Home Healthcare Staff Scheduling: A Clustering Particle Swarm Optimization Approach

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Abstract

The home healthcare staff scheduling problem is concerned with the allocation of care tasks to healthcare staff at a minimal cost, subject to healthcare service requirements, labor law, organizational requirements, staff preferences, and other restrictions. Healthcare service providers strive to meet the time window restrictions specified by the patients to improve their service quality. This paper proposes a clustering particle swam optimization methodology (CPSO) for addressing the scheduling problem. The approach utilizes the strengths of unique grouping techniques to efficiently exploit the group structure of the scheduling problem, enabling the algorithm to provide good solutions within reasonable computation times. Computational results obtained in this study demonstrate the efficiency and effectiveness of CPSO approach.

1. Introduction

Home health care (HHC) organisations are concerned with the provision of coordinated medical and paramedical services to patients while at their homes (Mutingi and Mbohwa, 2013). Within the health care service domain, the HHC service sector is one of the fastest growing areas (Mutingi and Mbohwa, 2013) [2]. In providing coordinated home care services, the healthcare workers have to attend to acute illness, post-hospitalization treatment, post-operation treatment, chronic illness, permanent disability, terminal illness, or pandemics such as HIV/AIDS (Akjiratikarl et al., 2007). The home care services provided include nursing, therapy activities, medical and social services, house cleaning, and drug deliveries. These services are necessitated by the ever increasing ageing population, chronic diseases, pressure from societies for improved healthcare service quality, and pressure from governments for healthcare organisations to contain their healthcare costs. Oftentimes, it is an advantage to allow elderly people and patients with varying degrees of healthcare needs to live in their own homes as long as possible, since a long-term stay in nursing homes is often much more costly. Consequently, healthcare service providers are compelled to offer home care services in an attempt to limit costs and to improve their quality of service. In most cases, it is desirable to keep the relationship between individual care givers and specific patients (clients) over the long-term, lasting for several years (Bachouch et al. 2010; Akjiratikarl et al., 2007). In so doing, HHC organisations can keep clients and care givers satisfied, which is crucial in the medium- to long-tem. Overall, the provision of home health care services is known to improve the quality of life of the patients. Thus, home care services are an essential cost-effective and flexible instrument for modern social systems.

To stay competitive, healthcare service providers need to optimize their healthcare operations, considering the target management goals, client satisfaction, and healthcare staff satisfaction. Overtime work and long distance trips to clients should be minimized, while providing satisfactory services to patients, visiting them at their preferred time of day. Thus, in the home healthcare setting, decision makers are often faced with complex decision problems involving care task assignment (Bachouchi et al., 2010), patient assignment (Hertz and Lahrichi, 2009), outsourcing (Drake and Davis, 2006), as well as routing (Bertels and Fahle, 2006). In particular, the assignment of home care tasks to care givers is a complex but important assignment problem in healthcare operations. High quality staff schedules are especially important since poor schedules may lead to low worker morale, job dissatisfaction, absenteeism, inefficiency, poor service quality, and ultimate loss of business (Borsani et al., 2006). To obtain high quality schedules, staff workloads should be assigned equitably or at least in a fair manner. For instance, a high quality schedule is expected to be fair among care givers. Retrospectively, the end goal is to balance the workloads of care givers while minimizing distance travelled visiting patients. However, oftentimes, the desired goal is not stated or known precisely as it is subject to human perception. Ideally, the aim is to satisfy as much as possible, the care givers, the management, and the patients. This makes the goal imprecise or fuzzy, which complicates the problem. Moreover, the problem is characterized by a myriad of constraints making the problem difficult to solve using conventional methods. Consequently, the scheduling problem is time-consuming, especially performed manually. Therefore, robust and interactive decision support tools are essential necessary for assisting decision makers when designing staff schedules in home healthcare organizations. As more and more healthcare services move into home care setting, the need for novel innovative solution approaches continues to increase.

A few research articles addressed the home health care scheduling problem. For example, Cheng and Rich (1998) presented the problem as a vehicle routing problem with time windows and multiple depots. In the same vein, Akjiratikarl et al. (2007) proposed a particle swarm based algorithm for a home care staff scheduling problem arising the United Kingdom. Bertels and Fahle (2006) proposed a hybrid approach combining heuristics, linear programming, and constraint programming, with the objective of minimizing transportation costs and maximizing satisfaction of care providers and patients. Similarly, Borsani et al. (2006) proposed a mathematical model based on integer linear programming techniques. Bachouch et al. (2010) proposed an optimization model focusing on task assignment in a home health care environment. The authors proposed a mixed-integer programing (MIP) model and solved the problem using LINGO solver and MS Excel. Eveborn et al. (2006) used a set partitioning approach to model a homecare scheduling problem for a variety of care providers. An MIP model and a heuristic approach wer used to minimize labour costs. Begur et al. (1997) developed a decision support system based on simplified scheduling heuristics. Though the research articles addressed the staff scheduling problem in a home care setting, fuzziness and uncertainties in such problem environments have not been considered sufficiently. The current study seeks to address this challenge.

