Genetic Algorithm based Timetable Generating System

(Case Study: Nurse Rostering Problem)

Khaing Hsu Pyae , Khin Nweni Tun
supyae25@gmail.com

Abstract

Combinatorial problems are prominent in Artificial Intelligent and Operation Research. They can't be solved in a given polynomial time with deterministic algorithm, also known as NP complete. Some researchers survey these problems as optimization problems and others examine as constraint satisfaction problems according to the techniques they used to implement. Many problems for instance frequency assignment, facility layout, vehicle routing, propositional logic satisfiablity, graph coloring, temporal and spatial reasoning and also scheduling are in combinatorial nature. Nurse Rostering Problem (NRP) stands as a subclass of scheduling problem. A nurse roster is composed of duty shifts and respite of nurses working at a hospital. The excellent scheduling of nurses has impression on the superiority of healthcare, the employment of nurses, the progress of budgets and other nursing utilities. In this study, metaheuristics such as Genetic Algorithm and Tabu Search are applied to deal with NRP.

1. Introduction

Combinatorial problems involve finding values for discrete variables such that certain conditions are satisfied [3]. They can be classified either as optimization or satisfaction problems. In optimization problems, the goal is to find an optimal arrangement, grouping, ordering, or selection of discrete objects usually finite in number [4]. The probably most widely known example is the traveling salesman problem (TSP) [5] in which a shortest closed tour through a set of cities has to be found. In satisfaction problems, a solution satisfying given constraints has to be found. A prototypical example is the constraint satisfaction problem (CSP) [6] in which one has to decide whether an assignment of values to variables can be found such that a given set of constraints is satisfied.

. In recent years, metaheuristics have been proved to be very efficient in obtaining near-optimal solutions for a variety of hard combinatorial problems including the NRP [1]. Genetic Algorithm, Tabu Search and Simulated Annealing are well-known metaheuristics. They were iterated procedures used to find optimal solutions for the user defined objective function. In this study, Genetic Algorithm utilizes the genetic operators, multipoint crossover, swap mutation and Tabu Search for performing local refinements, a local search (individual learning procedure).

2. Related works

Distributed computer network topologies are designed by GA [8], using three different objective functions to optimize network reliability parameters, namely diameter, average distance, and computer network reliability.

The GA has successfully designed networks with 100 orders of nodes. GA has also been used to determine file allocation for a distributed system. The objective is to maximize the programs' abilities to reference the files located on remote nodes. The problem is solved with the following three different constraint sets:

1. There is exactly one copy of each file to be distributed.
2. There may be any number of copies of each file subject to a finite memory constraint at each node.
3. The number of copies and the amount of memory are both limited.

GA can also used in learning robot behaviors [7]. Genetic Algorithms are adaptive search techniques that can learn high performance knowledge structures. The genetic algorithms' strength come from the implicitly parallel search of the solution space that it performs via a population of candidate solutions and this population is manipulated in the simulation. The candidate solutions represent every possible behavior of the robot and based on the overall performance of the candidates, each could be assigned a fitness value. Genetic operators could then be applied to improve the performance of the population of behaviors. One cycle of testing all of the competing behavior is defined as a generation, and is repeated until a good behaviors' is evolved.

3. Theoretical Background

The emergence of metaheuristics for solving difficult combinatorial problems is one of the most notable achievements of the last two decades in operation research [9]. Metaheuristics are divided into two categories, single solution metaheuristics where a single solution is considered at a time and population metaheuristics where a multiplicity of solutions is evolve concurrently. GRASP (Greedy Randomized Adaptive Search Procedure), Simulated Annealing (SA), Tabu Search (TS) and Variable Neighborhood Search (VNS) are categorized as single solution metaheuristics where Ant Colony Optimization (ACO), Evolutionary Algorithms (EA) and Scatter Search (SS) are population metaheuristics.

GA is a kind of Evolutionary Algorithm used in computing to find exact or approximate solutions to optimization and search problems. TS is a kind of heuristic search method which has the advantage of having internal memory. The experiments show that TS approach can produce better timetables than those of GA approach can. The search time spends in TS is less than that of GA. However, GA can produce several different near optimal solutions simultaneously [2].

