A Fuzzy Genetic Algorithm for Healthcare Staff Scheduling

Michael Mutingi and Charles Mbohwa

Abstract**—**In the presence of multiple conflicting objectives and constraints, healthcare staff scheduling is complex. This research presents a fuzzy-based genetic algorithm (FGA) for handling multiple conflicting objectives and constraints common in healthcare manpower scheduling problems. Fuzzy set theory is used for genetic evaluations of alternative staff schedules by representing the fitness of each alternative solution as a fuzzy membership functions. The proposed FGA framework is designed to incorporate the often imprecise decision maker's preferences and choices in terms of weights. The framework is also designed to provide a population of alternative solutions for the decision maker, rather than prescribe a single decision. It is anticipated that the FGA procedure forms a useful decision support tool for healthcare staff scheduling in a fuzzy environment with multiple conflicting objectives and constraints.

Keywords**—**Fuzzy modeling, genetic algorithms, healthcare staff scheduling, healthcare manpower systems

I. INTRODUCTION

IN the presence of multiple, imprecise and conflicting objectives and constraints, healthcare staff scheduling is a complex undertaking. Furthermore, the management goals and the possible impact of the alternative actions taken are usually not precise at the planning and scheduling stage [1]. As health service quality continues to be a key concern all over the globe, healthcare providers have to devise efficient and effective methodologies for healthcare personnel planning and scheduling. In addition, healthcare personnel shortages are rampant in almost every society [2]. Furthermore, labor costs have a significant contribution to the total operating costs of healthcare organizations. In general, the consideration of the expectations and preferences of the healthcare personnel, the patients, and the healthcare providers is becoming more and more significant in staff planning and scheduling [3]. Howbeit, the more these preferences are considered, the more complex and fuzzy the healthcare staff scheduling problem becomes [4].

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Staff scheduling in healthcare systems involves constructing work schedules spanning over a given planning horizon so as to meet organizational goals, customer service expectations, and to satisfy worker preferences [4] [5]. Suitable combinations of shifts are selected from a number of possible shifts, subject to a myriad of constraints. Healthcare staff scheduling is commonly constrained in three closely linked dimensions: (i) time constraints, relating to the working time of an individual staff, (ii) the coverage constraints relating to the staff demand requirements over the course of day, and (ii) the schedule cost, which relates to the total labor cost over the planning horizon. Three players are involved in constructing staff schedules: (i) the management, (ii) the staff, and (iii) the patients. As such, the aim is to satisfy all the three players in the scheduling process. The focus of the decision maker involves schedule cost, worker preferences, and service quality. This implies that the preferences of these players should always be taken into account, if high quality schedules are to be constructed. Low cost schedules, high quality schedules, and high service quality offer a competitive advantage to healthcare service providers in the medium to long term. However, the available information on management goals, employee preferences and client expectation is often imprecise.

Fuzziness in management objectives and employee preferences is an important area of concern in most organizations [4]. For instance, fuzzy management goals and objectives, as well as employee preferences are a common cause for concern when allocating work schedules to employees [1] [3]. Oftentimes, the management objectives are not expressed precisely but rather in linguistic terms such as " preferably about 7 working hours", or "at most 10 working hours", or "preferably 2 night shifts per week" and other related expressions. Likewise, employee preferences are often expressed in natural language terms, such "preferably 8 workings hours per day", "at least 2 off days", among other examples. As such, fuzzy modeling approach is a potential tool in addressing imprecise and conflicting goals and employee preferences in manpower scheduling.

The practice of manpower scheduling seeks to balance individual workloads and satisfy staff preferences leading to high quality schedules, higher worker morale, hence a more effective workforce. However, organizational objectives and individual staff preferences are usually conflicting; workers prefer individualized schedules that consider their preferences while organizations will always try to fulfill demand coverage.

