9 are desirable, and the selection of soft constraints determines the quality of the nurse schedule. Table i and ii list the set of hard and soft constraints to be considered in this study to solve the NSP.

Algorithm: Modified Genetic Algorithm Based on Neighborhood

1. Start
2. t = 0; {current evaluation}
3. Initialize (POP);
4. Evaluate (POP)
5. While (t<MaxGenerations) do
6. *For* (i=1, i<POP_Size, i++) *do*
7. K=Select_neighbour (POP, k) {*random selection of neighborhood K with k Individuals*}
8. Parent=Select(K) *{select the second parent by binary tournament selection}*
9. Offspring=recombine (POPi, parent, pc)*{only one child is generated}*
10. Offspring=mutate (Offspring; pm)*;*
11. POPaux[i]=replace POPi, offspring; {*select offspring if it is equal or better than POP [i], in other case POP [i], goes to next generation*}
12. *End for*
13. POP= POPaux
14. t=t+1]
15. End While
16. Return (Best individual from POP)
17. Stop

Figure 1: The Modified Genetic Algorithm

Table I: The Hard Constraint (HC)

HC	Description
HC1	All demanded shifts assigned to a nurse.
HC2	A nurse can work with only a single shift per day.
HC3	The minimum number of nurses required for the shift.
HC4	The total number of working days for the nurse should be between the maximum and minimum range.
HC5	A day shift followed by night shift is not allowed.

Table II: The Soft Constraint (SC)

SC	Description
SC1	The maximum number of shifts assigned to each nurse.
SC2	The minimum number of shifts assigned to each nurse.
SC3	The maximum number of consecutive working days assigned to each nurse.
SC4	The minimum number of consecutive working days assigned to each nurse.
SC5	The maximum number of consecutive working days assigned to each nurse on which no shift is allotted.
SC6	The minimum number of consecutive working days assigned to each nurse on which no shift is allotted.
SC7	The maximum number of consecutive working weekends with at least one shift assigned to each nurse.
SC8	The minimum number of consecutive working weekends with at least one shift assigned to each nurse.
SC9	The maximum number of weekends with at least one shift assigned to each nurse.

III. CONCLUSION AND FUTURE WORK

In this paper, we have been able to develop a Modified Genetic Algorithm for solving nurse scheduling problem. The modified GA has two principal differences with a standard GA: the selection operator for mating does not work at population level and all individuals in the population participate in the mating loop as the first parent. It is recommended that future research may be geared towards implementing and analyzing the performance of the developed algorithm.

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