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Hybrid Model of Genetic Algorithms and Tabu Search Memory for Nurse Scheduling Systems

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ABSTRACT

The main challenge of the nurse scheduling problem (NSP)is designing a nurse schedule that satisfies nurses preferences at minimal cost of violating the soft constraints. This makes the NSP an NP-hard problem with no perfect solution yet. In this study, two meta-heuristics procedures—genetic algorithm (GA) and tabu search (TS) memory—were applied for the development of an automatic hospital nurse scheduling system (GATS_NSS). The data collected from the nursing services unit of a Federal Medical Centre (FMC) in Nigeria with 151 nursing staffs was preprocessed and adopted for training the GATS_NSS. The system was implemented in Java for selection, evaluation, and genetic operators (crossover and mutation) of GA alongside the memory properties of TS. Nurse shift and ward allocation were optimized based on defined constraints of the case study hospital, and the results obtained showed that GAT_NSS returned an average accuracy of 94%, 99% allocation rate, 0% duplication, 0.5% clash, and an average improvement in the computing time of 94% over the manual approach.

KEYWORDS

Genetic Algorithm (GA), Heuristics, Nurse Scheduling, Optimization, Tabu Search (TS) Memory

1 INTRODUCTION

Scheduling is the course of action of substances (individuals, undertakings, vehicles, addresses, tests, gatherings, and so forth) into an example in space-time so that requirements are fulfilled and certain objectives are accomplished (Rivera & Mesa, 2015). Developing schedules is not an easy task because several factors must be considered, some of which are time, space and other (frequently restricted) resources. The limitations are connections among the resources or between the elements and the patterns that limit the construction of the schedule. Most scheduling tasks are described as NP-hard problem due to the enormous administrative reuirements and optimizations.Shift Scheduling

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Problem (SSP) is considered as an advanced N-P hard problem (Özder, Özcan&Eren, 2019) and Nurse Scheduling Problem (NSP) fall in this category. ShiftScheduling (NS) has found application in different sectors such as examination scheduling (Abayomi-Alli *et al.*, 2019a); (Abayomi-Alli *et al.*, 2019b); Transportation (Guo*et al.*, 2017), flight scheduling (Chen *et al.*, 2019), machine scheduling (Nedaei, 2018;Wu *et al.*, 2018), social event scheduling (Bikakis, Kalogeraki&Gunopulos, 2019), occupation shop planning (Piroozfard, Wong&Hassan, 2016), e.t.c.

The service sector like the health care industry is presently experiencing massive expansion while still contributing positively to the Gross Domestic Product (GDP) of several countries(Ishola and Olusoji, 2020).The sector is highly service oriented and constitutes an important part of the service sector(Sisodia, 2019)but it involves varaious parties such as physicians, administrators, nurses, lab scientist, etc. to collaborate in order to provide care to patients(Barhoun*et al.*, 2019).Nurse's satisfaction with their schedules or roster helps in motivating them to provide quality care to patientsespecially when nursing services is the most important predictor of the patient's overall satisfaction with the hospital care (Olowe and Odeyemi, 2019;Gishu*et al.*, 2019).

Causmaecker&Berghe (2011) defined NSP as the appointment of several nurses to several shifts in such a way that hospital rules are not violated. In NSP, the objective is to appoint shifts to the nurses while satisfying the hospital's rules during the planning period. Hospitals and medical clinics' human resource, represent an extensive piece of the clinic's annual budgets. Hospital policy makers are therefore tasked with the responsibility of maximizing the available nurses and other health workers effectively. The issue is worsened by the inadequate number of nurses in most hospitals and medical centre especially in developing countries where the shortage of healthcare workers is more prevalent(Miseda*et al.*, 2017)and poor working environments in the work place will lead to unmotivated employees (Galli, 2020).

NSP is a subset of Staff or Shift Scheduling Problems (SSP) which appoints nurses to shifts and also wards each day while taking hard constraints (rules of hospitals) and soft constraints (preferences of nurses) into consideration. Designing the schedule is done such that the preferences of nurses are satisfied while reducing the cost of violating the soft constraints (Baskaran, 2016). NS can be defined as the act of appointing nurses to carry out set of tasks at certain wards in a hospital at a particular period. One obstacles associated with nurse scheduling is the constant lack of enough resources to satisfy the needs of the hospital. NS is usually done manually at the risk of not fulfilling some nursing rules set by the hospital or accommodating some staff's preferences.

Constraints are criteria or rules that must be followed or satisfied in order to develop the hospital nurse schedule or roster successfully. There two types of constraints, namely hard constraints and soft constraints. Hard constraints are the type of constraints that must be satisfied, they are compulsory and unavoidable. Hard constraints normally incorporate compulsory requirements from the nurse's contracts and other ground rules in hospital workflow. Soft constraints are typically those included with time prerequisites or close to personal calendars of the nurses. Soft constraints may not be satisfied, but it is desirable not to violate them so as to have a good and user centred schedule.

This study is motivated to develop a scheduling system that deals with the allocation of nurses to different shifts while satisfying the hard and soft constraints (Kim *et al.*, 2014). This issue is daring for any algorithm as:

1. Nurses with higher ranks can substitute those with lower ranks, but the reverse is not the case, thereby making it difficult to schedule different grades separately.
2. NS has a special day-night format where majority of the nurses are made to work either days or nights in a week but not both.