Perceived fairness in schedule assignments is an important measure of the quality of schedules, without which low morale, poor performance, absenteeism and high job turnover are inevitable. Thus, it is crucial to satisfy workers' preferences. On the other hand, the manpower scheduling problem has several possible objectives including (i) minimizing workforce size, (ii) maximizing worker preferences (iii) minimizing personnel cost, (iv) minimizing violation of demand coverage and time-related constraints. While hard constraints must always be satisfied, soft constraints such as worker preferences can be violated at a cost in order to provide a feasible solution. In healthcare systems, staff scheduling is associated with uncertainties arising from vagueness of information on target management objectives, personnel preferences and patient expectations. Burke et al. [4] emphasizes the need to consider fuzzy modeling in healthcare staff scheduling in order to deal with inherent uncertainties in the problem. The motivation behind the use of fuzzy-based approach is three-fold: (i) Decision makers often sacrifice the aspiration levels for organizational goals so as to reflect workers' preferences, hence the need to define goals using fuzzy rather than crisp sets; (ii) given the real-world vagueness of information on management goals and workers' preferences, crisp methods fail to represent such complexity, (iii) real-world staff scheduling is often multi-objective with incommensurable goals. Fuzzy modeling uses normalization to treat the problem in a more realistic way.

The purpose of this research is to develop a fuzzy genetic algorithm (FGA) for healthcare staff scheduling in a fuzzy environment. In this vein, our objectives are as follows:

(1) To explore the fuzzy conflicting goals in the healthcare staff scheduling;

(2) To propose a fuzzy evaluation approach for alternative decisions;

(3) To develop a fuzzy-based genetic algorithm approach for the scheduling problem.

While fuzzy set theory addresses the fuzzy objective goals [6] [7] [8] [9], genetic algorithm addresses the high combinatorial nature of the problem [10] [11] [12]. Therefore, this study suggest a more realistic and adaptable approach to healthcare staff scheduling.

The rest of the paper is as follows: Section II describes the healthcare personnel scheduling problem. Section III presents an outline of the fuzzy multi-objective approach to healthcare staff scheduling. A fuzzy-based genetic algorithm is presented in Section IV. Section V highlights the managerial implications. Finally, Section V concludes the paper.

II. Problem Description

The healthcare staff scheduling problem is described thus: Let m be the number of healthcare workers; n denote the planning horizon in days; and k denote the shift types available. Then, the healthcare personnel scheduling problem can be viewed as a $m \times n$ matrix whose elements are denoted by x_{ijk} where worker i works on the k^{th} shift on day j;

$$x_{ijk} = \begin{cases} 1 & \text{if worker } i \text{ works shift } k \text{ on day } j \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Fig. 1 provides an example of healthcare worker schedule with m = 8, n = 7, and k = 4, where the pre-defined shifts are D = day shift, E = evening shift and N = late night shift. The firs column shows the staff identities. This is followed by 7 columns denoting shift assignments of the 7-day period. The last 3 columns on the right represent the count of shift days allocated to each staff. Table 1 describes typical shift types.

There are three conflicting goals in healthcare personnel scheduling: (i) minimize schedule cost, (ii) maximize client satisfaction, and (iii) maximize employee satisfaction. These goals should be satisfied to the highest degree possible. When minimizing schedule cost, the goal is to construct a work schedule that will incur an acceptable cost, which is subject to the humanistic judgment of the decision maker. On the other hand, maximizing service quality entails meeting service quality to the highest degree possible; to improve health standards, gaining business advantage. Maximizing employee satisfaction pertains to satisfying individual workers preference as much as possible. Retrospectively, the decision maker seeks to satisfy to the highest degree, all the goals of interest, which is complex. Finding a reasonable trade-off between the goals is imperative. Consequently, fuzzy modeling is most appropriate.

	Days/Date									
Staff ID	1	2	3	4	5	6	7	D	E	N
S1	N	E	N	E	D	N	E	1	3	3
S2		D	E	N	D	D	N	3	1	2
S3	D	D	D	D		E	D	5	1	0
S4	E	N	N		D	D	D	3	1	2
S5	D	D		E	E	N	E	2	1	1
S6	D		D	D	N	E	D	4	1	1
S7	N	E	D	D	N	D		3	1	2
S8	E	N	E	N	E		N	0	3	3
D	3	3	3	3	3	3	3			
E	2	2	2	2	2	2	2			
N	2	2	2	2	2	2	2			

Fig. 1 An example of a healthcare worker schedule

TABLE I
AN EXAMPLE OF SHIFT TYPES

Shift type (k)	Shift Description	Time allocation
1	D: Day shift	08:00 to 1600 hrs
2	E: Night shift	1600 to 0000 hrs
3	N: Midnight shift	0000 to 0800 hrs
4	R: Rest/off	-

III. Fuzzy-Based Interactive Approach

The proposed fuzzy-based framework starts by identifying objectives related to management goals, employee satisfaction, and service quality. All constraints in regards to the management, the employee, or the client are converted to their respective objective functions. For instance, a hard constraint may be changed to a soft constraint which is then converted to an objective goal which minimizes the violation of the constraints.