3.1 Genetic Algorithm

Genetic Algorithms (GAs) are adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetic. The basic concept of GAs is designed to simulate processes in natural system necessary for evolution, specifically those that follow the principles first laid down by Charles Darwin of survival of the fittest. As such they represent an intelligent exploitation of a random search within a defined search space to solve a problem. The Algorithms:

1. Randomly generate an initial population M(0) Compute and save the fitness u(m) for each individual m in the current population M(t)
2. Define selection probabilities p(m) for each individual m in M(t) so that p(m) is proportional to u(m)
3. Generate M(t+1) by probabilistically selecting individuals from M(t) to produce offspring via genetic operators
4. Repeat step 2 until satisfying solution is obtained.

A typical genetic algorithm requires:

1. a genetic representation of the solution domain,
2. a fitness function to evaluate the solution domain.

3.1.1 Selection

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a *fitness-based* process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected [11].

3.1.2 Reproduction

To generate a second generation population of solutions from the selected parents through genetic operators: crossover (also called recombination), and/or mutation. For each new solution to be produced, a pair of "parent" solutions is selected for breeding from the pool selected previously. By producing a "child" solution using the above methods of crossover and mutation, a new solution is created which typically shares many of the characteristics of its "parents"[11].

3.2 Tabu Search

The basic concept of Tabu Search as described by Glover (1986) is a meta-heuristic superimposed on another heuristic. The overall approach is to avoid entrainment in cycles by forbidding or penalizing moves which take the solution, in the next iteration, to points in the solution space previously visited (hence "tabu").

TS approach contains two basis mechanisms: tabu restrictions and aspiration criteria. The former represents the best solutions found now have already been recorded in the tabu list memory before. The latter one identify its solution quality is the best in all iterations so far. They can put into the tabu list memory again to test tabu restrictions in the next iteration.

4. Case Study

Hospitals need to repeatedly produce duty rosters for its nursing staffs [1]. Because of tedious and time-consuming manual scheduling, and for various other reasons, the nurse rostering problem has attracted much research attention. A roster is feasible if and only if hard constraints are satisfied. The assumptions are:

(1) There are two shift periods per day: day shift and night shift
(2) Each nurse is considered to be independent belong to a department
(3) A nurse has a rank (indicating the level of experience)
(4) The hospital authorities produce a weekly nurse schedule by satisfying the following hard constraints [10].

4.1 Hard Constraints

(1) Shift Constraint (SHC): At a department, during each shift there must be at least one nurse.
(2) Successive Night Shifts Constraint (SNC): A nurse cannot be assigned to more than two successive night shifts.
(3) Successive Day Shifts Constraint (SDC): A nurse cannot be assigned to more than three successive day shifts.
(4)Successive Shifts Constraint (SSC): A nurse cannot be assigned to two successive shifts. A night shift in one day and a day shift in the following day are considered as successive shift.
(5)On - duty Constraint (ODC): Each nurse cannot be assigned less than four shifts per week.
(6)Exclude Night Shifts Constraint (ENC): Night shift cannot be assigned to an experience nurse.

5. Proposed System

In Figure 1, the proposed system inputs number of total nurses, number of senior nurses, number of rostered days and number of population. According to GA, initial population is randomly generated and then calculates the individual fitness. If none of the chromosomes satisfied the proposed hard constraints (i.e. any of the individual fitness is not equal to target fitness), the system applied GA operations to produce new generation of population, in which the system expected to produce chromosomes which satisfied constraints. Two parents are selected by fitness and reproduce for next generation. After those GA operations, the system applies Tabu search and the system outputs a roster which satisfies all of the proposed hard constraints.

