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Intelligent Hybrid Algorithm using Constraint-Based Reasoning and Genetic Algorithm for Nurse Scheduling

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Abstract: *Almost all hospital has its own nurses and still use the old fashion manual way of managing nurse scheduling in daily business. Nurse scheduling problem represents a difficult class of multi-objective optimisation problems consisting of a number of interfering objectives between the hospitals and individual nurses. Nurse scheduling consists of assignment of shifts and holidays to nurses for each day on the time horizon, taking into consideration a variety of conflicting interests or objectives between the hospitals and individual nurses. Nurse scheduling can be modeled as a shift/rotation schedule that can be solved by several methods. The nurse scheduling has been solved by various methods like genetic algorithm, constraint logic programming, evolutionary algorithms, neighbourhood function, backtracking algorithms and lookahead algorithms. In this research the hybrid or combination of genetic algorithm with constraint-based reasoning are used for solving this scheduling problems. The constraint-based reasoning is used to prune the search space meanwhile, genetic algorithm is used for searching the solution in the search space. The proposed method is tested using data from Hospital Permai, Johor. The experimental results show that the hybrid technique has been proven to solve this problem effectively.*

Keywords: *Nurse Scheduling, Genetic Algorithm, Constraint-Based Reasoning, Hybrid Technique*

1. Introduction

Nurse scheduling problem (NSP) is a common problem found in almost all hospitals. NSP basically consists of assigning a number of tasks or shifts, holidays and other types of duties to nurses over a defined period of time under various constraints. NSP sometimes refers to staff scheduling, employee scheduling, nurse rostering and shift scheduling. NSP is a combinatorial optimization problem and it has been classified as NP-complete problem. Generally, NSP has a number of constraints. As a result, it needs a lot of knowledge and experience to make the schedule. The schedule normally prepared by head nurse or the authority in the hospital. The schedule preparation gives a lot of burden (time and efforts) to them and it has been growing the demand for automatic nurse scheduling system.

The NSP has been solved using various methods ranging from rule-based approach (Shaffer, 1991; Meisels et al., 1995), Tabu search (Dowsland, 1998), constraint-based programming (Darmoni et al., 1995; Weil et al., 1995; Adbennadher and Schlenker, 1999), evolutionary algorithm (Jan et al., 2000; Inoue et al., 2000; Miwa et al., 2002), genetic algorithm (Tanomaru, 1995, Burke et al., 2001, Kawanaka et al., 2001), heuristics and combination of above techniques. It is generally agreed that GA or EC is one of the promising techniques for solving combinatorial discrete optimization problem because of its inherent ability to deal with local minima phenomena. However GA cannot deal efficiently with the constraints of most of optimization problems without improvising or enhancement to handle constraint. There are two ways of dealing with constraints when using GA; one way is by devising special fitness function (Burke et al., 2001) or GA operators (Tanomaru, 1995) and the second way is by combining with other constraint processing techniques (Koole and Sluis, 1998; Kawanaka et al., 2001). In this study, a hybrid approach consisting of GA and CBR is proposed to solve the CSP's. The GA is used to generate potential solutions by using appropriate operators through effective fitness function. Then, the CBR procedures are applied to determine the consistency and validity of the solution followed by an appropriate repair procedures to improve the non-feasible solutions.

The CSP consists of a set of n variable X_i, $i=1,2,3\ldots\ldots,n$ which has an associated domain D_i of possible values. There is also a set of binary constraints C_{ij} which describe relations between variables X_i and X_j. A feasible solution is an instantiation of all variables which satisfy all constraints. If an objective function is given, an optimal solution can be found by instantiating all variables which satisfy all constraints and optimise the given objective function. The CBR is a problem solving technique that applies constraint propagation. Constraint propagation is implemented through an arc consistency (AC) algorithm. Binary constraints can be represented as a constraint graph where nodes represent variables, and arcs or edges represent the constraints between variables. Therefore, the AC algorithm is an algorithm that checks the consistency of value assignments for each couple of nodes linked by a binary constraint and removes the values (from its domain) that cannot satisfy this constraint.