Nonetheless, because of working agreements, number of days worked is usually not equal to the number of nights, also number of hours worked during the night shift is greater than the number worked during the day shift. Hence, it becomes crucial to schedule the 'right' nurses into days and nights shifts, respectively.

The main contribution of this study is to resolve the two common problems which introduces complexity into NSS which:

1. Accommodating nurses with different cadre and designations where the senior or more experienced ones can substitute for the junior or less experienced nurses but not vice-versa.
2. Allocating both day and night shifts in the schedule yet still maintaining the hard constraints relating to nurses shifts and weekend offs.
3. Use the hybrid of GA and TS in the proposed GATS_NSS framework to achieve 1 and 2 above within a short time.

The aim of this research is to solve the hospital nurse scheduling problem using Genetic Algorithm (GA) and Tabu Search (TS) memory and the specific objectives are to:

1. Design an algorithm to solve the problem;
2. Develop a Nurse Call Scheduling System using a hybridGenetic Algorithm and Tabu Search method;
3. Evaluate the performance of the developed system.

The remaining sections of this paper presents the literature review, the proposed methodology of the study, the system implementation and some of the obtained results. The paper concludes in the last section with directions for future work.

2 Literature Review

Nurse scheduling is a complicated exercise carried out every month with multiple and conflicting objectives such as reducing the total costs while increasing the satisfaction of the nurses' preferences or evenly dispersing the workload (Legrain, Hocine& Nadia, 2016). Scheduling problems in general are said to be NP-hard meaning there is no perfect solution for them. A number of hard constraints need to be discussed in order to develop an effective method to solve the problem (Jain *et al.*, 2015). Poorly designed schedules are not just inconvenient to the staffs but it also proves costly to the Health Care Establishment (HCE), whose aim is to improve quality of service delivery from the point of view of clients as well as that of managers(Azam*et al.*, 2017) while still saving time and money.Also satisfying all hard and soft constraints is becoming very difficult in NS. Legrain, Hocine& Nadia (2016) outlined some of the constraints associated with nurse scheduling:

1. The least number of nurses needed to cover the wards' needs for each shift;
2. The workload to be allocated to each nurse in terms of the number of shifts or the types of shifts (usually stated in the contract);
3. The skill required per unit;
4. The highest required number of working days.

In general, there are two fundamental types of scheduling used for the Nurse Scheduling Problem (NSP), they are cyclic and non-cyclic scheduling. In cyclic scheduling, each nurse works in a cycle which is repeated within a continuous scheduling period, while in non-cyclic scheduling new schedules are created for each scheduling period either weekly or monthly. Cyclic scheduling was initially used in the 1970s because of its decreased computational condition and the choice for manual solution. The methods used in the NSP, generally handles either cyclic scheduling or non-cyclic scheduling. Several methods have been presented to solve NSPs, the three most popular are Mathematical Programming

(MP), Heuristics and Artificial Intelligence (AI). Most heuristic approaches concentrate mainly on solving cyclic scheduling problems, while MP and AI approaches are found to performed on both cyclic and non-cyclic problems.

2.1 Optimization-Mathematical Programming

Optimization methods are mostly based on mathematical programming (MP). Few of the objectives for optimization include: low staffing condition, high fulfillment of nurses' preferences or their unique requests, e.t.c. Mathematical programming method is a traditional skill which has been generally applied to NSPs. This method intends to look through a large solution space so as to locate the perfect solution such that the objective function can be optimized.

El Adoly, Gheith&Fors (2017) presented mathematical model for the NSP, which was founded on multi-commodity network flow model. The model was proven using hypothetical and benchmark instances. The mathematical model takes care of the hard constraint and it helps to minimize the overall cost but it does not take into consideration the soft constraint i.e. the psychological needs of the staffs. Tsai & Lee (2010) developed a solution for NSusing a two stepped mathematical optimization model. In the first step, leave and holiday schedule was prepared for the nurses, so the base had been provided and the main limitations are not violated. Using the GA in the second step, the suitable working plan has been determined according to the nurses' preferences and the hospital management's needs.

2.2 Tabu Search

Tabu search (TS) methods have been broadly used to take care of numerous combinatorial isspues. Some TS methods have been proposed to comprehend the NSP. TShas versatile memory that is unique in relation to unbending memory utilized by branch and bound techniques(Harun, Engin&Burak, 2008). TS memory has four dimensions, namely: quality, recency, frequency, and impact. TS uses memory to monitor arrangements recently visited with the goal that it can avert returning to that arrangement. In TS, a move, for instance, can take on an allocated shift type starting with one nurse then onto the next around the same time until it arrives at a Tabu (an unpermitted move). In TS, hard constraints stayed satisfied, while for softconstraints it figures the most ideal move which isn't a Tabu, play out the move and add qualities of the move to the Tabu list.

2.3 Genetic Algorithm (GA)

Genetic Algorithm's (GA) are stochastic meta-heuristics methods. They have been utilized to comprehend the NSP. In GA, the fundamental thought is to locate a hereditary portrayal of the issue so that "attributes" can be acquired. Beginning with a populace of haphazardly made arrangements, better arrangements are bound to be chosen for recombination into new arrangements. Also, new arrangements might be shaped by transforming or arbitrarily changing old ones. For instance, with regards to NSP, for hybrid and change, either of the three is chosen: the best schedule from each one of the parents, an irregular selection from the individual schedule of parents, or the best occasion in a schedule. Probably the best arrangements in every age are kept while others are supplanted by recently shaped arrangements.

