A Satisficing Approach to Home Healthcare Worker Scheduling

Michael Mutingi and Charles Mbohwa

***Abstract*—**The homecare worker scheduling problem is inundated with fuzzy and often conflicting goals, constraints and preferences. In such an uncertain environment, the decision maker needs to find a satisficing solution approach that takes into account the humanistic judgments and the conflicting nature of the goals. This paper proposes a fuzzy satisficing approach, based on fuzzy set theory, for addressing the homecare worker scheduling problem. The aim is to provide a satisficing approach that considers the management goals, the worker preferences, as well as the service quality as specified by the healthcare clients. By addressing the desired goals or preferences of the three players, (i) the management, (ii) the worker, and (iii) the client, the approach provides a more realistic, flexible and adaptable method for real-world healthcare staff scheduling in an uncertain environment.

***Keywords*—**Satisficing solutions, multi-objective optimization, homecare worker scheduling, fuzzy theory

I. Introduction

THE provision of health care and assistance to patients in their own homes often occurs in an uncertain environment. Healthcare worker schedules in general, and homecare worker schedules in particular, are constructed under uncertain, imprecise, and often conflicting goals and restrictions. Some critical examples of the conflicting management goals include the minimization of schedule cost [1], the maximization of healthcare service quality, and the maximization of healthcare worker satisfaction [2]. Satisfying all these goals simultaneously is almost impossible due to their conflicting behavior. Common restrictions encountered while constructing homecare worker schedules include the need to satisfy all the health care requirements of the patients (clients), the need to provide service to every patient within a given time window at a specific location, and the limitation on the maximum working hours that can be assigned to each worker per day. These restrictions fall into two main categories, that is, demand constraints and time constraints. While demand constraints pertain to the satisfaction of all the healthcare requirements by clients, time constraints are concerned with time window restrictions, total work hours per day per worker, and other specific work time restrictions as stipulated by specific organizations and legislations. In the presence of all these constraints, the decision maker needs a robust decision support tool so that schedule cost, healthcare service quality, and worker schedule quality goals are met. As these goals involve humanistic perceptions and judgments from three players, i.e., the management, the clients, and the healthcare workers, the development of a more judicious approach to home healthcare scheduling is imperative. Thus, the concept of satisficing is appropriate.

Satisficing is a flexible and adaptable alternative to optimization for multiple objective problems, where the decision maker gives up the idea of obtaining the "best" solution and seeks a solution that is "good enough" to exceed the preset lower bounds. The satisficer believes that, in practice, there are too many uncertainties and conflicts in values for true optimization, such that it is more reasonable to do "well enough". There are two major approaches to solving multi-objective problems [3]. The first involves transformation of the multi-objective problem into a single-objective problem using such techniques as weighted sum method. When the solution is not satisfactory, the solution process should be repeated, adjusting the weighting coefficients till a satisficing solution is found. The second involves finding a group of Pareto-optimal solutions, considering trade-offs between objectives. However, it is difficult to find a satisficing solution in situations where the number of objective is large [4].

In developing a healthcare schedule, there are three important objectives to be considered, namely;

(1) Schedule cost and management preferences;
(2) Care worker preferences; and,
(3) Client preferences.

The decision maker needs to consider the schedule cost, which is normally measured in terms of the total distance travelled by care givers from point of origin to all the clients and back to the point of origin. Alternatively, the cost can be expressed in terms of the total working time for each worker. In either case, the total schedule cost is influenced by the nature of the routes assigned to healthcare workers to fulfill the demand requirements. For this reason, the homecare worker scheduling problem is an extension of the vehicle routing problem with time windows [1]. Not only should the decision maker consider the schedule cost, but also the service

Michael Mutingi is a doctoral student with the School of Mechanical and Industrial Engineering, University of Johannesburg, Johannesburg, Bunting Road Campus, P. O. Box 524,Auckland Park 2006, South Africa (phone: +27789578693; e-mail: mmutingi@gmail.com).

Charles Mbohwa is with the Department of Quality and Operations Management, University of Johannesburg, Johannesburg, Bunting Road Campus, P. O. Box 524, Auckland Park 2006, South Africa (e-mail: cmbohwa@uj.ac.za).

quality.