In view of the above issues, designing effective and efficient decision support tools is especially essential for staff scheduling in the HHC organisations. This is necessitated by the desire to improve the service quality or patient care, to improve the schedule quality that satisfies the expectations healthcare professionals and the management goals. The purpose of this research is to develop a clustering particle swarm optimization (CPSO) for optimizing staff schedules in a typical home health care organization. CPSO uses fuzzy evaluation techniques, deriving from fuzzy set theory. The specific objectives for this research are as follows:

(i) to describe the staff scheduling problem in a typical home health care environment;
(ii) to propose a clustering particle swarm optimization for optimizing; and,
(iii) to provide illustrative computation experiments.

The rest of the paper is structured as follows: The next section provides a brief description of the home healthcare scheduling problem and its underlying assumptions. Section 3 provides a preliminary background to particle swarm optimization and fuzzy set theory. Section 4 presents the CPSO approach proposed in this study. Section 5 provides illustrative computational experiments, results and discussions. Finally, Section 6 concludes the paper.

2. Problem Description

Deriving from our previous studies on the complex characteristics of healthcare staff scheduling (Mutingi and Mbohwa, 2013), we define the homecare staff scheduling problem as follows: Consider a home healthcare environment w healthcare staff and n healthcare tasks. Assume that a set of tasks $T = \{1,...,n\}$, where each task i ($i = 1,\dots,n$) is defined by task duration p_i and time window $[e_i,l_i]$, and e_i and l_i denote, respectively, the earliest and latest start times of the task i,. Tasks are in form of patient visits, administrative duties, drug delivery, and other related duties. The tasks are to be assigned to a set of staff $S = \{1, ..., w\}$, where each staff j ($j = 1,...,w$) has a working time window $[e_j,l_j]$. Each task must be allocated to a qualified care worker having skills indicated by q_j, according to the required competency c_i. The aim is to balance the workload allocation, meaning that the variation of individual workloads should be within acceptable limits. As such, the objective is to limit as much as possible, the variation of care workers' individual workloads from the average workload, while observing time window constraints specified by the clients. This maximizes the overall schedule quality.

In the real-world, the goal of balancing the workload involves non-stochastic uncertainties or imprecisions. The management goal associated with balancing the fairness of individual workload assignments is in most cases not precise, but rather, fuzzy. Therefore, there is need to make the modeling procedure more flexible and adaptable to the human decision making process. As such, in a fuzzy environment, the problem should be treated as a fuzzy optimization problem.

2.1 Assumptions

In developing our optimization approach for the staff scheduling problem, we make the following simplifying assumptions:

(i) The travel times involving patient visits are treated as part of the task duration (in minutes).
(ii) Each task i has a specific time window $[e_i, l_i]$ in which the assigned care giver must begin the task operation.
(iii) Each task i should only be assigned to a care worker with the necessary skills or competences.
(iv) All tasks assigned to a care worker have to be completed within the care worker's working, defined by $[e_j, l_j]$.
(v) Care worker skills are expressed as q_j in the range $[1, h]$, where 1 and h represent the lowest and highest skills, respectively.

2.2 Constraints

In this context, the scheduling problem can be addressed by minimizing the variation of each individual care giver's workload from the average workload. The following constraints must be realized (Mutingi and Mbohwa, 2013; Bachouch et al., 2010):

(i) Each task can only be assigned to one and only one available care giver.
(ii) Each task should begin within its respective time window, $[e_i, l_i]$.
(iii) Each care worker's workload must be within the lower and upper bounds, m and M, respectively.
(iv) All tasks assigned to each care giver must be completed within the care giver's working time $[e_j, l_j]$.

For ease of deliberation on the fuzzy evaluation technique applied in this problem, we provide a brief background of the basic concepts of particle swarm optimization and fuzzy set theory in the next section.