2.4 Related Works

Jafari&Salmasi (2015) focused on increasing the preferences of nurses which included having day shifts and weekends off while considering hospital rules and government policies in one of the largest hospitals in Iran i.e., Milad Hospital. A meta-heuristic algorithm based on simulated annealing (SA) is employed to heuristically solve the problem in a satisfactory time. The performance of the SA algorithm is improved with the application of an initial feasible solution generator. The results obtained from the evaluation of the algorithm showed that it provided solutions that were preferable to mathematical model.

El Adoly, Gheith&Fors (2017) presented mathematical model for the NSP, which was founded on multi-commodity network flow model. The model was proven hypothetically and also benchmarked witha case study in an Egyptian hospital. The resultsshowed the automatic schedule accommodated more nurses' preferences and reduces overall overtime cost by 36%.

Youssef &Senbel (2018) proposed a solution which is based on the practice of shift swapping done by nurses after they received a schedule that did not suit their preferences. The technique worked using two stages, at the initial stage a schedule was created that satisfied all the hard constraints and guaranteed equity. The second stage focused on satisfying more soft constraints without violating the hard constraints. Then it was implemented as a simulation and showed a satisfactory outcome.

Kim *et al.*(2014) implemented GA solution to the NSP. To reducecomputation timein the GA, a cost bit matrix was implemented wherea cell indicatesa violation of constraints. The results obtained showed an improved nurse schedule in term of time and quality.

Saluk&Bayhan(2016) presented an optimized complex goal programming model that considered the hospitals working hours and the personnel's leave situation in order to minimize the deviations of the nurses' day and night shifts. Results showed equilibrium distribution between shifts in monthly working period and reduced overtime hours.

Legrain, Hocine& Nadia(2016)proposed a simple heuristic approach on a spreadsheetprogram along with a commercial optimization software known as CPLEX. The multi-objective model and heuristics was presented, and the performance of the approach was evaluated.

Chen et al. (2016)analyzed two brute-force methods to the NSP which are: Integer Programming, and Tabu Search, by evaluating their runtime and complexity. It was observed that for a case involving four nurses, both the Integer Programming and Knapsack methods produced an optimal solution within a second while TS algorithm produced a solution close to optimality. However,with twenty nurses, the Knapsack method was not completed in an hour, the Integer Programming took about 10 minutes while TS returned a solution close to optimality. The study concluded that hospital staff size determines the best algorithm because TS outperformed the other methods when the staff size is larger while Integer programming is best forsmaller staff size.

Santos *et al.*(2015) presented a method based on weighted constraint satisfaction problem (WCSP). The WCSP, given both hard and soft constraints strives to reduce the total weight of all constraints not satisfied. A heuristic based approach to the WCSP was proposed and a general constraint solver was adapted.

Nasiri & Rahvar (2016) proposed a multi-objective mathematical model in which the main issue of the system (i.e. the three shifts) was tackled. Satisfying the nurses' preferences were also increased. The augmented epsilon constraint method was used to generate several tables. A two-step approach was used to solve the complexity of the NSP in which the effective solutions are found over the Pareto set and the best table was selected.

The existing system is carried out manually, which is cumbersome, sometimes inaccurate, ineffective, and does not provide optimal solution. The initial approaches were mainly mathematical and used linear models which focused on creating an optimized solution without taking into consideration, computation costs, multiple shifts and other inclusive list such as changing staffs' preferences. However, ðnding the optimal solution to most of the problem may not be possible or may take a considerable amount of time which is not practical since hospital administrations seek to quickly generate a working schedule that satisfies all the hard and soft constraints. Among other advantages, GA can decrease the possibility of being trapped into a local minimum and often produces high quality solutions in a shorter period of time. However, TB on the other hand is a local method that searches the solution space without entrapping into a local optimum. Literatures have shown that combining the advantages of GA and TS will bring out their strong points and cover their weaknesses, thus creating optimum solutions for the NSS with high accuracy and lower computation time (Naama *et al.*, 2013; Alharbi, 2018). Several successful applications of GA and TS hybrid provide strong argument for applying it in the NSP in order to resolve the issues we have identified.

This study aims to resolve some of the outstanding issues in NSS which are allocating different staff nurse designations while running multiple shifts in a cyclic schedule and developing the schedules within reasonable time.

3 Research Methodology

This session describes the methodology of the studyto design the automatichospital nurse scheduling system using GA and TS algorithm (GATS_NSS). The main aim was to assign shift and nurses to wards so as to satisfy the constraints as far as possible. The nurse scheduling problem (NSP) was structured as "a problem with four parameters: H, a finite set of shifts; N, a finite set of Nurse; L, a finite set of wards; and C, a finite set of constraints".

