Healthcare Staff Scheduling in a Fuzzy Environment: A Fuzzy Genetic Algorithm Approach

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Abstract

In the presence of imprecise management targets, staff preferences, and patients' expectations, the healthcare staff scheduling problem becomes complicated. The goals, preferences, and client expectations, being humanistic, are often imprecise and always evolving over time. We present a fuzzy genetic algorithm (FGA) approach for addressing healthcare staff scheduling problems in fuzzy environments. The proposed FGA-based approach can handle multiple conflicting objectives and constraints. To improve the algorithm, fuzzy set theory is used for fitness evaluations of alternative candidate schedules by modeling the fitness of each alternative solution using fuzzy membership functions. Furthermore, the algorithm is designed to incorporate the decision maker's choices and preferences, in addition to staff preferences. Rather than prescribing a sing solution to the decision maker, the approach provides a population of alternative solutions from which the decision maker can choose the most satisfactory solution. The FGA-based approach is potential platform upon which useful decision support tools can be developing for solving healthcare staff scheduling problems in a fuzzy environment characterized with multiple conflicting objectives and preference constraints.

Keywords
Healthcare staff scheduling, nurse scheduling, fuzzy modeling, satisficing, genetic algorithms, healthcare operations

1. Introduction

The nursing staff scheduling problem (NSSP) is a serious challenge to healthcare operations planners concerned with the assignment of shifts to nursing staff on a daily, weekly or monthly basis (Cheang et al., 2003). The goodness of nurse schedules has a great impact on the quality of health care, the recruitment of nursing personnel, the development of healthcare budgets and various operations of the healthcare organization. Though duty rosters may be generated manually on a smaller scale, scheduling nurses has always been a hard optimization problem for most practical situations (Topaloglu and Selim, 2010). The major factors behind this are that (i) health care organizations are staffed 24 hours a day and seven days a week, (ii) nursing staff are allowed to request for specific shifts, (iii) legislative restrictions are imposed on staff rosters (Alfares, 2004). In case of many staff requests, more time is consumed in re-rostering staff. For these and other reasons, the NSSP is has attracted much attention among the practicing healthcare operations managers and the research community.

The NSSP has been studied widely researched over the years. Remarkable literature surveys can be found in (Burke et al., 2004; Ernest et al., 2004a; Ernst et al., 2004b). A notable annotated bibliography of personnel scheduling and rostering studies is presented in Ernst et al. (2004b). Cheang et al. (2003) presented a bibliographical survey specifically on the nurse rostering problem. Various empirical and hypothetical studies have pointed out that the NSSP is a hard combinatorial problem that is best solved using heuristic methods, metaheuristic approaches, and other expert intelligent systems methods (Cheang et al., 2003; Topaloglu and Selim, 2010; Burke et al., 2004; Ernest et al., 2004a; Ernst et al., 2004b; Shaffer., 1991). To achieve the best results when solving hard combinatorial problems, metaheuristics such as genetic algorithm (Mutingi, Mbohwa, 2013), particle swarm optimization

(Akjiratikarl, 2007) and evolutionary algorithms (Jan et al., 2000) are normally combined with problem specific heuristics (Inoue et al., 2003). However, in most cases, the healthcare environment is characterized by multiple conflicting objectives that are difficult to formulate and evaluate in closed form. It is often difficult to achieve the required fairness when allocating schedules to nursing staff. In addition, it is difficult to incorporate the choices and preferences of the decision maker who has to take into account the wishes and preferences of the patients and the nursing staff, not forgetting the management goals which are often expressed imprecisely (Topaloglu, and Selim, 2010; Mutingi and Mbowha, 2013).

In view of the above discussions, the most common shortcomings of conventional staff scheduling approach are as follows:

- The scheduling problem is multi-objective; has a number of objectives, some of which are difficult to evaluate sufficiently;
- The solution methods prescribe a single, rather than provide a population of alternative solutions for decision support;
- The solution methods are often trapped in local optima before obtaining the desired solution;
- The methods often consume a lot of computation time.

