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Fuzzy Multi-Criteria Simulated Evolution for Nurse Re-rostering

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***Abstract*—In a fuzzy environment where the decision making involves multiple criteria, fuzzy multi-criteria decision making approaches are a viable option. The nurse re-rostering problem is a typical complex problem situation, where scheduling decisions should consider fuzzy human preferences, such as nurse preferences, decision maker's choices, and patient expectations. For effective nurse schedules, fuzzy theoretic evaluation approaches have to be used to incorporate the fuzzy human preferences and choices. The present study seeks to develop a fuzzy multi-criteria simulated evolution approach for the nurse re-rostering problem. Experimental results show that the fuzzy multi-criteria approach has a potential to solve large scale problems within reasonable computation times.**

Keywords—fuzzy simulated evolution; fuzzy theory; multiple criteria; nurse re-rostering

I. Introduction

Biologically inspired evolutionary algorithms have attracted the attention of many researchers concerned with multi-criteria decision making [1-4]. Some of the most popular algorithms are genetic algorithms, neural networks, particle swarm intelligence, ant colony algorithm, and simulated evolution algorithm. Significant research activities have implemented these algorithms with appreciable results [1][2]. However, when addressing complex multi-criteria decision problems under fuzziness, fuzzy evaluation techniques are an essential addition, if more realism is desired in the algorithm chosen. Fuzzy evaluation techniques accommodate imprecision, uncertainty, or partial truth, based on fuzzy theory concepts [5]. In addition, these techniques can also handle real world problems with multiple criteria. An important research direction is hybridizing efficient evolutionary approaches with fuzzy evaluation concepts [1]. The goal is to develop hybrid fuzzy evolutionary algorithms providing optimal or near optimal solutions within a reasonable computation time.

In this paper, a fuzzy multi-criteria evaluation approach is developed based on fuzzy set theory concepts. The approach is hybridized with simulated evolution algorithm to come up with a fuzzy simulated evolution algorithm. In this regard, the purpose of this paper is to present a fuzzy simulated evolution algorithm for solving complex multi-criteria decision problems under fuzziness.

The rest of the paper is structured as follows. The next section briefly describes the basic simulated evolution algorithm and the nurse re-rostering problem. Section III outlines the fuzzy multi-criteria simulated evolution algorithm. Section IV presents illustrative experiments. Section V concludes the paper.

II. Preliminaries

This section presents a background on the simulated evolution and the nurse re-rostering, a typical application area.

A. Simulated Evolution

Simulated Evolution (SE) is an evolutionary optimization approach originally proposed in [6]. Inspired by the philosophy of natural selection in biological environments, the SE algorithm evolves a single candidate solution from one generation (iteration) to the next by eliminating or discarding inferior elements in the solution. Thus, in each generation, elements with high fitness are retained. The desired goal is to gradually create a stable solution perfectly adapted to the given constraints. To escape from local optima, mutation perturbs genetic inheritance in anticipation of new improved genetic information, enabling the algorithm to effectively explore and exploit the solution space[1][6].

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The SE procedure comprises evaluation, selection and reconstruction operators that iteratively work on a single candidate solution. Prior to evaluation, initialization creates a valid starting solution and accepts input parameters. The evaluation operator then computes the fitness of each element in the solution, which is used to probabilistically select and discard weak elements. The resulting incomplete solution is rebuilt by the reconstruction operator using problem-specific heuristics. The complete solution is then passed on to the evaluation operator, repeating the procedure until a termination condition is fulfilled.

The basic SE procedure is a search and optimization heuristic that improves the solution through iterative perturbation and reconstruction. However, the iterative process ensures that the best solution is always preserved. To enhance its search and optimization, SE needs to incorporate fuzzy evaluation techniques.