The paper is organized in the following order. Section 2 describe nurse scheduling problem and model formulation, Section 3 describes the Hybrid genetic algorithm, Section 4 discusses results and implementation and followed by conclusion in Section 5.

2. Nurse Scheduling Problems

Nursing service schedules aim to distribute the nursing staff's human resources over a given period while satisfying personnel and hospital policy regulations as well as the anticipated activities of the department, nursing staff preferences, events and common sense. A schedule over a fixed period (1, 2, 4, and 8 weeks, etc.) that specifies working days and shift and days off is associated with each member of the nurses. A hospital is composed by several departments, and each department is composed of one or more nursing team called ward. The ward is makes up of a team of nurses, with a head nurse who manages the unit's schedule. Generally a unit operates 24 hours a day, 7 days a week, with the working say divided into 3 periods: a morning shift (M) of 8 hours, evening shift (E) of 8 hours, and night shift (N) of 10 working hours.

For the purpose of testing our algorithm, Hospital Permai, Tampoi, Johor is selected This hospital is a specialized hospital for psychiatric or mental illness. The set up and staff organization are different from district general hospital where in addition to nurses, there are medical assistants (MA).

There are 42 wards available for patients. Each nurse will be assigned to one or two wards depending on the load, ward with newly admitted patients require more attention than ward with senior patients. There are 40 beds per ward and each ward will be allocated with 4 nurses which will be working on rotational basis based on 3 shift per day; morning (7am-2pm), evening (2pm-9pm), night (9pm-7am). The scheduling cycle is 2 weeks (14 days).

Table 1: Basic information of Hospital Permai, Johor

No	Items	Values
1	Schedule cycle	14 day (2 weeks)
2	No. of wards	42
3	No. of bed per ward	40
4	No. of nurse per ward	4
5	No. of shifts per day	3 (Morning, evening, and night)

The following are the scheduling rules for a ward with nurses are summarized as follows:

a) In a day, there will be 3 nurses working, one each for "morning shift", M, "evening shift", E, and "night shift", N and one nurse will "off duty" or sleeping day (SD), night off (NO), or normal off day.

b) In one schedule of 14 days, one of the nurse must takes two night shifts, therefore the nurse who takes 2 night shifts have to be rotated every two weeks.

c) The staff who are assigned with 2 night shifts will reduce the night and evening shifts by one. These night and evening shift will be assigned to other staff

The nurse scheduling problem for this particular case is to find fair assignment of 3 shifts per day for 14 days for 4 staff while satisfying the above scheduling rules.

3. Model formulation

The first step to model nurse scheduling problem as a scheduling problem, we have to identify the scheduling activities, the machine to process activities, scheduling horizon and the machine to process activities. Before we can identify the activities, the shift patterns are identified. Since the scheduling rules stated that for every 3 consecutive night duty, the staff entitle for one sleeping day (SD) and normal off. There are altogether 6 night patterns and one each for morning, night and off respectively. There are altogether 38 activities (V1,V2,…, V38).

Scheduling problem can be solved using CBR by identifying variables, domain and constraints. The variables in this case are the start time of the activities. Let *Xij* be the start time for shift activity *j* performed by staff i, where i=1,2,,,4 and j = 1,2,.., 14.

The scheduling domain of CBR is 14 (1,2,3,…,14).

Table 2: Shift pattern for 4 staff in 14 days

Pattern type	Activity variable	Activity	No. of activity	No of days of the pattern	Shift pattern
P1	*V1*	Night shift type 1	1	4	N-N-SD-WO
P2	*V2*	Night shift type 2	1	4	WO-N-N-N
P3	*V3,V4,V5*	Night shift type 3	3	5	N-N-N-SD-WO
P4	*V6,…V19*	Morning shift	14	1	M
P5	*V20,..,V33*	Evening shift	14	1	D
P6	*V34,…,V38*	Off	5	1	O

The constraints for the CBR are as follows:

a) For a single day, there should be 1xM, 1xE, 1xN shifts.

b) Every staff should be allocation with a maximum 2 WO for every two weeks.

c) In every cycle, one of the staff shall be assigned two night shift patterns.