This research seeks to cover these voids by developing an interactive approach that utilizes fuzzy genetic algorithm. The approach uses a unique constraint centered coding mechanism to improve the computational efficiency of the algorithm. In this approach, we envisage the following objectives:

1. Describe the staff scheduling nurse scheduling and its various constraints;
2. Propose an interactive fuzzy genetic algorithm approach, with a unique constraint centered coding scheme,
3. Present illustrative examples, demonstrating the effectiveness of the approach.

The remainder of the paper is structure as follows: The next section describes the nursing staff scheduling problem. This is followed by a brief background to fuzzy concepts and genetic algorithm (GA) in Section 3. An interactive fuzzy genetic algorithm is proposed in Section 4, with its constraint centered coding scheme. Computational experiments and results are provided in Section5. Section 6 concludes the paper.

2. The Nursing Staff Scheduling Problem

The NSSP is a hard optimization problem that involves assignment of shifts and off days to nurses over the planning horizon of up to about one month. Oftentimes, the decision maker should consider a myriad of conflicting objectives and preferences between the healthcare organization and individual nurses (Cheang et al., 2003). Nurses have specific skills and contractual agreements limiting the number of shifts in a week, number of off days, and number of nurses for each shift, among other restrictions. Furthermore, personal preferences, though they may be imprecise in practice, should be taken into account in order to maximize on job satisfaction (Topaloglu and Selim, 2010; Mutingi and Mbohwa. (2013). For instance, nurses may desire specific days off, certain shifts, or number of working days per period. From our studies in actual hospitals in country “Z”, each nurse is entitled to three types of shifts: day shift d, night shift n, and late night shift l, with some holidays or off days o, as listed in Table 1.

Table 1. Common shift types in country Z

Shift, w	Shift Description	Time allocation
1	d: day shift	0800 - 1600 hrs
2	n: night shift	1600 - 2400 hrs
3	l: late night shift	0000 - 0800 hrs
4	o: off days as nurse preferences	

2.1 Problem Definition

The NSSP is described thus: Let N and M represent the number of nurses and days, respectively. Additionally, let w represent the shifts. We further define the following notations: The following notation is used:

Notation

i Index for nurses, $i = 1,\ldots, N$

j Index for days, $j = 1,\ldots, M$

w Index for shifts, $w = 1, 2, 3, 4$

X_{ijw} 1, if nurse i works shift w on day j; 0 if otherwise

Then, NSSP is a problem is an $M \times N$ matrix such that each X_{ijw} element of the matrix expresses that nurse i works shift w on day j. Generally, the objective is to search for a schedule that satisfies a given set of hard constraints. However, in practice, the wishes or preferences of individual nurses must be satisfied as much as possible.

2.2 Constraints

Most healthcare organizations classify shifts into two categories (a) hard constrains, which must always be satisfied, and (b) soft constraints, which must be satisfied to the highest degree possible. While violation of hard constraints constitutes an infeasible schedule, violation of soft constraints is permissible to some extent, but at the expense of the quality of the schedule. Soft constraints are added to improve the quality of the schedule. A study of the NSSP in country "Z" yielded the list of constraints as shown in Table 2. From the study, real world constraints can be categorized into daily restrictions (hard constraints, C1 to C5) and nursing staff preferences (soft constraints, P1 to P3). Our FGA-based algorithm seeks to incorporate these constraints in its coding structure.