Healthcare service quality is important for improving or maintaining the health of the community as governments and other stakeholders continue to put pressure on healthcare service providers. Providing a sound service quality is also a strategic initiative targeted at improving or maintaining the clientele base, hence the market share, in the medium to long term. To achieve this, the decision maker has to take into account the time window preferences of the clients, when constructing the schedules. In this connection, a good measure of service quality should be expressed as a function of the number of violations of time window preferences as specified by the clients. This will ensure that clients are served within the earliest and latest start times of their service time preferences. However, fulfilling all the time window preferences may be difficult, especially in the presence of care worker preferences.

Care workers make preference concerning total work hours that may be assigned to them on a daily basis. One of the most critical measures of schedule quality is the perceived fairness of the schedule. For instance, if the workers feel that their preferences are not being attended to, absenteeism, low morale, and poor job performance will affect service quality and the health of the community at large. In this regard, it is crucial to satisfy the workers' preferences in an equitable manner. However, the greatest challenge is on how to measure the perceived schedule quality given the imprecise nature of individual worker preferences.

As an extension of the vehicle routing problem with time windows, the homecare worker scheduling problem is highly combinatorial and complex [1]. Consequently, the application of metaheuristics and other intelligence-based methodologies is the most viable approach [6]. Metaheuristic approaches include genetic algorithms, group genetic algorithms [7] tabu search, ant colony optimization, evolutionary algorithms [8], and particle swarm optimization [9]. Additionally, the inclusion of fuzzy set theory in modeling scheduling problems characterized with imprecise variables is the most suitable option [11] [12] [13]. According to Zadeh [14], fuzzy theory is concerned about applying the natural language terms in model development. It is a robust method for representing and manipulating fuzzy terms called *fuzzy logic*. It provides a means of computing with words, therefore, it is well suitable for handling fuzzy and imprecise variables in home healthcare scheduling. Overall, developing robust healthcare worker scheduling approaches that can provide a cautious trade-off between schedule cost, healthcare service quality and healthcare worker schedule quality is crucial.

The purpose of this research is to develop a fuzzy satisficing-approach to solving homecare worker scheduling in a fuzzy environment. The specific objectives of the study, therefore, are structured as follows:

(1) Highlight and formulate common objectives inherent in the homecare worker scheduling problem;
(2) Develop a fuzzy satisficing model approach to address the fuzzy multi-objective problem;
(3) Propose an interactive satisficing procedure based on metaheuristic formalisms.

The rest of this paper is summarized as follows: The next section describes the homecare worker scheduling problem. Section III presents an overview of multi-objective modeling for homecare scheduling. A satisficing modeling approach is proposed in section IV. Section V concludes the paper.

II. The Home Care Worker Scheduling Problem

The home healthcare worker scheduling problem with time windows (see Fig. 1) can be described as follows: Consider a community healthcare centre with m care givers to visit n clients, where each care giver k (k = 1,2,…,m) is supposed to complete serving client j (j = 1,2…,n) within a given time window defined by earliest start time and latest start time, e_j and l_j, respectively. The aim of the management is to minimize the total cost incurred by each care giver in travelling from the point of origin to the clients and back to the point of origin. Furthermore, if the care giver arrives at the client earlier than e_j or later than l_j, then a penalty cost is incurred in each case. Let a_j denote the time when a care giver reaches client j, and p_e and p_l denote the unit penalty costs incurred when the care giver arrives too early or too late, respectively. This implies that the functions, $\max[0,e_j - a_j]$ and $\max[0,a_j - l_j]$ have to be minimized. The aim is to maximize client satisfaction by constructing schedules with minimum violation of the preferred time window constraint as specified by the client. On the other hand, the decision maker seeks to improve the schedule quality by developing the most equitable schedule allocations. Therefore, the individual workloads or worker capacity should, as much as possible, be kept within the limits of the workers preferences.

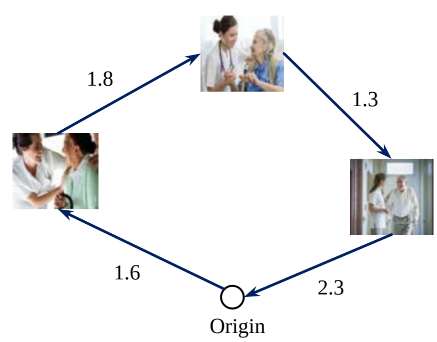

Fig. 1 Homecare worker schedule example

III. Multi-objective Modelling

Due to the presence of multiple conflicting objectives, multiple goals are considered when developing a suitable solution approach to the homecare worker scheduling problem. Contrary to most approaches in the literature, three goals are considered simultaneously, namely: (i) minimizing the schedule cost, (ii) maximizing client satisfaction, and (iii) maximizing worker satisfaction. In practice, this means that all the targets are considered at the same time. This essentially involves finding a trade-off between the goals, considering preferences and choices of the decision maker.