3.1 Data Source

The nurse scheduling roaster of the Federal Medical Center (FMC), Abeokuta, Nigeria was used as a case study. The dataset was obtained from the Nursing Department of FMC Abeokuta. The dataset contained the nurses' roaster between March, 2018 to January, 2019 with 151 nursing staffs (112 main staffs and 39 sub-staffs). There are three duty shifts: morning, afternoon and eveningshifts. Other information provided in the dataset include:nursing staff rank, wards, day-off, night-off, essential-days, public holidays, e.t.c.

3.2 Design Objective of GATS_NSS

The objective of this research is to develop a Nurse Call Scheduling System for the Federal Medical Centre, Abeokuta, Nigeria using Genetic Algorithm (GA) and Tabu Search (TS). The following considerationswere made when creating the nurse roaster. They include:

1. A certain number of nurses must be scheduled to work in each shift.
2. Shifts assigned to nurses must not exceed the hospital's agreed limit.
3. Nurses' preferences should be adequately satisfied as much as possible.

3.3 Constraints

Constraints in NSPs can be separated into two classes: hard constraints and soft constraints. The objective is to maximize all human and other resources to develop an optimized schedule that satisfies all hard constraints but meets the soft constraints as much as possible. The following constraints were identified during interactions with the experts at the Federal Medical Centre**,** Abeokuta and were classified as hard or soft constraintbased on the necessity to meet them.

3.3.1 Hard Constraints (Compulsory)

1. A nurse can only work one shift per day;
2. No nurse should work more than the number of hours stated in their contract;
3. There are minimum staff needs and skills required for each shift;
4. The most senior nursing officer must lead the shift;
5. Nurses cannot work more than eight hours in a day except during a night shift;
6. Nurses cannot work more than 5 days a week excluding night or call duty;
7. A nurse cannot be on two different duties at the same time;
8. A night shift cannot be followed by a corresponding morning shift.

3.3.2 Soft Constraints (Optional)

1. Assign more day shifts than night shift to each nurse in a month schedule.

2. Requests for day off should be granted.
3. Grouping days off and extending the weekend off.

3.4 Design Method

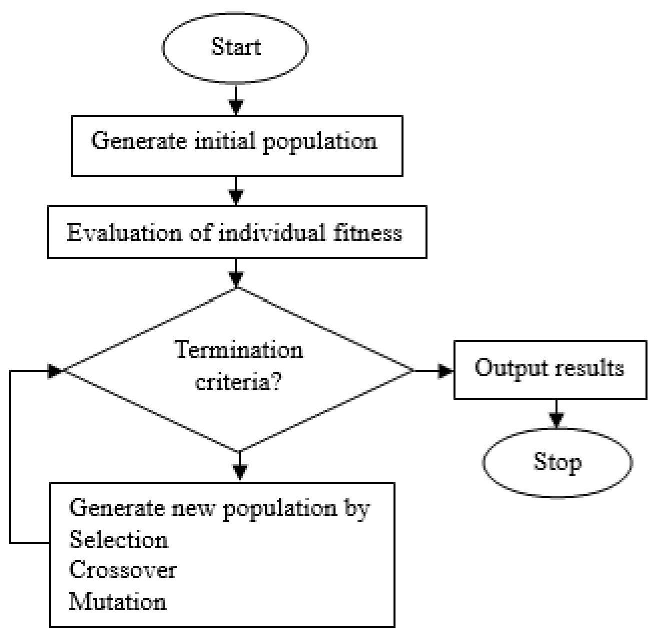
In this study, Genetic Algorithm (GA) a meta-heuristics method is an approach dependent on standards of genetics and natural selection.

The Concepts of Genetic Algorithm for example Selection, Evaluation, Genetic Operators (Crossover and Mutation) wasimplemented along sidethe memory properties of Tabu Search algorithm. The flowchart for the GA method is shown in Figure 1.

3.4.1 Initialisation Phase

In this phase, a particular number of scheduling arrangements are arbitrarily produced as determined toward the start of the execution. After introduction of populace, the wellness of every Scheduler is assessed by utilizing a straightforward goal or fitness function to learn the level of reasonability of the particular Scheduler. The fitness function inferred is a basic one to avert complex computations and reduce execution time. The flow chart for the GA is shown in Figure 1.

Figure 1. A flowchart of Genetic Algorithm



The fitness of each schedule produced is assessed and depends significantly on the hard constraints. The schedule with the least inconsistency (for example that best fulfills the limitations) is chosen as the best fit and is moved to the following period of this calculation.

Fitness Function, $f(x_1)$ = Nurse Population (N_i) /Shifts (h_a) i=1… N

Where x_1 = first constraint

N_i = population of Nurses at index i

h_a= Shifts assigned to Nurse at index i

$f(x_2)$ = N:Hij
x_2 =second constraint
Ei= a nurse
Hij= number of hours within a rangeiand j
L = total number of Wards

3.4.2 Selection Steps

The second part of the flowchart in Figure 1 is handled by this sub-section which is the selection phase.The following are the steps taken in the selection phase:

Step 1: Randomly generate a population with Nurses as Chromosomes (initial population)
Step 2: Evaluate the Total fitness of the population based on the individual fitness of each Nurse.
(Fitness of each nurse = Shifts / Population)