B. The Nurse Re-rostering Problem

The nurse rerostering problem can be defined as follows: A set of n heterogeneous nurses, indexed i (i =1,…,n), are scheduled over a period spanning over d days, indexed j (j =1,…,d). The nurses are currently assigned to one of the available shifts, indexed k (k=1,…,s), where the last shift s is treated as the day off. In this connection, the decision for nurse rerostering is defined according to the expression;

$$x_{ijk} = \begin{cases} 1 & \text{If nurse } i \text{ is scheduled to work on day } j\text{, shift } k \\ 0 & \text{0 otherwise} \end{cases} \qquad (1)$$

This implies that each available nurse is assigned to a single schedule, subject to all organizational and goals, as well as labour policies. The shift assignment or roster should satisfy hard constraints affecting individual shift schedules of each nurse. In addition, decisions regarding the conflicting multiple goals are made, for instance, maximizing satisfaction of nurse preferences [1][7], maximizing satisfaction of quality of patient service, minimizing understaffing and minimizing overstaffing costs, and constructing schedules that are as fair as possible.

In addressing the nurse rerostering problem, it is assumed that the nurse rostering problem has been solved satisfactorily. Following this assumption, the decision in the prior or original roster is defined as follows;

$$x'_{ijk} = \begin{cases} 1 & \text{If nurse } i \text{ was originally scheduled to work on day } j\text{, shift } k \\ 0 & \text{If otherwise} \end{cases} \qquad (2)$$

The problem of rerostering nurse schedules arises when unforeseen schedule disruptions occur due to nurse i who can no longer shift k on one or more of the future work days j. In this view, the rerostering problem is concerned about reconstructing shift schedules, based on the original schedule, over the short-term to medium-term horizon. Fig. 1 shows an example of a nurse roster with a schedule disruption in (a) and a suitable roster in (b).

	Day 1	Day 2	Day 3	Day 4
Nurse 1	D	D		N
Nurse 2	E	E	E	E
Nurse 3	N	N	N	
Nurse 4	D	D	D	D
Nurse 5			D	D
Nurse 6	D	D	D	D
Σ*D*	3	3	3	3
Σ*E*	1	1	1	1
Σ*N*	1	1	1	1

(a)

	Day 1	Day 2	Day 3	Day 4
Nurse 1	D		N	N
Nurse 2	E	E	E	E
Nurse 3	N	N		
Nurse 4	D	D	D	D
Nurse 5		D	D	D
Nurse 6	D	D	D	D
Σ*D*	3	3	3	3
Σ*E*	1	1	1	1
Σ*N*	1	1	1	1

(b)

Fig 1 A disrupted nurse schedule and a re-roster

Table 1. A typical set of assignable shifts

Shift Type	Shift Description	Period
D	Day shift	8 am to 4 pm
E	Night shift	4 pm to 12 am
N	Late night shift	12 am to 8 am
O	Off day or holiday	

Nurses are originally assigned either day shift (D, 8 am to 4 pm), night shift (E, 4 pm to 12 am), or late night shift (N, 12 am to 8 am), shown in Table 1. The day off shift is represented by a blank space. Schedule disruptions are reported by nurse 1 and nurse 2 for day 2 and day 3, respectively. Like in rostering, rerostering seeks to reconstruct the disrupted schedule subject to various hard and soft constraints. However, rerostering requires that schedule changes are to be as minimal as possible. In this view part (b) presents a feasible roster where nurse 1 and nurse 5 are assigned the disrupted shifts on day 3 and day 2, respectively. In this case, the rerostering period spans over 4 days, preferably from the day of disruption to the last day of the planning horizon.

1) Common Constraints

There are two basic categories of nurse scheduling constraints: (i) time-related constraints, related to labour policies, organizational regulations, and contract specifications, which control the sequence of individual nurse schedules [1][8-10], and (ii) staffing requirements constraints ensure adequate coverage of healthcare tasks that need to be performed. This implies that overstaffing should be as low as possible, where zero values are most favourable.

However, the nurse rerostering problem is also restricted by disruption constraints, which is the third type of constraints. This requires that some of the nurses must not be assigned any working shift due to the reported inability to show up for the duty. Therefore, due to reported unplanned absences, the following restriction is imposed as a hard constraint;

$$x_{ijk} = 0 \qquad \forall (i, j, k) \in A \tag{3}$$

where, A is a set of reported unplanned absences.

Due to the imposed disruption constraints, the roster should necessarily undergo some shift changes in order to accommodate the unplanned absences and to ensure continuity of service. However, in practice, it is essential to minimize the number of changes as much as possible in order to avoid dissatisfaction of the affected nurses [8]. For high quality schedules, all the three identified types of constraints must be satisfied to the highest degree possible.