The next stage is to represent the objective functions in terms of membership functions. Information in regards to preferences and goals of management, employees and clients is used to construct the membership functions. Linear membership functions are most ideal for this application, though other functions may be used [3] [6] [9]. The normalized membership functions can be combined into a single objective function for evaluating alternative solutions in the solution space S_j, which is controlled by preferences and goals.

The search process utilizes the fuzzy multi-objective formulation based on fuzzy-based genetic search or any other population based metaheuristic. Being population-based, FGA provides alternative solutions from which the user can interactively choose the most satisfactory.

The most satisfactory solution X_i is then implemented while observing the feedback from the management, the employee, and the clients. At the end of each planning horizon, individual preferences are expected to evolve over time, such that at each iteration j, it is important to obtain new feedback information from the three players and update the goals and preferences accordingly.

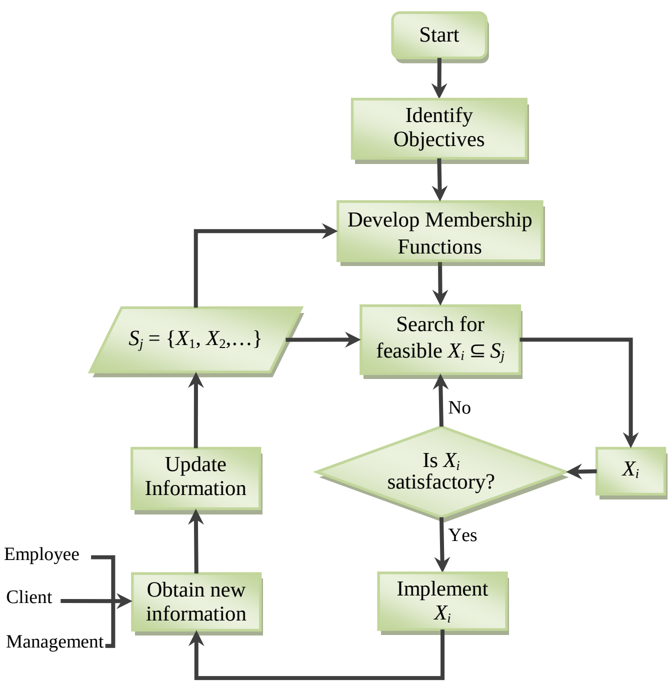

Fig. 2 A conceptual framework for the fuzzy-based scheduling approach

At each iteration j, information update from the previous horizon will affect the solution space S_j of the current horizon, which in turn affects membership function development. The iterative process then repeats in the same way, forming a continuous improvement cycle based on evolving goals and preferences.

IV. A Fuzzy Genetic Algorithm Approach

In this section, we present an outline of the proposed fuzzy genetic algorithm approach for healthcare staff scheduling.

A. Fuzzy Multi-Objective Model

In a fuzzy environment, the decision maker seeks to consider a trade-off between schedule cost, employee satisfaction and client satisfaction. In this connection, the multi-objective formulation is obtained by transforming constraints to objective functions, such that all the goals are optimized simultaneously. This is achieved through the use of membership functions for the objective functions, which makes the approach more applicable and adaptable to the real life human decision process.

B. Membership Functions

Fuzzy set theory permits gradual assessment of membership, defined in terms of a suitable membership function that maps to the unit interval [0,1]. A number of membership functions such as Generalized Bell, Gaussian, Triangular and Trapezoidal can be used to represent the fuzzy membership. Though various functions can be used, it has been shown that linear membership functions can provide equally good quality solutions with much ease [6]. The triangular and trapezoidal membership functions have widely been recommended [9] [13]. Therefore, in this study, we suggest the use of linear functions to define the fuzzy membership functions of the objective functions.

Let m_t and M_t denote the minimum and maximum of the feasible values of each objective function $f_t(x)$, $t = 1,2,\dots,h$, where h is the number of objective functions. Let $\mu_t(x)$ denote the membership function corresponding to f_t. Then, the membership function corresponding to minimization and maximization can be defined based on the satisfaction degree. Fig. 3 illustrates the linear membership functions for minimization and maximization cases. We define the membership functions for both cases.