Condition: Fitness =100%

Step 3: Select the population based on its Total fitness

```
Find the selection algorithm below:
Input: Population {(E_i,P(E_i) for i = 1 to n
(H_k, C(H_k)  for k = 1 to h
Where n= total number of Nurses,h= total number of Shifts
Initialize: Population (Pop) Fitness=0; Best Fit Pop = 0;
Output: {(E_i: H_i) for i = 1 ton
Process: Step 1E_ie Population, get P (E_i)
Step 2: do fitness = P (E_i) / H_i
Step 3: If (fitness = 100%)
Step 4: Pop. Fitness= Pop. Fitness +1;
Else,
Step 5: Pop. Fitness = Pop. Fitness;
Step 6: If Pop. Fitness> Best Fit Pop
Step 7: Best Fit Pop = Pop Fitness;
Else,
Step 8: Best Fit Pop= Best Fit Pop
Step 9: End (Fitness function test)
Where:
E- Nurse;
H- Shift;
N- Nurse population;
pop.fitness- Population fitness;
P- Population.
```

The steps taken in for the implementation of the Genetic Algorithm is as follows:

Stage 1: Generate arbitrary populace of n chromosomes
(appropriate answers for the issue);
Stage 2: Evaluate the wellness f(x) of every chromosome x in the populace;
Stage 3: Create another populace by continuing after advances (i.e Step 4 to 6) until the new population is complete;
Stage 4: Select two parent chromosomes from a populace as per their wellness (the bet

ter fitness, the greater opportunity to be chosen);
Stage 5: With crossover likelihood, traverse the parents to frame another posterity (kids). On the off chance that no hybrid was performed, posterity is a precise of parents;
Stage 6: With mutation likelihood, transform new posterity at every locus (position in chromosome);
Stage 7: Place new posterity in another populace;
Stage 8: Use new produced populace for a further keep running of calculation;
Stage 9: If the end condition is fulfilled, stop, and return the best arrangement in current populace;
Stage 10: Go to stage 2.

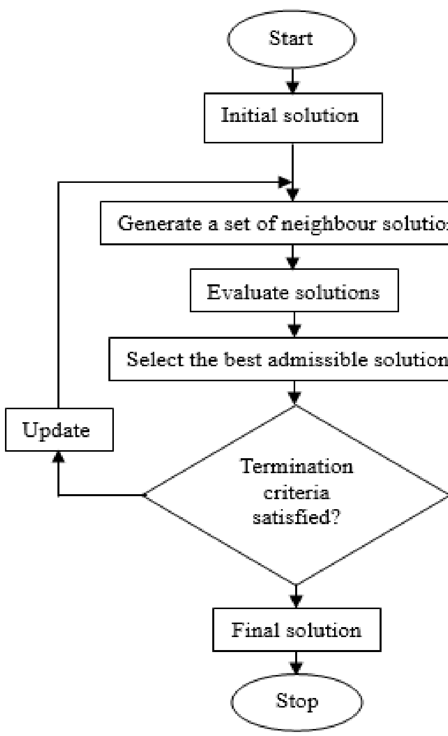
3.4.3 Tabu Search

This is a more elevated heuristic technique for taking care of enhancement issues, it is intended to manage different strategies (or their part forms) to get away from nearby optimality. It has been applied for a wide assortment of traditional and handy issues in applications going from booking to broadcast communications and from character acknowledgment to neural systems. It utilizes adaptable structures memory. The flowchart for the Tabu search is shown in Figure 2.

The steps taken in for the implementation of the Tabu Search is as follows:

```
Stage 1:    Pick an underlying arrangement i in S. Set i*=i
```

Figure 2. Flowchart of Tabu Search method



and k=0.
Stage 2: Set k=k+1 and produce a subset V* of arrangement in $N_{(i,k)}$ with the end goal
that both of the tabu conditions t_r (i,m) ÎT$_r$ is abused
(r=1,...,t) or possibly one of the goal conditions a_r(i,m)ÎA$_r$(i,m) holds (r=1,...,a).
Stage 3: Choose a best j=iÅm in V* (as for f) and set i=j.
Stage 4: If f(i) < f(i*) at that point set i*=i.
Stage 5: Update tabu and aspiration conditions.
Stage 6: If a ceasing condition is met, then stop.
Else go to Step 2.
Where:
i = solution
j = next solution
k = counter at each solution
m= moves (or modification)
i* = current best solution
V* = subset of solution
$N_{(i,k)}$ =Neighborhood

3.4.4 Taburization

Taburization is the process involved so as to place the allocations in its corresponding Tabus. The steps required in the Taburization stage is listed below (Abayomi-Alli *et al.*, 2019a):

Stage 1: After choosing the populace dependent on absolute wellness, the individual wellness of the allotted nurse is utilized to put each chromosome (nurse) into its Corresponding 'Tabu'.
Stage 2: The chromosomes that are ideal (for example get together with the wellness condition) are set in the Long Tabu List while those that are generally are placed in the Short Tabu List.