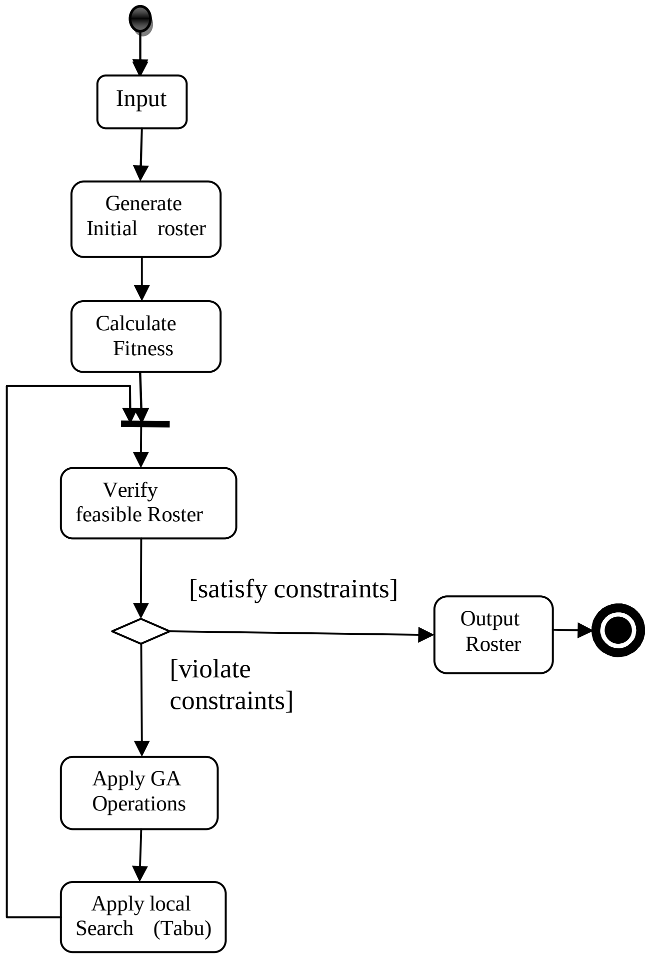

Figure 1: System overview

5.1 Genetic Representation

Genetic Algorithm encodes the solution domain as chromosome like structure known as Genetic Representation or chromosome representation. Chromosome representation has two type of representation either binary-coded or real (integer)-coded. In this study, chromosome was coded as integers (0, 1, 2) where, 0 represents for off duty, 1 represents for day shift duty and 2 represents for night shift duty.
Chromosome: a roster for nurses
Meme: Roster for each nurse
Length of chromosome: number of nurses x number of rostered days

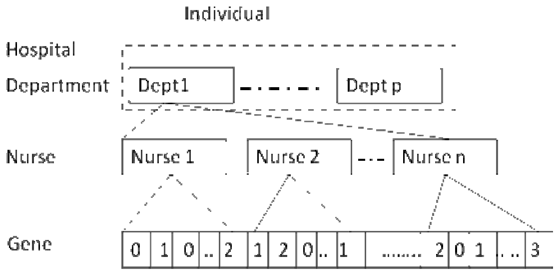

Figure 2: Genetic Representation

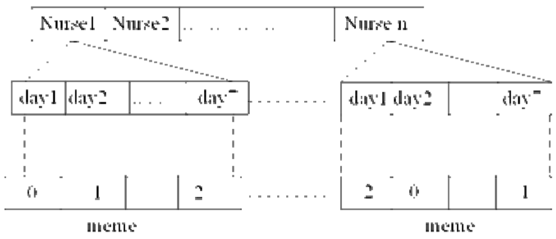

Figure 3: Chromosome Representation

5.2 Fitness Function

An optimum nurse roster is the one with no violations on the hard constraints.
Let NR (Nurse Rostering) represent a proposed schedule of all nurses in the hospital.

$$f(NR) = \sum_{\forall_i \forall_j} C_j + C_O$$

Where, j = 1 to 5

C_0 = SHC
C_1 = SNC
C_2 = SDC
C_3 = SSC
C_4 = ODC
C_5 = ENC

The values of C_j, where j=1, 2.., 4 are the value 1 for each nurse, for j=5 is the value 1 for each senior nurse and the values of C_0 is only '1'over all nurses.

5.3 Parent Selection

Individual solutions are selected through a fitness-based process where fitter solutions are typically more likely to be selected. In this system, Linear Rank Selection method is applied for parent selection. Individuals are sorted in order of raw fitness then new fitness is assigned according to rank. Parents are selected by rank.
Example:
Parent No.): f(x) = SHC+SNC+SDC+SSC+ENC+ODC
Parent0 : 0 + 5 + 5 + 3 + 2 + 4 = 19
Parent1 : 0 + 4 + 5 + 5 + 2 + 4 = 20
Parent2 : 0 + 4 + 5 + 3 + 2 + 4 = 18
Parent3 : 0 + 4 + 4 + 3 + 2 + 4 = 17
Parent4 : 0 + 5 + 4 + 3 + 2 + 2 = 16
The target fitness value=23
Parents are sorted according to fitness:
Parent1 : 0 + 4 + 5 + 5 + 2 + 4 = 20
Parent0 : 0 + 5 + 5 + 3 + 2 + 4 = 19
Parent2 : 0 + 4 + 5 + 3 + 2 + 4 = 18
Parent3 : 0 + 4 + 4 + 3 + 2 + 4 = 17
Parent4 : 0 + 5 + 4 + 3 + 2 + 2 = 16

First : Parent (1) & f(x) =20
Second: Parent (0) & f(x) =19
Last : Parent (4) & f(x) =16

............Parents Selection..............