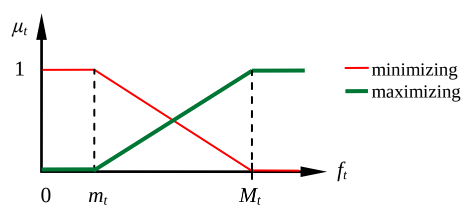

Fig. 3. Fuzzy membership function for $f_t(x)$

For minimization, the linear membership function can be formulated according to the following expression;

$$\mu_t(x) = \begin{cases} 1 & f_t(x) \le M_t \\ \dfrac{M_t - f_t(x)}{M_t - m_t} & m_t \le f_t(x) \le M_t \\ 0 & f_t(x) \ge M_t \end{cases} \qquad (2)$$

Clearly, the function $\mu_t(x)$ is monotonically decreasing in $f_t(x)$. On the other hand, for the case of maximization, the membership function can be defined as follows;

$$\mu_t(x) = \begin{cases} 1 & f_t(x) \geq M_t \\ \dfrac{f_t(x) - m_t}{M_t - m_t} & m_t \leq f_t(x) \leq M_t \\ 0 & f_t(x) \geq m_t \end{cases} \tag{3}$$

It can be seen that $\mu_t(x)$ is a monotonically increasing function of $f_t(x)$.

The use of fuzzy evaluation in FGA allows the algorithm to accept inferior which would otherwise be infeasible when using conventional crisp formulation. The advantage of this approach is that it makes the algorithm robust enough to cope with any infeasibility. Allowing the FGA to pass through inferior solutions gives the algorithm speed and flexibility, which ultimately improves the search power of the approach.

C. Corresponding Crisp Model

To further incorporate the decision maker's preferences and to enhance the interactive flexibility of the model, a set of user-defined weights $\omega = \{\omega_1, \omega_2, \ldots, \omega_h\}$ are introduced. We model the multi-objective scheduling optimization problem into a single objective optimization problem:

$$\begin{aligned} &\text{Max } z = \left(\frac{\lambda_1(x)}{\omega_1} \wedge 1\right) \wedge \left(\frac{\lambda_2(x)}{\omega_2} \wedge 1\right) \wedge \ldots \wedge \left(\frac{\lambda_h(x)}{\omega_h} \wedge 1\right) \\ &\text{Subject to:} \\ &\lambda_t(x) = \mu_t(x) \qquad t = 1, \ldots, h \\ &x_q^l \leq x_q \leq x_q^u \qquad q = 1, \ldots, p \end{aligned} \tag{4}$$

Here, $\mu_t(x) = \{\mu_1(x), \mu_2(x), \ldots, \mu_h(x)$ signifies a set of fuzzy regions that satisfy the objective functions; λ_t denotes the degree of satisfaction of the t^{th} objective, x is a vector of decision variables, p is the number of decision variables, ω_t denotes the weight of the t^{th} objective function suggested by the expert judgment of the user or decision maker, and the symbol "$\wedge$" is the aggregate min operator. For instance, the expression $\left(\frac{\lambda_1(x)}{\omega_1} \wedge 1\right)$ gives the minimum between 1 and $\frac{\lambda_1(x)}{\omega_1}$.

To solve, the optimization problem P5, we employ the genetic algorithm metaheuristic approach, a global optimization approach inspired by the theory of genetics and philosophy of natural selection and survival of the fittest (Goldberg, 1989; Holland, 1975).

D. Genetic Algorithm Approach

Genetic algorithm, first introduced by Holland [11], is a stochastic global optimization technique that attempts to evolve a population of candidate solutions by giving preference of survival to quality solutions, whilst allowing some low quality solutions to survive in order to maintain a level of diversity in the population. Each candidate solution is coded into a string of digits, called chromosomes. New offspring are obtained from probabilistic genetic operators, such as selection, crossover, mutation, and inversion. A comparison of new and old (parent) candidates is done based on fitness function, retaining the best performing candidates into the next population. Thus, characteristics of candidate solutions are passed from generation to generation through probabilistic selection, crossover, and mutation.

1) Representation

The proposed FGA approach uses the structure in Fig. 1 to represent a single candidate solution. Therefore, each chromosome represents a candidate schedule.