2) Problem Objectives

The overall objective is to maximize the quality of a nurse roster, which includes satisfaction of patient expectations, nurse preferences, and organizational goals. Most of these decision criteria are difficult to quantify in real life. As such, the nurse rerostering problem is a multi-criteria decision problem with complex imprecise or fuzzy objective. These criteria are classified into four categories: (1) maximize or maintain quality of service, ensuring that a minimum level of healthcare service quality is offered, (2) maximize satisfaction of individual nurse preferences, (3) maximize schedule fairness, and (4) minimize schedule changes.

III. Fuzzy Multi-Criteria Approach

Fuzzy simulated evolution (FMSE) is an enhanced iterative algorithm developed from the general simulated evolution (SE) [6][11], where one or more of the original SE operators are fuzzified. FMSE, like SE, is inspired by the philosophy of natural selection in biological environments. Following initialization, where a candidate solution is generated, the algorithm iteratively goes through evaluation, selection, mutation, and reconstruction operators, which work on the single candidate solution. Fig. 2 presents the flowchart for the FMSE algorithm.

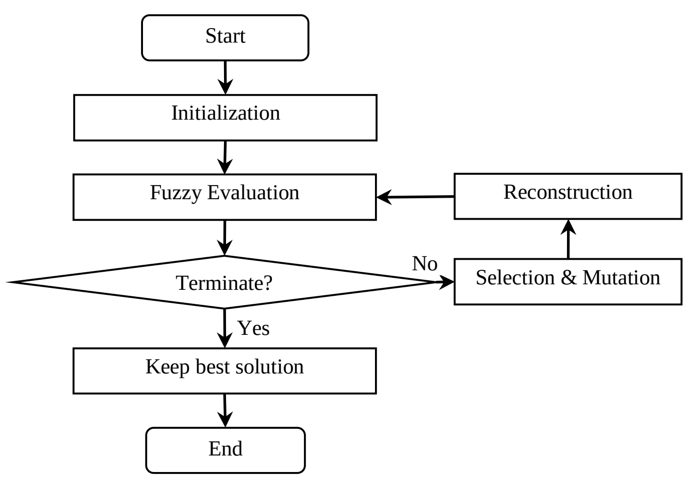

Fig. 2 Flow chart of the FMSE algorithm

In initialization, input parameters and a valid starting solution are generated. Evaluation computes the fitness of each element in the current solution. A goodness measure is used to probabilistically discard some elements in selection based on the fitness of that element. The resulting partial solution is then fed into the reconstruction operator that heuristically forms a new complete solution from the partial solution. The current complete solution is re-evaluated in a loop fashion until a termination condition is satisfied. Therefore, FMSE is a search heuristic that achieves improvement through iterative perturbation and reconstruction. To enhance its evaluation, selection, mutation and reconstruction processes, FMSE needs to incorporate intelligent techniques such as fuzzy set theory which enables fuzzy evaluation of candidate solutions.

A. FMSE Coding

The proposed FMSE coding scheme represents a candidate solution S as a sequence of elements, where each element ei denotes a schedule for nurse i, $i=1,\ldots,m$, typically covering a weekly planning horizon. This implies that each schedule is a feasible sequence of shifts D, E, N and O for a particular nurse. A combination of schedules of all the nurses, $i=1,\ldots,m$, form the overall schedule, called roster. A roster should satisfy the work requirements for each shift on each day. Furthermore, a solution space E is a set of all possible combinations of elements e_i.

Fig. 3 shows a typical candidate solution for a complete schedule or roster. Shift "O" is represented by a blank space. The roster allocates schedules to 8 nurses, covering a period of 7 days. The shift requirements for the D, E, and N shifts are 3, 2 and 2, respectively. A closer look at the proposed coding scheme reveals that evaluating a population of candidate solutions is potentially time consuming. Therefore, FMSE works on a single solution to reduce computations.