The Long Tabu List has the ability to hold the nurses for quite a while the Short Tabu is a memory structure to keep esteems put away in it for an impermanent period. Find below the Taburization calculation:

Input: {(E_i: H_i) for $i = 1$ to n
n= number of nurses
Initialize: Population (Pop) Fitness= Best Fit Pop;
Long Tabu= [], Short Tabu = []
Output: Long Tabu = {(E_i: H_i) for $i = 1$ to l
Short Tabu ={(E_j: H_j) for $j = 1$ to s where l= total number of nurses in Long Tabu,
s= Total number of nurses in Short Tabu, n=l+s;
Process: Step 1: E_ie Population, get P (E_i)
Step 2:do fitness = P (E_i) / H_i
Step 3: If (fitness >= 100% and fitness <= 120%)
Step 4: Put E_i in Long Tabu
Else,
Step 5: Put $E_i$in Short Tabu
Step 6: End

3.4.5 Mathematical Formula and Objective Function

Objective and the confinement conditions are made under the conditions dependent on the data acquired from the clinic. The accompanying records are utilized in the succeeding dialogs.

I = {1, 2,..., n} is the arrangement of all nurses having a place with a similar expertise level in every division;

J = {1,2, 3}is the arrangement everything being equal, that is, morning, evening and night shifts;

K = {1,2,..., 7}is the set comprising days of the week, Monday through Sunday;

L = {1,2,…, 7}is the arrangement of nurserank/designation.E.g. Assistant Director of Nursing Services (ADNS), Chief Nursing Officer (CNO), Assistant Chief Nursing Officer (ACNO),e.t.c.

Thus, Let

$$x_{ijkl} = \begin{cases} 1, & if\ nurse\ i\ with\ skill\ level\ l\ works\ on\ a\ shift\ pattern\ j\ on\ day\ k \\ 0, & otherwise \end{cases} \quad (1)$$

Considering Equation1, the hard constraint considered are listed below. These constraints may vary from one clinic to another depending on thehospital's rules, ward organization andnurses' preferences.

1. Each nurse can only work once per day.

$$\sum_{k}^{7} x_{ijkl} = 1\forall_{i} \quad (2)$$

2. There are minimum staff needs for each shift and skill.

$$\sum_{i}^{n} x_{ijkl} \leq N\forall_{j}\forall_{l}\ N = total\ number\ of\ staff \quad (3)$$

3. Assigning two consecutive days must be legal according to the scenario.

$$\sum_{k}^{2} x_{ijkl} = 2\forall_{i} \quad (4)$$

4. Each nurse must have the required skill for a shift.

$$\sum_{l}^{n} x_{ijkl} = 1\forall_{i} \quad (5)$$

5. Each nurse must work more than a given minimum number of hours and less than a given maximum number of hours per day.

$$\sum_{k}^{7} x_{ijkl} \geq H\forall_{i} \quad (6)$$

Where H is the given hours.

In order to evaluate the quality of solutions obtained by hard constraints of the nurse schedule, the fitness function is defined as:

$$f\left(x\right) = \sum_{i=1}^{L} HCi + \sum_{i=1}^{M} SCi \tag{7}$$

Where L is the number of hard constraints and M is the number of soft constraints. HC is the hard constraint and SC is the soft constraint.

4 SYSTEM IMPLEMENTATION

The minimum hardware requirements for implementing GATS_NSS are:

1. PC with Intel(R) Pentium(R) CPU B980 @ 2.40GHz;
2. 3GB of RAM;
3. 32-bit Operating System;

The minimum software requirements are:

1. Windows 7 Operating System;
2. Microsoft Excel;
3. Ellipse as the IDE (Integrated Development Environment).

Java programming language was used in the implementation alongside with some of its library that makes it easier and faster. Some of the library used includes:

1. Random;
2. GA problem;
3. Chromosome.

The parameters of the algorithm are:

1. The total Number of Nurses;
2. The total Number of Wards;
3. The total number of shifts.

All the system parameters were automatically encoded into the system during implementation. When the parameters are supplied, each nurse represents a Chromosome which is used to form the initial population. Applying the GA concept of selection which is based on the fitness of the nurse population and the shift allocated, the schedule with a good fitness i.e. that meets up with the fitness condition is said to be strong and capable for survival.Figure 3, Figure 4, and Figure 5 showsthe GATS_NSS implementations and screenshots.Figure 3 shows the list of some staff nurses at the centre with theirPost or designations such as Chief Nursing Officer (CNO), Assistant Chief Nursing Officer (ACNO), Principal Nursing Officer (PNO), Senior Nursing Officer (SNO), and Nursing Officer 1 (NO1). Figure 4 shows the seven different wards or departments where nursing staffs are required for shifts. The wards are Post-natal labour ward, Gynae emergency ward, Gynae ward, Ante-natal, OOA private ward, Post-natal ward, and First-aid ward.

Figure 5 shows a typical 4-weeks schedule listing the nurses, the senior officer in charge of particular wards, the shift and the day of the shift. Where M, A and N means morning, afternoon and night shifts, respectively.

Figure 3. Screenshot of the nurses and their rank.