Table 2: Typical real world constraints for the nursing staff scheduling problem

Constraints	Description of the constraint
Daily Restrictions	C1. Assign each nurse at most 1 shift per day.
	C2. The assigned d, n or l shifts $\geq$ required d, n or l shifts, respectively.
	C3. A (n-d), (n-l), or (l-d) shift combination (sequence) is not permissible.
	C4. Assigned legal holidays = number of legal holidays.
	C5. Interval between night shifts should be at least 1 week.
Nursing Staff Preferences	P1. Preferred or desired day off or holidays.
	P2. Fairness or equality of shifts for each nursing staff
	P3. Congeniality - Compatible or preferable shift assignments among work mates

3. Preliminaries

The proposed approach in this study rests upon the mechanics of genetic algorithm and fuzzy set theory concepts.

3.1 Genetic Algorithm

Genetic algorithm (GA) is a stochastic search and optimization technique developed from the mechanics of genetics and the philosophy of survival of the fittest (Holland, 1975; Goldberg, 1989). The algorithm uses a collection of sub procedures which are executed iteratively till a desirable solution is obtained. Initially, a population of candidate solutions (chromosomes) are generated at random. These chromosomes consist of codes (genes) that represent typical candidate solutions to be evaluated for goodness (fitness) calculated according to a given fitness function. The codes or genes contain information upon which genetic procedures operate iteratively, transforming the chromosomes into increasingly better ones. For instance, the crossover operator probabilistically exchanges partial information between chromosomes, so as to improve the fitness of the chromosomes,. Mutation operator acts on an individual chromosome by altering individual genes at a very low probability with the aim of improving the fitness of the chromosome. Basically, the process of evaluation, crossover, and mutation occurs iteratively, until a termination criterion is reached, and the desired final solution is obtained. However, since its inception, various additional procedures have been developed to enhance the performance of the algorithm. One possible enhancement involves the inclusion of fuzzy theory concepts to enable GA to handle global search and optimization problems where some of the goals, the constraints, and the implications of the decisions taken are imprecise.

3.2 Fuzzy Sets

Fuzzy set theory models imprecision and uncertainty in a non-stochastic sense [6]. A fuzzy number represents imprecise quantities, such as "about 10," and "substantially greater than 10." Thus, a fuzzy set is a class of objects with no sharp boundary between the objects that belong to that class and those that do not. Fuzzy set theory, unlike Boolean logic, deals with degrees of membership, rather than membership or non-membership [7]. To further clarify the concept of fuzzy theory, we distinguish fuzzy sets from crisp sets: A Crisp Set is defined thus: Let X be the universe of objects having elements x, and A denote a proper subset of the universe X; $A \subseteq X$. Then, the membership of x in a classical crisp set A is defined by a characteristic transformation function μ_A from X to $\{0,1\}$, such that,

$$\mu_A(x) = \begin{cases} 1 & \text{If } x \in A \\ 0 & \text{If } x \notin A \end{cases} \tag{1}$$

Contrary to the crisp set, a fuzzy set is defined thus: Let X be the universe of discourse whose elements are denoted by x. Then, the grade of membership of x in a fuzzy set A is be defined as $\mu_A(x)\in[0,1]$, where $\mu_A(x)$ is the membership function of x in A, which maps each element of X to a membership value in [0,1]. The closer the value of $\mu_A(x)$ is to 1.0, the more x belongs to A, and vice versa. The elements of a fuzzy set indicate the value of each element in the set and its grade of membership. Thus, the fuzzy set A in X is a set of ordered pairs;

$$A = \{x, \mu_A(x) \mid x \in X\} \tag{2}$$

4. Fuzzy Genetic Algorithm Approach

In this study, we develop an interactive approach which supports the iterative generation and improvement of good alternative solutions from the decision maker can select the most appropriate solution. The general flow of the interactive approach is shown in Figure 1. A population of candidate solutions is generated based on a set of rules pre-set by the decision maker. The rules are defined by hard or absolute constraints, thus, ensuring feasibility right from the start of the search process. This is followed by the FGA–based global optimization from which a population of good solutions are obtained and displayed. Subsequently, the solutions are evaluated by the decision maker who then selects a satisficing solution, based on other practical considerations that could not be captured in the objective function formulations.