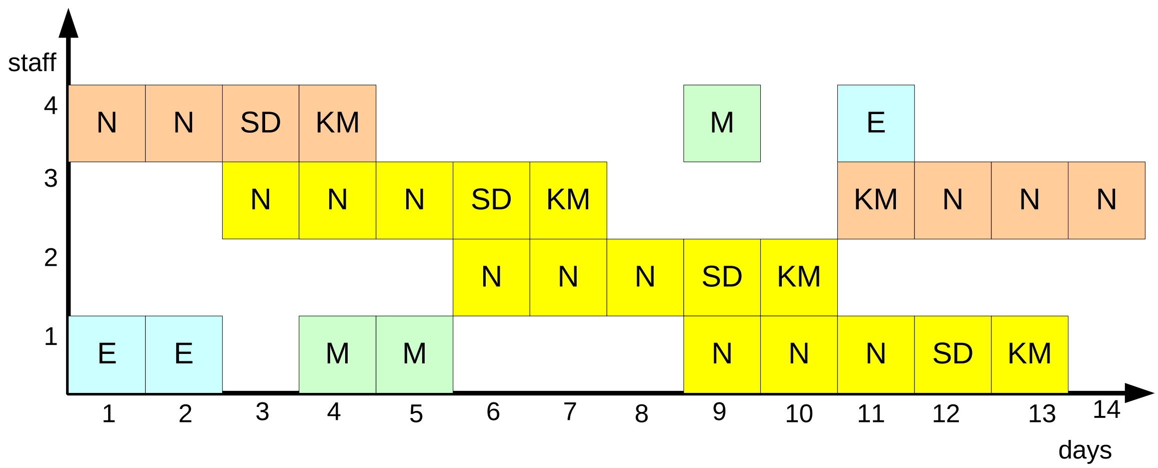

Fig. 1: An example of some nurse scheduling problem modeled as a scheduling problem.

a) Chromosome representation

In order for the GA to search for the best solution, the scheduling problem is represented as follows; the chromosome is the solution, i.e. the biweekly nurse schedule

where the start time *Xij* of shift activity *i* performed by staff *j* is the gene, and the allele is the days in the scheduling cycle.

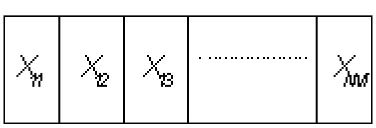

Fig. 2: Chromosome representation

b) Fitness functions

The schedule generated by the GA is evaluated based on the fairness of the assignment to the staff. The fairness is calculating and comparing the number of M, E, N, SD, WO such the best solution is the one with total minimum differences.

4. Hybrid Scheduling Algorithm

The optimisation of a CSP can be stated as optimising a function of one or more variables subject to various constraints. The requirement is to

maximise or minimise $f(\mathbf{x})$

where f is the objective function and $\mathbf{x} = (x_1, x_2,\ldots\ldots,x_n)$ is an n-dimensional vector, subject to

$c_i(x) > 0, \quad i=1,2,\ldots\ldots,k.$

$c_i(x) = 0, \quad i=k+1,\ldots\ldots,m.$

The solution space of the CSP can be classified as feasible and non-feasible. The GA alone is inadequate to solve constrained optimisation problems such as CSP (Michalewicz, 1996). The arc consistency algorithms (Hentenryck, 1992) of CBR is used to isolate feasible from non-feasible solutions generated by the GA. We adopt the following strategies in designing the hybrid algorithm:

- Use simple problem representation.
- Minimise the size of chromosomes.
- Minimise the size of alleles.
- Find the optimum solution among the feasible solutions.
- Minimise the processing time.