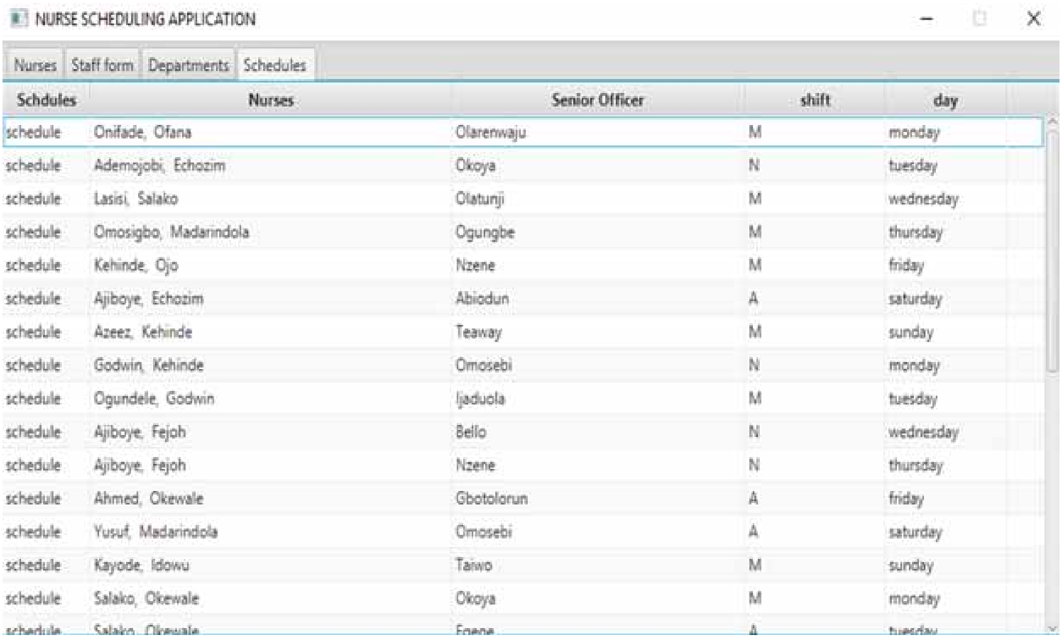
id	firstname	lastname	post
1	Ibrahim	Ogungbe	cno
2	Michael	Ololade	cno
3	Musibau	Zanin	acno
4	Eniola	Akanbi	pno
5	Oladimeji	Adeneye	sno
6	Amori	Atolabi	sno
7	Peter	Ogundele	no1
8	Beatrice	Omosigbo	no1
9	Adetutu	Fagbenro	no1
10	Christiana	Erinoso	no1
11	Oladeji	Madarindola	no1

Figure 4. Screenshot of the duty wards

id	department
1	post-natal labour ward
2	gynae emergency ward
3	gynae ward
4	ante-natal ward
5	ooa private ward
6	post-natal ward
7	first-aid ward

5. PERFORMANCE EVALUATION

Figure 5. Screenshot showing generation of the schedule for the available nurses for a month



Schdules	Nurses	Senior Officer	shift	day
schedule	Onifade, Ofana	Olarenwaju	M	monday
schedule	Ademojobi, Echozim	Okoya	N	tuesday
schedule	Lasisi, Salako	Olatunji	M	wednesday
schedule	Omosigbo, Madarindola	Ogungbe	M	thursday
schedule	Kehinde, Ojo	Nzene	M	friday
schedule	Ajiboye, Echozim	Abiodun	A	saturday
schedule	Azeez, Kehinde	Teaway	M	sunday
schedule	Godwin, Kehinde	Omosebi	N	monday
schedule	Ogundele, Godwin	Ijaduola	M	tuesday
schedule	Ajiboye, Fejoh	Bello	N	wednesday
schedule	Ajiboye, Fejoh	Nzene	N	thursday
schedule	Ahmed, Okewale	Gbotolorun	A	friday
schedule	Yusuf, Madarindola	Omosebi	A	saturday
schedule	Kayode, Idowu	Taiwo	M	sunday
schedule	Salako, Okewale	Okoya	M	monday
schedule	Salako, Okewale	Egene	A	tuesday

In this session, the performance of GAT_NSS was presented. GAT_NSS was evaluated using metrics such as accuracy, percentage of unallocated nurses, percentage of duplicated shifts, percentage of clashes and average computing time (ACT). The formulas for the metrics are presented below:

$$\text{Accuracy}=(TNA/TNN) * 100 \quad (8)$$

$$\% \text{ of } UN = (\text{No. of } UN/TNN) * 100 \quad (9)$$

$$\% \text{ of clashes} = (\text{No. of clashes}/TS) * 100 \quad (10)$$

$$\% \text{ of } DS = (\text{No. of } DS/TS) * 100 \quad (11)$$

$$\% \text{ of } ACT =(TMS-TAS)/TMS*100 \quad (12)$$

Where:
UN = Unallocated Nurses;
DS = Duplicated Shift;

TS = Total Shift;
ACT = Average Computing Time;
TNN = Total Numberof Nurses;
TNA = Total Number of Allocations;
TMS = time taken to compute manual schedule, which is gotten from the hospital;
TAS = time taken to compute automated schedule which is gotten after the system was run.

Allocation is the total number of nurses assigned to a shift and from the results from the system. Duplication is when two nurses are assigned to the same shift in a day. A clash occurs when a nurse is assigned more than one shift in a day.

Table 1 shows the result of comparison between Genetic Algorithm (GA), Tabu Search (TS) and the proposed GATS_NSS implementations on the FMC dataset. The results showed GATS_NSS with allocation, clash, nurse duplication, and computing time score of 99%, 0.5%, 0%, and 94%, respectively.

Table 1. Comparing GATS_NSS with GA and TS based Scheduling.