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Nurse 1	D	D		E	E	N	E
Nurse 2	E	N	E	N	E		N
Nurse 3	D	D	D	D		E	D
Nurse 4	E	N	N		D	D	D
Nurse 5	N	E	N	E	D	N	E
Nurse 6	D		D	D	N	E	D
Nurse 7	N	E	D	D	N	D	
Nurse 8		D	E	N	D	D	N
ΣD	3	3	3	3	3	3	3
ΣE	2	2	2	2	2	2	2
ΣN	2	2	2	2	2	2	2

Blank space represents shift "O"

Fig. 3 Coding scheme for a typical candidate solution

B. Initialization

A good initial solution is generated as a seed for ensuing iterations. Generally, the quality of the seed influences the quality of the final solution. The FMSE algorithm obtains the original roster and uses it as a seed or initial solution. Following the initialization phase, the algorithm sequentially iterates through evaluation, selection, and reconstruction, in a loop fashion till a termination criteria is satisfied. The termination criterion is defined in terms of (i) predetermined number of iterations, or (ii) number of iterations without significant solution improvement.

C. Fitness Evaluation

Fuzzy evaluation determines the fitness of the candidate solution as a function of the fitness of individual elements (nurse schedules) in the solution (roster). Thus, the aim is to determine the relative contribution of each element e_i to the fitness of the current solution S, and to determine those elements that contribute below the acceptable level. The fitness of each element $F(e_i)$, is a combination of normalized functions.

The goodness, fitness, or quality of a solution is a function of how much it satisfies soft constraints. As such, fitness is expressed as a function of the weighted sum of the satisfaction of the desired goals and preferences. Thus, each soft constraint is represented as a normalized fuzzy membership function in [0,1]. In this study, we use two types of membership functions: (a) triangular functions, and (b) interval-valued functions, as show in Fig. 4.

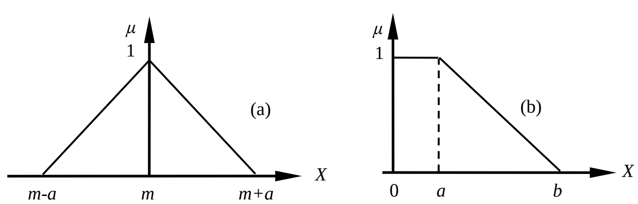

Fig 4 Linear membership functions

In (a), the satisfaction level is represented by a fuzzy number *A*<*m*,*a*>, where *m* denotes the centre of the fuzzy parameter with width *a*. Thus, the membership function is,

$$\mu_A(x) = \begin{cases} 1 - \dfrac{|m-x|}{a} & \text{If } m-a \le x \le m+a \\ 0 & \text{If otherwise} \end{cases} \quad (4)$$

In (b), the satisfaction level is represented by a decreasing linear function where [0,*a*] is the most desirable range, and b is the maximum acceptable. Therefore, the corresponding function is,

$$\mu_B(x) = \begin{cases} 1 & \text{If } x \le a \\ (b-x)/(b-a) & \text{If } a \le x \le b \\ 0 & \text{If otherwise} \end{cases} \quad (5)$$

The respective membership functions for the problem are derived, based on the above described interval-valued functions.

Membership Function 1 - Fair Workload Assignment

High quality rosters have fair workload assignment. Therefore, the variation of workload should be as low as possible. For each nurse schedule i, the deviation xi of workload ω_i from the average workload is,

$$x_{1i} = \frac{|\omega_i - \alpha|}{\alpha} \quad (6)$$

Assuming the interval-valued function, the membership function for fair workload assignment is as follows,

$$\mu_1(x_{1i}) = \mu_A(x_{1i}) \quad (7)$$

Where, the values *a* and *b* reflect the fuzzy parameters of the interval-valued membership function.

Membership Function 2 – Minimal number of shift changes

For each nurse *i*, let ci be the number of shift changes, and *J* be the number of days or planning horizon, which is equivalent to the length of a shift pattern. It follows that satisfaction according to the objective of minimal number of changes x_{2i} for each nurse *i* is measure by the expression,

$$x_{2i} = c_i / J \quad (8)$$

Similarly, we assume the interval-valued membership function for fair days-off assignment. The corresponding membership function is as follows,

$$\mu_2(x_{2i}) = \mu_B(x_{2i}) \quad (9)$$

where, the values a and b reflect the fuzzy parameters of the membership function.

Other membership functions are formulated in a similar manner, that is, (a) variation of night shifts, (b) forbidden shift sequences, (c) shift variation, and (d) congeniality, a measure of compatibility (congeniality) of staff allocated similar shifts, (e) overstaffing, (b) understaffing.