We propose a hybrid GA by embedding the CBR procedure into the GA (Figs. 3, 4, and 5) to process and validate individuals generated by the GA operators in each generation, thus enhances faster convergence.

Procedure *PROCESS_ CONSTRAINT* (S_i,v) validates and repairs genomes when necessary to ensure that all individuals generated by the GA operators are legal. After the values of genes are copied to the values of constraint variables, then these values are passed to the constraint propagation procedure which produces valid and legal values. These values are then returned to the genomes to be processed in the next generation.

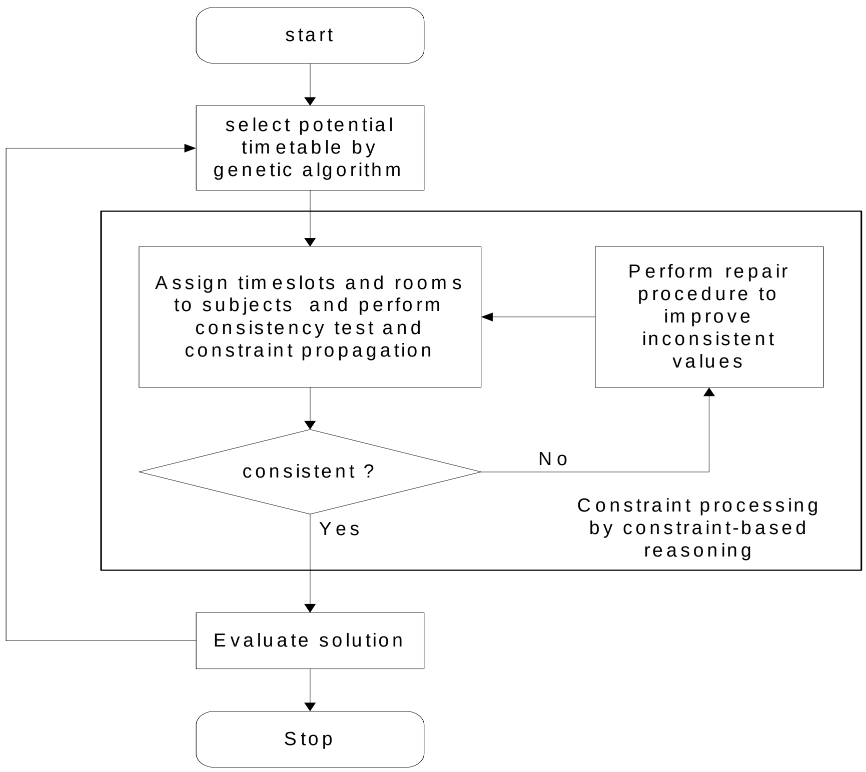

Fig. 3: The flowchart of hybrid GA algorithm

```
Procedure GENERAL_GA
begin
  t ← 0
   initialise P(t)
   evaluate P(t)
   while (not termination-condition) do
        begin
            t ← t + 1
            select P(t) from P(t-1)
            alter P(t) by GA operators
            evaluate P(t)
        end
   end
end GENERAL_GA
```

Fig. 4: A general genetic algorithm.

```
Procedure HYBRID_GA
begin
    create constraint variables S_i
    read constraints C(S_i)
    post constraints C(S_i) to variables S_i
    t ← 0
    initialise P(t)
    evaluate P(t)
    while (not termination-condition) do
        begin
          t ← t + 1
          select P(t) from P(t-1)
          alter P(t)
          copy allele values from P(t) to values v
                of constraint variables S_i
          PROCESS_CONSTRAINTS(S_I,v)
        return legal values v to genomes
              in population P(t)
        evaluate P(t)
end HYBRID_GA
```

Fig. 5: Proposed hybrid genetic algorithm.