Conditions		GA	TS	GATS_NSS
		Score (%)	Score (%)	Score (%)
1	Allocation	88.93	98.6	99
2	Un-allocation	26.56	-	-
3	Clash	12.80	5.63	0.5
4	Duplication	6.52	9.05	0
5	Multiple shifts	4.70	-	-
6	Computing time	87.33	95.81	94

It was also observed that only the obligation movements were distributed, the non-obligation movements like three-day weekend, night-off were not indicated in the calendar, thus not all requirement were fulfilled.

Simulation experiment was conducted for 10 independent initial runs and objectve function was trturned in GATS_NSS, GA and TS for 10 interations. The experiment compared the Objective Function Values (OFVs), average OFVs, minimum OFVs and computational time (ms) of the three methods. The quality of the solution returned is summarized in Table 2 and 3.

In Table 2, the OFV of GAT_NSS was fairly stable and showed only slight differences. The OFV approached optimum solution as the nuber of iterations increases. For GAT_NSS the average OFV, minimum OFV and computation time returned the range 48,760–49,442; 47,332–48,314; and 47.29–61.06 ms, respectively while for GA and TS: 53,081–58,194; 52,009–56,905; 47.29–66.2ms and 51,906–59,536; 51,733–58,268; 45.01–70.11ms was obtained, respectively. GAT_NSS had the lowest Average and minimum OFVs both in the upper and lower bounds, GA and GAT_NSS had the same minimum value of 47.29ms for computation time but GA had a much higher maximum value of 66.2ms as against 61.06ms of GAT_NSS. TS on the other hand returned the optimum solution within the lowest computational time of 45.01ms but also had the highest of 70.11ms.

The experimental results prove that the proposed GATS_NSS system is capable of producing near optimum results in a highly constrained nurse scheduling scenario. In all the experiemental runs, GAT_NSS fulfilled all the hard constraints and most of the soft constraints. The tests were run 10 times for each combination to obtain the results. Finally, GAT_NSS out performed GA and TS methods by obtaining the best solution within the shortest computational time.

Table 2. Objective Function Values (OFVs) of GATS_NSS in ten iterations

Senario	Objective Function Values (OFV) for 10 iterations									
1	49494	48402	49945	49727	49110	49115	48314	49820	48506	49016
2	48903	49932	49448	48359	48532	47898	49459	49917	48602	47946
3	48857	49171	48758	48304	48291	49149	48637	48454	50083	48593
4	49806	48733	48653	48998	50052	49795	48597	48005	49251	47454
5	48950	50823	49588	48672	49994	49542	48185	48463	49389	49606
6	49047	48272	49147	49130	48629	47573	52717	48543	51073	47332
7	49459	48911	49312	49683	48154	49444	49031	49362	49050	48620
8	48214	48987	53734	48655	48440	48826	48809	49606	49303	49847
9	47919	48736	48462	48625	48488	48793	49244	49314	48814	49204
10	49532	49554	4737	49681	48641	49687	49646	49867	49590	48283

Table 3. Comparing the Average OFVs, minimum OFVs and Computational time of GATS_NSS, GA and TS based methods

Senario	GAT_NSS			GA			TS		
	Avg. OFV	Minimum OFV	Computational Time (ms)	Avg. OFV	Minimum OFV	Computational Time (ms)	Avg. OFV	Minimum OFV	Computational Time (ms)
1	49145	48314	52.45	57391	56905	53.01	51960	51733	45.01
2	48900	47898	47.65	58173	55224	49.17	58415	57240	61.52
3	48830	48291	55.36	57111	54134	47.29	55426	52334	54.49
4	48934	47454	47.29	54950	52243	53.08	59246	58268	63.20
5	49321	48185	56.13	57508	56197	50.00	56183	55534	65.49
6	49146	47332	60.58	58194	55120	57.02	56469	54682	50.31
7	49103	48154	55.01	56935	53126	64.17	59536	56639	46.91
8	49442	48214	60.43	55738	52049	48.26	58641	56085	70.11
9	48760	47919	59.28	53081	52009	66.20	56354	53220	47.89
10	49422	48283	61.05	53945	53658	64.72	56337	52904	46.56

6 Conclusion

GATS_NSS was implemented for automatic scheduling of hospital nurses with seven wards; it was implemented using a hybrid of Genetic Algorithm (GA) and Tabu search (TS) algorithms. Genetic algorithm was used to create a fitness function and also a number of possible best solutions for the problem and Tabu search was used as an adaptive memory that stored the solutions and picked out the best one while a list of new solutions was being generated.

The results obtained proved that the system does not gurantee 100% efficiency because the following constraints were very difficult to accommodate:

1. Night shifts have more hours than day shifts;
2. Nurses should not work more than 5 days a week;
3. A nurse must not work more than a certain number of hours in a day/week/month.

This limitation can be attributed to the current situation in most Nigerian public hospitals, where:

1. the number of nurses available is far less than the number required;
2. nurses have to work more than the maximum required hours;
3. not all personal requests/preferences can be accomodatied or granted by the system.

These challenges make some of the constrainsts difficult to meet,thus, it too GAT_NSS mmore time befoee near optimum solutions were obtained. If not the computational time would ahe been far lower. Future research should consider accommodating more of this soft constraints.

Conflict of interest

There is no conflict of interest on the part of any of the Authors in publishing the outcome of this study.

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