D. The Overall Fitness Function

For each nurse *i*, schedule fitness is obtained from the weighted sum of the first four membership functions. As such, the fitness for each shift pattern (or element) *i* is obtained according to the following expression;

$$\eta_i = \sum_{z=1}^{6} w_z \mu_z (x_i) \qquad \forall i \qquad (10)$$

where, w_z is the weight of each function μ_z, such that condition $\sum w_z = 1.0$ is satisfied. Similarly, the fitness according to shift requirement in each day j is given by,

$$\lambda_j = \sum_{z=7}^{8} w_z \mu_z (x_j) \qquad \forall j \; (11)$$

where, w_j is the weight of each function μ_j, with $\sum w_z = 1.0$. From the above membership functions, the overall fitness of the candidate solution is given by the expression,

$$f = \left(\frac{\eta}{\omega_1} \wedge 1 \right) \wedge \left(\frac{\lambda}{\omega_2} \wedge 1 \right) \qquad (12)$$

where, $\lambda = \lambda 1 \wedge ... \wedge \lambda I$; $\mu = \mu_1 \wedge \mu_2 \wedge \ldots \wedge \mu_J$; I is the number of nurses, J is the number of working days; ω_1 and ω_2 are the weights associated with η and λ, respectively; "$\wedge$" is the min operator. The weights w_z, w_j, ω_1 and ω_2 offer the decision maker an opportunity to incorporate his/her choices reflecting expert opinion and preferences of the management and the nurses.

The selection operator probabilistically determines whether or not an element or shift pattern i should be retained for the next generation. Elements with a high fitness value F_i have a higher probability of surviving into the next generation. Discarded elements are reserved in queue for the reconstruction phase. Selection compares fitness F_i with an allowable fitness f_t at iteration t;

$$f_t = \max[0, p_t - p] \qquad (13)$$

where, p_t is a random number in [0,1] at iteration t; p is a predetermined constant in [0,1].

Selection Algorithm

```
Set constant p = 0.2;
Initialize i = 1;
While (i ≤ m) do
    Compute fitness of element i; F_i;
    Let p_t = Random [0,1];
    Let f_t = max [0, p_t – p];
            If (F_i < f_t) Then,
                    discard i, return;
              Else return i;
            End If;
    i = i + 1;
End While
Return Solution;
```

Fig 5 Algorithm for the selection phase

Fig. 5 presents a summary of the selection algorithm. The algorithm begins by computing the allowable fitness ft. At each iteration t, compare fitness $F(e_i)$ of element e_i. Compare $F(e_i)$ with the allowable fitness ft, and return the element with better fitness. The expression $f_t = p_t - p$ enhances convergence; when p_t is high, the probability of discarding good elements is very high, which is inefficient. As a result, the search power can be controlled by setting the value of p to a reasonable value (e.g., p = 0.22 in this study).

E. Mutation

Mutation performs intensive and explorative search, around solution S and in unvisited regions of the solution space, respectively. Intensification is performed by swapping randomly chosen pairs of elements within a group. On the other hand, exploration enables the algorithm to move from local optima. This involves probabilistic elimination of some elements, even the best performing ones. Generally, mutation is applied at a very low probability pm, to ensure convergence. In this application, we use a decay function to model a dynamic mutation probability as follows,

$$p_m(t) = p_0 e^{(-t/T)\cdot\ln(2)} \qquad (14)$$

where, t is the iteration count; T is the maximum count; and p0 is the initial mutation probability. This expression can be used for both explorative and intensive mutation probabilities. Any infeasible partial solutions are repaired in the reconstruction phase.

F. Reconstruction

The reconstruction phase re-builds into a complete solution the partial solution evolved from the previous phases. This essentially means assigning clients to empty spaces in every incomplete group. A greed-based constructive heuristic is used for the reconstruction process, based on the attractiveness of adding a shift k into the current incomplete solution, thereby increasing the fitness F_i of a shift sequence i in that solution. The algorithm keeps a limited number of discarded elements in a set Q. Fig. 6 shows the generalized reconstruction algorithm procedure.