The first objective is a management goal concerned with minimizing the cost associated with the trips. Let $t(i,j)$ represent a feasible trip, where the worker departs from point of origin 0 and visits nodes i+1, i+2,…, j-1, and j, consecutively. Then, the cost of each trip, c_{ij} can be estimated in terms of the total distance from the care giver's point of origin to the first client, the distances between successive clients, and from the last client back to the care giver's point of origin, and the penalty cost of infeasible assignments;

$$f_1 = c_{ij} = w\left(d_{0,i+1} + \sum\nolimits_{h=i+1}^{j-1} d_{h,h+1} + d_{j,0}\right) \tag{1}$$

where, w is the variable cost per unit distance (or time); d_{ij} is the travelling distance between successive clients i and j.

The second objective concerns the maximization of client satisfaction which can be expressed as a function of the violations of time windows preferred by the clients. Let the number of violations or infeasible assignments in trip $t(i\ j)$ be represented by n_{ij}. Then, client satisfaction can be estimated;

$$f_2 = s_{ij} = \left(g_{ij} - n_{ij}\right)\big/ g_{ij} \tag{2}$$

The third and final objective is concerned with maximizing healthcare worker satisfaction, which entails meeting the worker preferences to the highest degree possible. Normally, each worker indicates specific preferences in terms of individual working hours, work starting time, work finishing time, among others. The most common specification is the total individual working hours. For each trip $t(i,j)$ assigned to an individual worker k, the total working hours h_{ij} between i and j are estimated by the following expression;

$$f_3 = h_{ij} = \tau_{0,i+1} + \sum\nolimits_{h=i+1}^{j-1} \tau_{h,h+1} + \tau_{j,0} \tag{3}$$

where, τ_{ij} denotes the travelling time between successive clients i and j;

In practice, the decision maker seeks to consider a trade-off between client satisfaction, worker satisfaction and cost minimization. In this connection, the multi-objective formulation is achieved by optimizing the three objective functions jointly. In a fuzzy environment, the goals and preferences are expressed in imprecise linguistic terms [2]. Each imprecise goal can be represented in terms of its minimum and maximum acceptable values. For instance, an individual worker preference can be specified as fuzzy numbers in terms of the minimum and maximum daily working hours. We present a fuzzy satisficing approach to homecare worker scheduling in the next section.

IV. A Satisficing Approach to Homecare Scheduling

In this section, we explain the proposed multi-objective satisficing approach to homecare worker scheduling, in terms of the satisficing heuristic approach, the multi-objective satisficing model and the fuzzy interactive satisficing model.

A. Satisficing Heuristic Approach

Fig. 2 shows the proposed satisficing heuristic for interactive homecare scheduling decisions. Formally, the heuristic begins by searching from the solution space S_j, an untested solution $X_i \subseteq S_j$, and testing whether or not it is satisficing. If X_i is not satisficing, the search process continues, otherwise the solution is selected and implemented. After the implementation of the schedule, the perceptions of the three players – employee, client, management – will change over time, such that the decision maker needs to acquire and assess new information on their satisfaction or preferences and goals. If the new preferences reach the pre-specified thresholds, then the solution space S_j should be updated accordingly. The decision maker updates his preferences according to the new information obtained. The search for a satisficing solution starts again with the update information. The heuristic makes the approach more applicable and adaptable to the real life human decision process. However, the information pertaining to constraints and preferences is usually imprecise or uncertain. As such, we introduce fuzzy theory concepts in the next section.