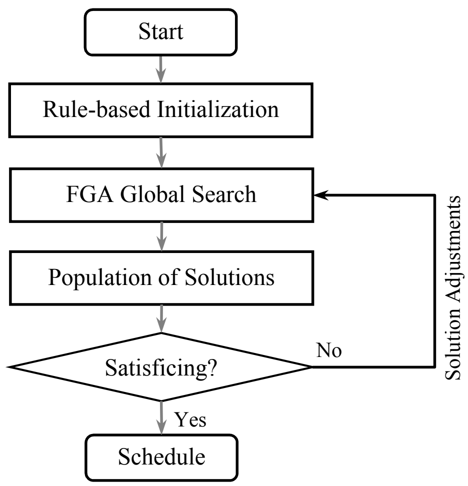

Figure 1: Interactive nursing staff scheduling approach

The main component of the interactive approach is the FGA search mechanism. The FGA follows through a number of stages. The approach and its elements are presented in the next section.

4.1 FGA Coding Scheme

To enhance the performance of FGA, we develop a unique coding scheme as shown in Figure 2. The scheme covers a planning period of 7 days. In this coding scheme, the nursing staff, s_1, s_2,…,s_9, are allocated one of the four shifts in each day, including the off shift, *o*.

		Days									
Nurse	Skill	1	2	3	4	5	6	7	*d*	*n*	*l*
s_1	1	*l*	*n*	*l*	*n*	*d*	*l*	*n*	1	3	3
s_2	1	*o*	*d*	*n*	*l*	*d*	*d*	*l*	3	1	2
s_3	1	*d*	*d*	*d*	*d*	*o*	*n*	*d*	5	1	0
s_4	2	*n*	*l*	*l*	*o*	*d*	*d*	*d*	3	1	2
s5	2	*d*	*d*	*h*	*n*	*n*	*l*	*n*	2	1	1
s6	2	*d*	*o*	*d*	*d*	*l*	*n*	*d*	4	1	1
s7	2	*l*	*n*	*d*	*d*	*l*	*d*	*o*	3	1	2
s8	2	*n*	*l*	*n*	*l*	*n*	*o*	*l*	0	3	3
	d	3	3	3	3	3	3	3			
	n	2	2	2	2	2	2	2			
	l	2	2	2	2	2	2	2			

Figure 2: An example of a nurse schedule table – a candidate solution

4.2 Enhanced Initialization Algorithm

We propose an enhanced coding algorithm that satisfies all hard constraints of the NSSP, as shown in Figure 3. An initial population of candidate solutions size *p* is created by random assignments. The enhanced algorithm begins by randomly allocating days off, that is, the "*o*" shifts to individual staff, where each staff is probabilistically assigned at most 2 off shifts.