Reconstruction Algorithm
1. Input incomplete solution;
2. **For** $\boldsymbol{i}$ **= 1 to** $\boldsymbol{I}$
3. Initialize shift sequence position $k = 1$
4. **Repeat**
5. **If** sequence $[s_k s_{k+1}] \notin$ Forbidden set F, **Then**
7. Insert shift s_{k+1} = rand (D, E, N)
8. **If** workload w_i of sequence $[s_1 s_2 \ldots s_k{+}1] \geq w_{max}$ **Then**
9. $s_{k+1} = O$
10. **End If**
11. Increment counter $k = k+1$
12. **End If**
13. **Until** (Shift sequence P_i is complete
14. Increment counter $i = i + 1$
15. **End For** (Required schedules, I, are generated)
16. //*Check for shift requirements*
17. **For** each shift k in day j
18. **If** shift requirement r_k is not met, **Then**
19. Adjust number of k shifts in that day, accordingly.
20. **End If**
21. **Return** solution S

Fig. 6 FMSE reconstruction algorithm

Each shift assignment is subject to sequence and workload restrictions, where a shift "O" is assigned in the case of violation of the restrictions. The iterative loops run till each nurse is assigned a feasible shift pattern, which make a complete roster for the nursing staff.

Subsequently, the complete roster is checked for compliance with shift requirement. This implies that the total assignment for each shift k is checked against the pre-determined shift requirement r_k. In the case that requirement r_k is not met, eliminate surplus or add missing shift k accordingly. This operation is performed over all shifts in each day.

IV. Illustrative Experiments

To test the efficiency and effectiveness of the FMSE algorithm, complex data sets were obtained from literature [2], while some were artificially generated. The test data presented here assumes that there are no days off, and a perfect initial roster satisfying all preference constraints is disrupted by reported absences from nurses 1, 5, 8, 12, as shown in Fig 7. The nurses report that they can only show up for shifts other than the ones indicated in the shaded ones. The aim is to reconstruct the roster, so that the disruption constraints are satisfied, while minimizing the total number of changes to the original roster.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	Fitness η_i
Nurse 1	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	1.000
Nurse 2	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	1.000
Nurse 3	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	1.000
Nurse 4	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	1.000
Nurse 5	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	1.000
Nurse 6	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	1.000
Nurse 7	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	1.000
Nurse 8	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	1.000
Nurse 9	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	1.000
Nurse 10	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	1.000
Nurse 11	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	1.000
Nurse 12	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	1.000
Nurse 13	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	1.000
Nurse 14	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	1.000
Nurse 15	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	1.000
Fitness λ_j	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.000

Fig. 7 Initial roster with disruptions as indicated

Fig. 8 shows the computational results for the first experiment. Due to unplanned absences of nurses 1, 5, 8 and 12, the roster was rescheduled, yet with minimal changes to the original roster; only those disruptions were changed. It is interesting to note that the overall satisfaction of the new roster is still at an acceptable level of 1.00. The average computation time was less than 180 minutes. This demonstrates that the FMSE algorithm can satisfactorily address complex multi-criteria rerostering problems even in the presence of fuzzy goals and preference constraints. The algorithm has potential to solve large scale problems with reasonable computation time.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	Fitness η_i
Nurse 1	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	1.000
Nurse 2	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	1.000
Nurse 3	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	1.000
Nurse 4	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	1.000
Nurse 5	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	1.000
Nurse 6	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	1.000
Nurse 7	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	1.000
Nurse 8	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	1.000
Nurse 9	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	1.000
Nurse 10	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	1.000
Nurse 11	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	1.000
Nurse 12	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	1.000
Nurse 13	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	1.000
Nurse 14	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	1.000
Nurse 15	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	D	D	D	D	D	D	D	D	D	N	N	E	E	D	D	1.000
Fitness λ_j	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.000

Fig. 8 Final re-roster with minimal disruptions

V. CONCLUSIONS

In an environment where human preferences and expectations are imprecise; the use of fuzzy set theory concepts is beneficial. This chapter proposed an FMSE algorithm that incorporates a fuzzy multi-criteria fitness evaluation method, with heuristic perturbation and improvement heuristics. FMSE enables the decision maker to use expert opinion deriving from information from patients, nurses, and managers to make adjustments to the solution process based on weights. Therefore, FMSE is an effective and efficient approach for decision support in nurse rerostering.

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