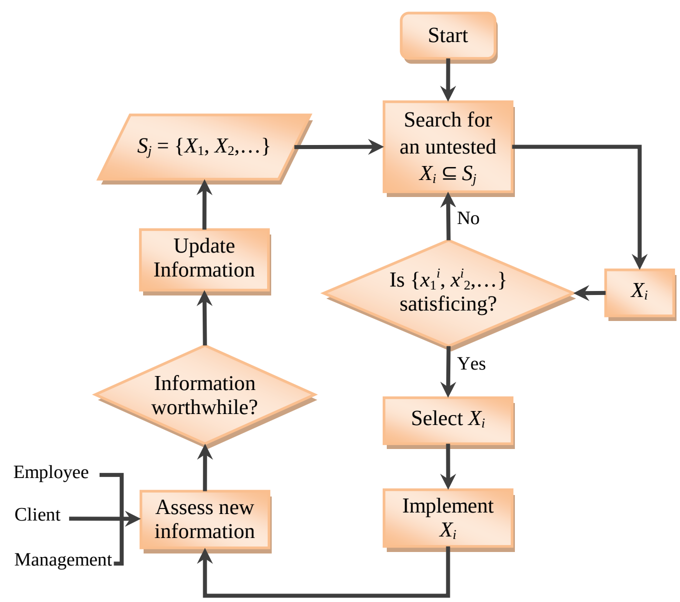

Fig. 2 Proposed satisficing heuristic approach

B. Multi-Objective Satisficing Model

The homecare worker scheduling problem can be formulated as a multi-objective model as follows:

$$\begin{aligned} &\text{Min} \quad \{f_1(x),.f_2(x),\ldots, f_d(x)\} \\ &\text{Subject to:} \\ &g_z(x) \le 0 \qquad z = 1,2,\ldots, p \end{aligned} \tag{3}$$

where, x is a vector of decision variables controlling worker schedules; d is the number of objective functions; p is the number of constraints.

In practice, the decision maker's desires are expressed in linguistic terms such as "The first objective function should be somewhat less than this value" or "I must make the first objective function greater than this value". As such, we introduce an aspiration level for each objective. Therefore,

$$f_t(x) \leq f_t^a \quad (t = 1,...,d) \tag{4}$$

Assume that the set of constraints in model (3) is equivalent to (4). Then, model (3) is transformed as follows;

$$\begin{aligned} &\text{Find } x \\ &\text{Satisfying}: \\ &h_t(x) \leq h_t^* \quad (t = 1,...,d) \end{aligned} \tag{5}$$

Here, $h_t(x)$ corresponds to $f_t(x)$ and $g_t(x)$, and h_t^* corresponds to f_t^a and g_t^*. The set of constraints in (4) are transformed into constraints of the same order by the following expression [3];

$$\bar{h}(x) \equiv \frac{h_t(x) - h_t^*}{|h_t^*|} \leq 0 \tag{6}$$

As a result, the homecare scheduling problem is formulated as a satisficing problem;

$$\begin{aligned} &\text{Find } x \\ &\text{Satisfying}: \\ &\bar{h}_t(x) \leq 0 \quad (t = 1,...,d) \end{aligned} \tag{7}$$

C. Fuzzy Satisficing Model

In the real world, constraint values are not provided in the strict sense, but usually have some imprecision, uncertainty or ambiguity. Consequently, the aspiration levels f_t^a ($t = 1,\ldots, d$) are determined based on the decision maker's judgment or expert knowledge, experience and other information sources. Fuzzy logic is capable of addressing such vagueness and ambiguity, or fuzziness expressed in form of membership function $\mu(x)$ in the range [0,1]. Most fuzzy optimization methods use the membership function concept [15] [16]. On the contrary, an unsatisfying function $\eta(x)$ in the range $[0,\infty]$ is defined [3] [4] [5].

$$\eta(x) = \frac{1}{\mu(x)} - 1 \tag{8}$$

It can be seen that the unsatisfying function has a one-to-one mapping with the membership function $\mu(x)$. Therefore, the fuzzy logic concepts can possible be applied based on the satisfying function.

Assume that the decision maker can accept $h_t(x)$ up to the magnitude $(1+\alpha_t)h_t^*$, meaning that the constraint is violated. It follows that the unsatisfying function

$$\eta_t(x) = \max\left\{\frac{1}{\alpha_t}\bar{h}_t(x), 0\right\} \tag{9}$$

is acceptable, with the values around the value one. In this sense, α_t ($\alpha_t \geq 0$) is the unsatisfying coefficient, as conceptualized in Fig. 3. Unlike in conventional fuzzy optimization models where a membership function represents the decision maker's satisfaction, $\eta_t(x)$ represents the decision maker's unsatisfaction, and the less the desirable. Clearly, the unsatisfaction function is convex, which is a favorable property for solution search. The overall unsatisfying function vector is $\eta(x) = [\eta_1(x),\ldots,\eta_d(x)]^T$. The scheduling model can conveniently be formulated as a multi-objective minimization problem of the unsatisfying functions as follows;