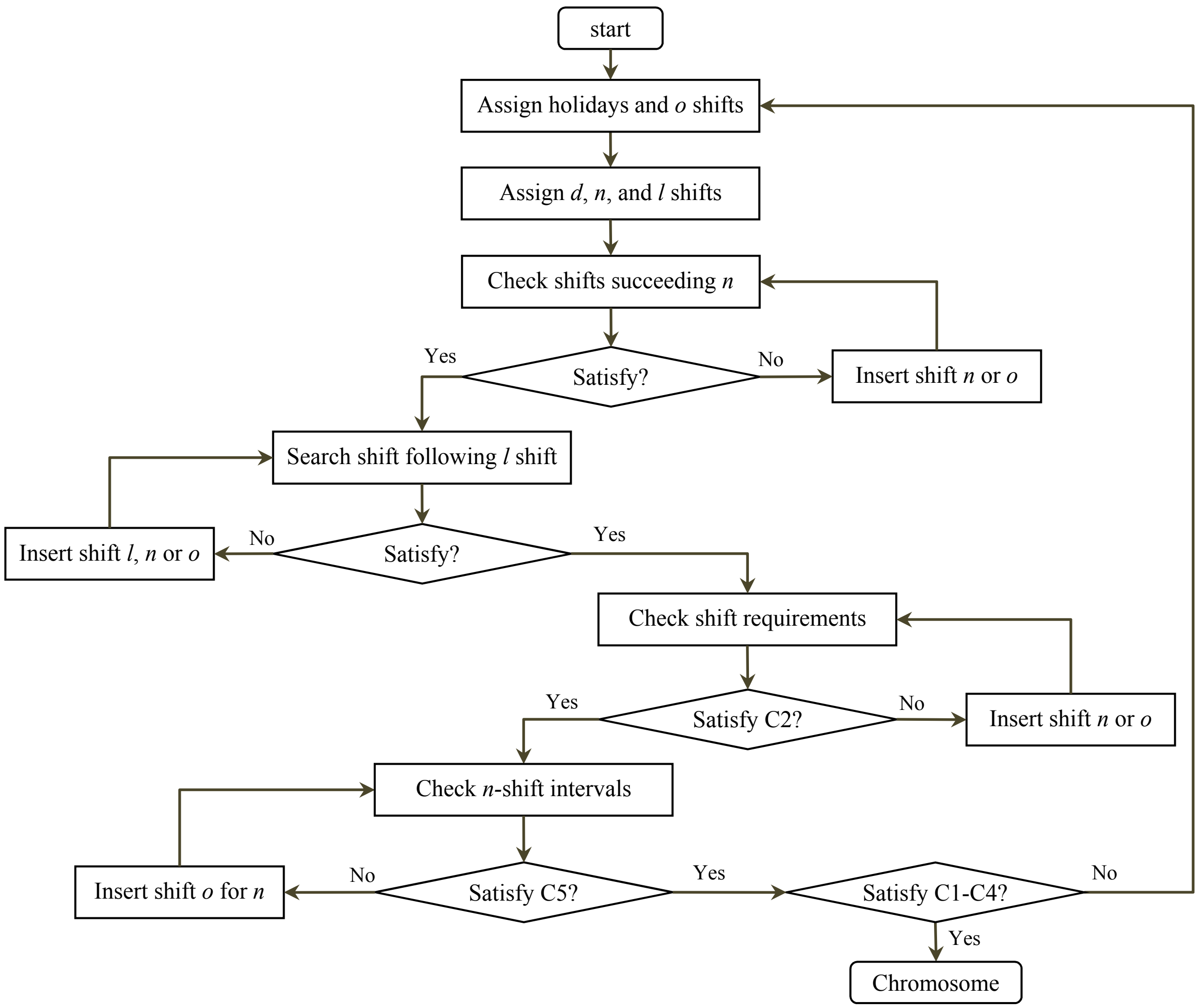

Figure 3: Enhanced initialization algorithm

4.4 Fitness Evaluation

In this study, the goodness or fitness of a solution is a function of how well it satisfies the soft constraints. As such, fitness is obtained from the weighted sum of the satisfaction of each of the soft constraints. We assume that the weights normalized. Furthermore, we represent each soft constraint as a normalized fuzzy membership function whose values are in the range [0,1].

4.4.1 Membership Functions

To model the goodness of a schedule (shift allocation) in relation to staff preferences, we use three fuzzy membership functions to represent the measure of satisfaction of specific preference functions.

Membership function 1

This membership function measures the quality of shift allocation in terms of compatibility (congeniality) of staff allocated similar shifts. Clearly, the higher the number of uncongenial shift allocations, the less the quality of that particular schedule, and vice versa. A practical approach would be to set a range of acceptable number of uncongenial allocations within which the acceptability of the schedule is 100%, for instance, range [0,*c*], where *c* is the maximum. Figure 4 demonstrates this phenomenon as a membership function. Therefore, the membership function is represented by expression (4).