The parents are the owners of best Fitness value:
Parent no. 1 & 0
Parent1 (Mother): 1
10101010111010112022211002202001000
Parent2 (Father): 0
01011101010110202101002110120020220

5.4 Genetic Operators

To generate a second generation population of solution from those selected through genetic operators, crossover and mutation. For the proposed chromosome representation, multipoint crossover and swap mutation are applied.

5.4.1 Crossover

In multipoint crossover, two individuals are joined at multipoint and exchange sections after points. In this study, two point crossover is used.

Crossover points C1=4, C2=18

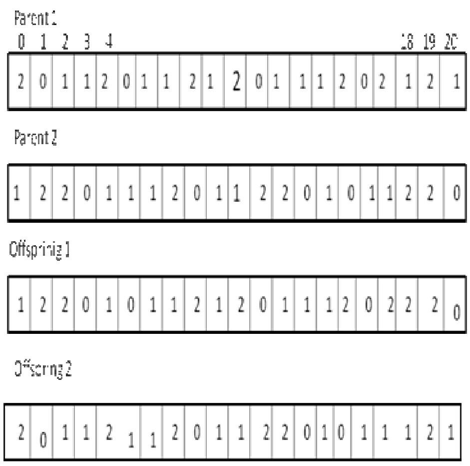

Figure 4: Two point Crossover

5.4.2 Mutation

In swap mutation operation, pick two alleles at random and swap their positions.

Mutation points 3 &12

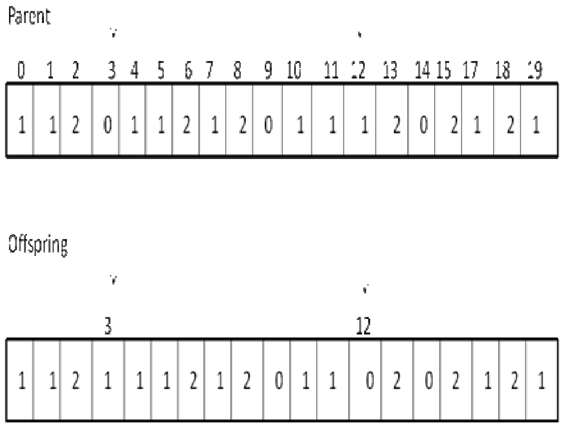

Figure 5: Swap Mutation

5.5 Reproduction

Genetic Algorithms are characterized by type of replacement strategies they use. Steady state genetic algorithm is applied in the proposed system. Instead the replacement of all individual in each generation, the system replaces only some individuals in each generation. In this study, only one individual is replaced in each generation.

Example:

Generation 0: Parents are sorted according to fitness:

Parent1 : 0 + 4 + 5 + 5 + 2 + 4 = 20
Parent0 : 0 + 5 + 5 + 3 + 2 + 4 = 19
Parent2 : 0 + 4 + 5 + 3 + 2 + 4 = 18
Parent3 : 0 + 4 + 4 + 3 + 2 + 4 = 17
Parent4 : 0 + 5 + 4 + 3 + 2 + 2 = 16

After mating Parent1 & Parent0: The new child become…

01011101010110202101211002200020220: f(x) =20

Generation1: Parent with least fitness 16 (Parent4) is replaced by child with fitness 20.

Parent0 : 0 + 5 + 5 + 3 + 2 + 4 = 19
Parent1 : 0 + 4 + 5 + 5 + 2 + 4 = 20
Parent2 : 0 + 4 + 5 + 3 + 2 + 4 = 18
Parent3 : 0 + 4 + 4 + 3 + 2 + 4 = 17
Parent4 : 0 + 5 + 5 + 4 + 2 + 4 = 20

6. Conclusion

Although combinatorial problems require large computational times to produce optimal solutions, heuristics approaches can produce satisfactory results in reasonably short times. The use of Tabu Search avoid from exploring the previous explored solutions. By using integer genetic representation, the chromosome length is shorter than those of binary representation. In contrast, the proposed approach reduces time complexity.

Genetic Algorithm is a non deterministic algorithm and so it is not sure that genetic operation can produce better fitness child than mating parents. Local search can only satisfied five hard constraints and have to apply GA for the last constraint satisfaction. We just consider about weekly schedule and it may be unexpected processing time for large scale of nurses and rosrered days.

In this Nurse Rostering System, it will be used Hybrid Genetic Algorithm to weekly roster for nurses in a hospital. It will be used Linear Rank Selection method for parent selection and it is considered replacement strategy on steady state, Multi points crossover method, swap mutation method and Tabu Search for individual learning procedure.

7. References

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