$$\text{Min } \{\eta_1(x),...,\eta_d(x)\} \tag{9}$$

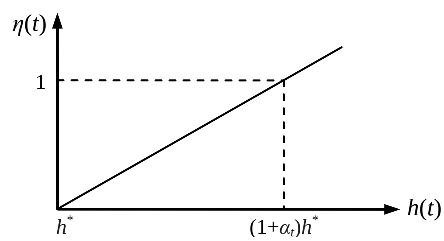

Fig. 3 The unsatisfying function $\eta(t)$

The unsatisfying function makes it easier for the decision maker to select the most preferred or satisficing solution according to his preferences. Metaheuristics such as genetic algorithms [17] and particle swarm optimization [9] [18] can be applied to find a group of Pareto-optimal solutions for the non-constrained multi-objective optimization problem.

D. Fuzzy Interactive Satisficing Approach

Metaheuristics such as PSO and GA offer a population of candidate solutions from which the decision maker can choose a satisficing solution. The decision maker can adjust the unsatisfying coefficient α_t as well as the aspiration level h_t^* based on information updates from the employees, clients and management. The search procedure can then be repeated interactively until a satisficing solution is reached.

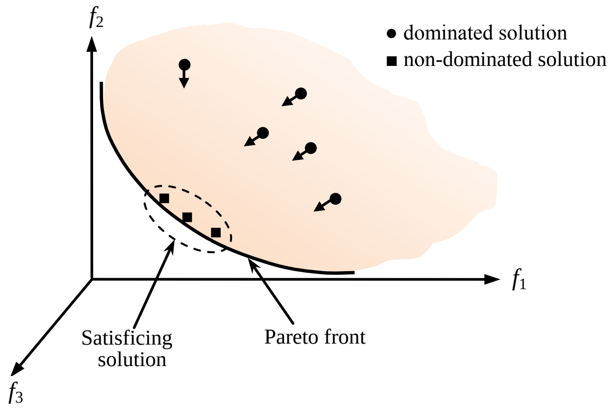

Fig. 4 Satisficing search process

The proposed search approach seeks to find a group of solutions in the interest of the decision maker, that is, a compromise solution. In other words, the aim is to generate a set of solutions that are Pareto-optimal and all the satisfaction ratings are as much as possible. Fig. 4 illustrates the proposed search method.

V. Conclusion

In the real world, decision makers concerned with homecare worker scheduling encounter problems of finding a cautious trade-off between maximizing client satisfaction, minimizing cost, and maximizing worker satisfaction, to an acceptable degree of satisfaction. In a fuzzy environment, the management goals, the constraints, and the impact of the actions taken are not precisely known at the time of planning. Moreover, the goals are often conflicting, which complicates the scheduling problem even further. A fuzzy satisficing approach that accommodates the decision maker's expert preferences, judgments and choices is the most viable option. We proposed a proposed a fuzzy satisficing approach for addressing homecare worker scheduling problems in a fuzzy environment. A fuzzy unsatisfying function is introduced for handling the fuzziness inherent in the scheduling problem.

This study is a useful contribution to decision makers in the field of home health care. Contrary to most single-objective approaches, the approach provides a trade-off between management goals, worker satisfaction, and client satisfaction, which is more practical. The use of fuzzy evaluation is handy since, in most cases, the information required for healthcare scheduling is imprecise. Thus, reliance on human expert information is inevitable. Using the satisficing approach, the vagueness and imprecision of the information is addressed effectively, taking into account the multiple conflicting objectives. Iteratively, the information is updated over time by acquiring perceptions from employees, clients and the management. Furthermore, the use of population-based meta-heuristics provides a population of alternative solutions, rather than a single solution, offering the decision maker a wide choice of practical solutions and an opportunity to consider other practical factors that could not be included in the problem formulation. Therefore, the fuzzy satisficing approach is a useful interactive decision support tool for homecare worker scheduling problems, specifically when considering the multiple conflicting objectives in a fuzzy environment where the goals, the constraints, and the impact of alternative actions are not imprecise.

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