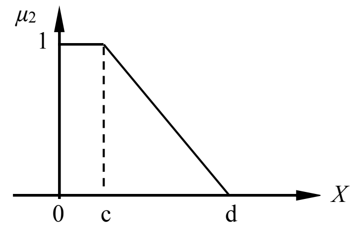

Figure 4: Linear membership function for congeniality

$$\mu_1 = \begin{cases} 1 & n_u \leq a \\ \dfrac{b - n_u}{b - a} & a \leq n_u \leq b \\ 0 & n_u \geq b \end{cases} \tag{4}$$

where, b is the maximum limit to the number of uncongenial shift allocations; a is the upper limit to the most preferred number of uncongenial shift allocations; n_u is the actual number of uncongenial allocations.

Membership Function 2

Regarding the workload, that is, the total number of hours allocated to each staff i, the aim is to minimize the variation of each staff workload h_i from the average workload a. This is equivalent to minimizing a function f,

$$f = \sum_i \left| h_i - a \right| \tag{5}$$

Since the workload assignment should be as fair as possible, the workload variation should be close to zero as much as possible. Therefore, we define the following membership function;

$$\mu_2 = \begin{cases} 1 & v_w \leq c \\ \dfrac{c - v_w}{c - d} & c \leq v_w \leq d \\ 0 & v_w \geq d \end{cases} \tag{6}$$

where, d is the maximum limit to the workload variation; c is the upper limit to the most preferred workload variation; v_w is the actual workload variation from the mean workload.

Membership Function 3

This membership function measures the quality of shift allocation in terms of the variation of the allocated days off or holidays from the mean number of allocated off days or holidays.

$$\mu_3 = \begin{cases} 1 & v_o \leq p \\ \dfrac{q - v_o}{q - p} & p \leq v_o \leq q \\ 0 & v_o \geq q \end{cases} \tag{4}$$

Here, q is the maximum limit to the number of days off shift allocations; p is the upper limit to the most preferred variation of the number of days off shift allocations; n_u is the actual variation of days off shift allocations from the mean. Other membership functions can also be included in the same manner, to improve the quality of the schedule. The overall fitness function is formulated as a function of these normalized membership functions.

4.4.2 The Overall Fitness Function

Since fitness is obtained from the weighted sum of the satisfaction of each of the soft constraints. As such, the final objective function is a function of the normalized functions (membership functions) as follows;

$$z = \sum_f w_f \mu_f \tag{7}$$

where, w_f is the weight of each objective function f, such that $\sum w_f = 1.0$. The weight w_f offers the modeller an opportunity to model his/her choices or preferences to reflect the preferences of the management and the nursing staff. Thus, the approach provides FGA an advantage over other metaheuristic approaches.

4.5 Selection and Crossover

The selection operator selects the best performing chromosomes into a mating pool, called *tempp*. We adopt the remainder stochastic sampling without replacement approach (Goldberg, 1989; Michalewicz, 1996; Holland, 1975). By this method, each chromosome k is selected and stored in the mating pool according to its expected count e_k,

$$e_k = \frac{z_k}{1/p \sum_k z_k} \tag{7}$$

Here, z_k is the fitness function of the k^{th} chromosome. Furthermore, each chromosome receives copies equal to the integer part of e_k, plus additional copies obtained by using the fractional part of e_k as a success probability of getting additional copies the same chromosome k into *tempp*. Consequently, the best performing candidates are selected with higher probability.

Crossover mechanism mates selected chromosomes to produce new offspring, called selection pool. This enables FGA to explore unvisited regions in the solution space. Genes in selected chromosomes are exchanged at a probability *pcross*. First, two crossover points are randomly generated. Second, the genes in between the crossover points are swapped. Third, the offspring are repaired by the encoding heuristic to ensure that the hard constraints are always satisfied. The process is repeated till the desired pool size, *poolsize*, is achieved.