2) Initialization and Evaluation

An initial population of the desired size, *pop*, is randomly generated randomly from the solution space. FGA applies fuzzy evaluation for each candidate solution according to the model in (4).

3) Selection and Recombination

Selection strategies exist in the literature Goldberg (1989), for instances, deterministic sampling, remainder stochastic sampling with/without replacement, stochastic tournament, and stochastic sampling with/without replacement. The remainder stochastic sampling without replacement is most preferred in this study. In this strategy, each chromosome *j* is selected and stored in the mating pool according to the expected count e_j;

$$e_j = \frac{f_j}{\sum_{j=1}^{pop} f_j / pop} \tag{3}$$

Here, f_j represents the objective function value of the j^{th} chromosome. Each chromosome receives copies equal to the integer part of e_i, that is, $[e_i]$, while the fractional part is treated as success probability of obtaining additional copies of the same chromosome into the mating pool.

4) Crossover operator

The crossover operator exchanges genetic information between selected chromosomes, producing new offspring with new shift structures. The crossover is done at a probability.

5) Mutation Operator

To maintain diversity of the population and avoid premature convergence, mutation is applied to every new chromosome, at a very low probability. The operator causes slight changes to the shift structure in each chromosome prospectively resulting in improved solutions.

6) Replacement Strategy

In every generation, new offspring are created, which implies that they may be better or worse. Therefore, nonperforming chromosomes are replaced with better ones using a replacement strategy such as probabilistic replacement, crowding strategy, and elitist strategy [12].

7) Termination Criteria

Termination conditions used to stop the FGA iteration are two-fold: when the number of generations exceeds the preset maximum iterations, or when average change in the fitness of the best solution over specific generations is less than a small number.

The overall structure of the FGA for the manpower scheduling problem is summarized in the pseudo code listed in Algorithm 1. The next section presents the computational results of our FGA computations.

ALGORITHM 1: PSEUDO CODE FOR FMGA

1: randomly generate initial population
Repeat
    2: evaluation of fitness, objective: $f(x)$, $x = (x_1, x_2,\ldots,x_h)$
    3: selection strategy
    4: crossover
    5: mutation
    6: replacement
    7: advance population; *oldpop* = *newpop*
Until (termination criteria is satisfied)

V. Managerial Implications

The proposed FGA approach proposed in this study is a potential tool for decision makers in the health sector, where imprecise multiple conflicting objectives and constraints exist. The approach offers a number of practical advantages to the decision maker, including the following:

- The FGA addresses the imprecise and fuzzy nature of the scheduling problem based on fuzzy theory;
- The method address the conflicting multiple objectives, giving a trade-off between the objectives;
- The approach can accommodate the decision maker's preferences in its procedure;
- The method can give a population of alternative solutions for the decision maker, rather that prescribe a single solution;
- The method is practical, flexible and easily adaptable to specific problem situations.

In view of the above advantages, FGA is a useful decision support tool for the practicing decision maker concerned with healthcare manpower scheduling.

VI. Concluding Remarks

Decision makers concerned with healthcare manpower scheduling face problems in finding a cautious trade-off between maximizing client satisfaction, minimizing schedule, and maximizing worker satisfaction to an acceptable degree of satisfaction. In such uncertain environments, the management goals are not usually known with precision. This study proposed a fuzzy multi-objective approach based on genetic algorithm. The method is designed to satisfy worker preferences, management goals, and client needs to an acceptable degree. It captures the expert judgments of the decision maker, providing a platform interactive manpower scheduling. The fuzzy multi-objective model is transformed into a single-objective model which uses a fuzzy evaluation method. The FGA uses fuzzy evaluation method to evaluate the fitness of candidate shift structures in each population at every generation.

This work suggests a useful tool for the practicing decision maker in healthcare manpower systems. The FGA provides a trade-off between multiple goals, contrary to single-objective approaches which seek to optimize schedule costs only. Oftentimes, the information required for staff scheduling is imprecise and incomplete. The problem becomes ill-structured such that reliance on expert information is inevitable. Using fuzzy-based method, the vagueness and imprecision of the information can be addressed effectively while taking into account the multiple conflicting objectives. Furthermore, FGA provides a population of good alternative solutions in an interactive manner, which offers the decision maker a wide choice of practical solutions. Therefore, the proposed approach is a potential tool for effective decision support in healthcare manpower scheduling when the management goals, the employee preferences, and the client expectation are not precisely known.

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