The main objective of constraint processing procedures is to test the consistency of the solution to the specified constraints. If the timeslot value is consistent, then a room that satisfies the constraints is selected for that particular timeslot. If the room is not available then the next timeslot is selected by the random function. Consistency test will be performed on all new values selected by the random function. During the consistency test, the constraints are propagated by removing values from its domain if it is not supported (not allowed by constraints) by values from the related variables. By restricting the permissible values that a variable can take, the search space is reduced. Subsequently, the search for a solution can be performed in a shorter time. The proposed hybrid algorithm has been tested on various applications including university lecture timetabling (Safaai et al., 1997, 1999, 2000) and ship maintenance scheduling (safaai et al., 1999).

6. Results and Implementation

The model developed in Section 3 is implemented using the proposed algorithm described in Section 5. The program is developed and compiled using IBM compatible Pentium III 866 MHz PC under Window environment. The GA parameters used to run the program are shown in Table 3.

Table 3: GA parameters

Parameters	Values
Population	250
No. of generation	150
Crossover rate	0.6
Mutation rate	0.1
No. of genes per Chromosome	38
Size of *alleles*	14
Type of crossove	Two-point crossover
Type genetic algorithm	Stable state

The performance evolution of the timetable generation by the hybrid algorithm is shown in Fig. 5. The stable solution achieved after 50 generation with fitness value of 270. The sample nurse schedule generated by the algorithm is shown in Fig. 6. This demonstrated that all the constraints were not violated.

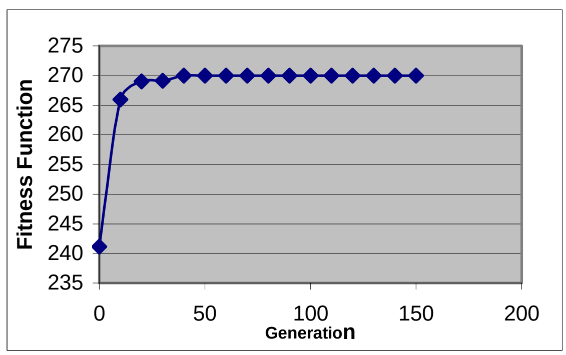

Fig. 5: GA evolution

	Days													
Staff	1	2	3	4	5	6	7	8	9	10	11	12	13	14
MA1	N	N	SD	WO	M	M	E	E	E	M	WO	N	N	N
MA2	E	E	N	N	N	SD	WO	M	M	E	M	M	M	WO
MA3	M	WO	M	M	E	N	N	N	SD	WO	E	E	E	E
MA4	WO	M	E	E	WO	E	M	WO	N	N	N	SD	WO	M

Fig. 6: Sample nurse schedule

It is found out that NSP is very much problem dependent in term of characteristics of the schedule such as schedule cycle, number of nurses, scheduling rules or constraints and it is normally involve integration with previous rotational schedule outside of the shift schedule. For example, we have 4 staff available but the schedule requires 5 sets of night (N-N-N-SD-WO) shifts. In the process of assigning the staff to current cycle we must have information about the night shift of the previous cycle.

7. Conclusion

Nurse scheduling is a difficult and multi-faceted NP- complete combinatorial problem. Various solutions have been proposed and until now there are still many aspects of solutions open for refinements. We presented an example of small nurse scheduling problem of a hospital and we observed that the problem of this size is enough to display the interrelation between the activities (shifts) and the constraints. The problem is formulated as a CSP model and the solved using hybrid GA and CSP. This study shows that NSP can be solved by the proposed hybrid algorithm efficiently. This reason for increasing efficiency is that the constraint processing is separated from search for optimal solution as compared to many GA-based solution where both constraint handling and searching for optimal solution are performed by fitness function of GA. For future development, the model can be scaled up to solve bigger size of nurses of bigger hospitals. The model can be refined further if the evaluation of the schedule can further formalized in term of evaluating the degree of fairness to all nurses involved as this is the main concern of the successful schedule.

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