4.7 Mutation

Mutation is applied to every new chromosome using single point mutation procedure. Each gene is mutated at a very low probability, hoping for an improved structure. This mechanism enables the algorithm to search in the neighbourhood in the current solutions in the population, a phenomenon called intensification.

4.8 Inversion and Diversification

It is critical to control the population diversity. This is because as iterations proceed, the population of candidate solutions may prematurely converge to a particular solution. As a result, we apply the inversion operator, a mechanism that rearranges, at a very low probability, the genes of a chromosome. For instance, a schedule or shift allocation [*l n l n d l n*] may be rearranged to [*n l d n l n l*] in a reverse order. To check population diversity, we define an entropic measure H_j for each shift j;

$$h_j = \sum_{k=1}^{n} \frac{x_{jk} \cdot \ln(x_{jk}/p)}{\ln(n)} \tag{9}$$

where, x_{jk} is the number of chromosomes in which shift j is assigned position k in the current population; n is the number of shifts. Then, diversity H becomes,

$$h = \sum_{j=1}^{n} h_j / n \tag{10}$$

Inversion is applied whenever diversity falls below a threshold value, h_d. However, the best performing candidates are preserved (we preserve 3 candidates in this application).

4.9 Overall FGA Algorithm

FGA incorporates the operators discussed in the previous sections, starting with the selection of suitable input parameters. The selected input parameters were: crossover probability (0.4), mutation probability (0.1), and inversion probability (0.05). An initial population, $P(0)$, is generated randomly by an enhanced heuristic that seeks to satisfy absolute constraints during chromosome encoding. The enhancing heuristic is also useful for chromosome repair. FGA then follows through an iterative loop involving selection, crossover, mutation, inversion, and until termination condition, based on maximum number of pre-specified T. Figure 5 presents the overall structure of the proposed FGA. We present illustrative examples, computational results, and relevant discussions in the following section.

Algorithm 1. Fuzzy genetic algorithm

```
BEGIN
        Input: parameters; t = 0;
        Initialize population, P(0);
    REPEAT
        Selection:
            Evaluate P(t);
            Create temporal population, tempp(t);
        Crossover:
            Select 2 chromosomes from tempp(t);
            Apply crossover operator and repair as necessary;
        Mutation:
            Mutate P(t);
            Add offspring to newpop(t);
        Replacement strategy:
            Compare successively, spool(t) and oldpop(t) strings;
            Take the ones that fare better;
            Select the rest of the strings with probability 0.55;
        Inversion and diversification:
            Compute diversity H;
            IF (H < hd) THEN diversify till H ≥ hd;
            Re-evaluate P(t);
        New population:
            oldpop(t) = newpop(t);
            Advance population, t = t + 1
    UNTIL (t ≥ T)
END
```

Figure 5: Overall FGA pseudo-code

5. Computational Experiments, Results and Discussions

The proposed FGA procedure was implemented in JAVA on a 3.06GHz speed processor with 4GB RAM. For the purpose of illustration, we present a typical experiment, together with computational results and pertinent discussions.

Figure 6 (a) presents a typical candidate solution obtained using our proposed enhanced coding method. The solution satisfies all the hard or absolute constraints. Furthermore, the solution shows a schedule or shift assignment covering a planning horizon of 7 days, where 9 nursing staff is allocated shift types d, n, l, or o. The initial population normally comprises a number of candidates obtained in a similar manner. In this problem, combinations (s_1,s_2), (s_5,s_8) and (s_6,s_9) are known to have a very low congeniality, and we should avoid, as much as possible, assigning them the same shifts. The workload assignment is fair across all the staff. However, hard constraints are always satisfied. Figure 6 (b) shows an improved solution obtained after 150 iterations, considering the congeniality preferences.

		Days									
Nurse	Skill	1	2	3	4	5	6	7	*d*	*n*	*l*
s_1	1	*o*	*d*	*l*	*l*	*o*	*n*	*n*	1	1	2
s_2	1	*d*	*d*	*d*	*o*	*l*	*l*	*o*	3	0	2
s_3	1	*o*	*d*	*d*	*d*	*l*	*n*	*o*	3	1	1
s_4	2	*d*	*l*	*o*	*l*	*n*	*o*	*d*	2	1	2
s_5	2	*d*	*l*	*l*	*o*	*d*	*d*	*n*	3	1	2
s_6	2	*n*	*n*	*o*	*d*	*d*	*d*	*l*	3	2	1
s_7	2	*n*	*o*	*d*	*d*	*d*	*l*	*l*	3	1	2
s_8	2	*l*	*o*	*n*	*n*	*n*	*o*	*d*	1	3	1
s_9	2	*l*	*n*	*n*	*n*	*o*	*d*	*d*	2	3	1
	d	3	3	3	3	3	3	3			
	n	2	2	2	2	2	2	2			
	l	2	2	2	2	2	2	2			

(a)

		Days									
Nurse	Skill	1	2	3	4	5	6	7	*d*	*n*	*l*
s_1	1	*o*	*l*	*l*	*l*	*o*	*n*	*n*	0	2	3
s_2	1	*d*	*d*	*d*	*o*	*l*	*l*	*o*	3	0	2
s_3	1	*o*	*d*	*d*	*d*	*l*	*n*	*o*	3	1	1
s_4	2	*d*	*d*	*o*	*l*	*n*	*o*	*d*	3	1	1
s_5	2	*l*	*l*	*l*	*o*	*d*	*d*	*n*	2	1	3
s_6	2	*n*	*n*	*o*	*d*	*d*	*l*	*l*	2	2	2
s_7	2	*n*	*o*	*d*	*d*	*d*	*d*	*l*	4	1	1
s_8	2	*d*	*o*	*n*	*n*	*n*	*o*	*d*	2	3	0
s_9	2	*l*	*n*	*n*	*n*	*o*	*d*	*d*	2	3	1
	d	3	3	3	3	3	3	3			
	n	2	2	2	2	2	2	2			
	l	2	2	2	2	2	2	2			

(b)

Figure 6: Initial candidate solution and final solution

Further experimentations with large numbers of staff indicated that FGA can solve large scale scheduling problems within a reasonable computation time, while respecting all the hard constraints and fulfilling preference constraints as much as possible, in the range of 80%.

6. Conclusions

Designing decision support tools that can address the healthcare staff scheduling problem is a cause for concern in most healthcare organizations, such as hospitals. Schedule quality is necessary to maintain or improve worker moral and avoid absenteeism and attrition. In an environment where staff preferences are ill-defined or imprecise, the use of fuzzy set theory concepts is beneficial. In this paper, a FGA with a fuzzy goal-based fitness function coupled with heuristic chromosome generation is proposed to solve the healthcare staff scheduling problem, producing near-optimal solutions. Experimental results demonstrated that FGA is capable of solving large scale staff scheduling problems. The approach provides useful contributions to academicians as well as practitioners in the health service industry.

The proposed algorithm is a contribution to the Industrial engineering and operations management community as it provides an approach to solve staff scheduling problems where the desired goals and preferences are ill-structured. Unlike other metaheuristic approaches, our approach incorporates more realism to the solution process. As opposed to conventional linear programming methods, FGA is capable of handling large-scale problems, while providing good solutions within a reasonable computation time. The approach can be developed further into a decision support system to assist decision makers in the field. The method also provides useful contributions to the practicing decision maker.

By providing the user an opportunity to use weights, the decision maker can incorporate preferences and choices in an interactive manner. The use of interactive decision support tools that provide a list of good alternative solutions is more acceptable to practicing decision makers than prescriptive optimization methods that provide a single solution. Hence, the decision maker can use information from staff and management to make adjustments to the solution process based on weights. In sum, FGA is an effective and efficient approach, a platform for developing decision support tools for staff scheduling problems in a healthcare setting.

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