3. Preliminaries

3.1 Basic Particle Swarm Optimization

Particle swarm optimization (PSO) is a stochastic optimization technique motivated by the social behavior of fish schooling and bird flocking (Kennedy and Eberhart, 1995; Shi and Eberhart, 1998). In PSO, the swarm of particles flies through the search space. The PSO mechanism uses a velocity vector to update the current position of each particle in the swarm. While flying, each particle adjusts its position based on its own experience and that of the most successful particle. The velocity v_i and the position x_i of each particle i are updated, respectively, follows:

$$v_i(t+1) = v_i(t) + c_1 \cdot \eta_1 \cdot (pbest_i(t) - x_i(t)) + c_2 \cdot \eta_2 \cdot (gbest(t) - x_i(t)) \tag{1}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{2}$$

where, $v_i(t)$ and $x_i(t)$ are, respectively, the velocity component and the location component of particle i at iteration t; $v_i(t+1)$ and $x_i(t+1)$ are, respectively, the velocity component and the location component of particle i at iteration $t+1$; $pbest_i$ is the best location of particle i, and $gbest_i$ is the global best location of the whole swarm; c_1 and c_2 are, respectively, the cognitive and social parameters, and η_1 and η_2 are uniform random numbers in the range [0, 1].

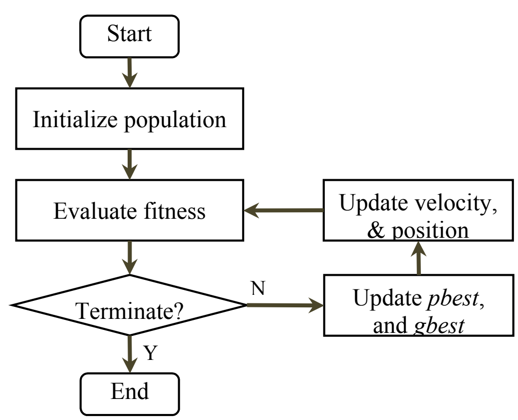

Figure 3: Flowchart for the proposed CPSO

3.2 Fuzzy Set Theory

3.2.1 Basic Concepts

Fuzzy set theory concepts were originally developed to model imprecision and uncertainty in a non-stochastic sense (Bellman and Zadeh, 1970; Sakawa, 1993; Bezdek, 1993). Fuzzy numbers are used to represent imprecise quantities such as "about 8 ½ hours," preferably 9 hours," and "substantially greater than 7 hours." Therefore, a fuzzy set can be visualized as a class of elements without a sharp boundary between the elements that belong to that class and those that do not. Contrary to Boolean logic, fuzzy set theory deals with degrees of membership rather than membership or non-membership (Sakawa, 1993). For clarity, we distinguish fuzzy sets from crisp sets according to the following definitions:

Definition 1: Crisp Set. 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,

$$\mu_A(x) = \begin{cases} 1 & \text{If } x \in A \\ 0 & \text{If } x \notin A \end{cases} \tag{3}$$

Definition 2: A Fuzzy Set. If X is the universe of discourse with elements denoted by x, then the grade of membership of x in a fuzzy set A is defined by $\mu_A(x)\in[0,1]$, 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 fuzzy set A in X is a set of ordered pairs;

$$A = \{x, \mu_A(x) \mid x \in X\} \tag{4}$$

Therefore, the closer the value of $\mu_A(x)$ is to 1, the more x belongs to A, and vice versa. Therefore, elements of a fuzzy set indicate the value of each element in the set as well as its grade of membership.

3.2.2 Membership Functions

A number of membership functions in different applications to represent uncertainty or fuzzy membership (Sakawa, 1993). Among other functions, the most widely applied functions are Generalized Bell, Gaussian, Triangular and Trapezoidal functions. It has been shown that linear membership functions can be used to provide good quality solutions with much ease (Delgado et al., 1993). In the HHC sector, the triangular and trapezoidal membership functions or any other related forms of linear functions are quite applicable and sufficient to model most healthcare operations problems, particularly staff scheduling problems.

Workload can be expressed in terms of a symmetric triangular fuzzy numbers. Let the symmetric triangular fuzzy parameter be defined by $A = <c,w>$, where c denotes the center of the fuzzy parameter with width w, as shown by the membership function in Figure 2. Here, c is the most preferable workload. It follows that the membership function of x in the fuzzy set A, μ_A: $X \rightarrow [0, 1]$, is given by expression (5);

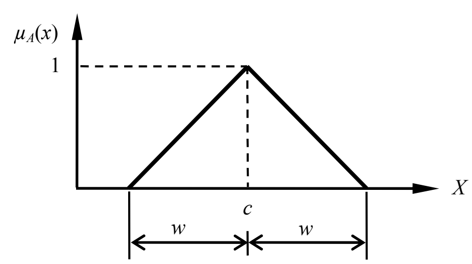

Figure 2: A symmetric triangular fuzzy membership function (c,w)

$$\mu_A(x) = \begin{cases} 1 - \dfrac{|c - x|}{w} & \text{if } c - w \le x \le c + w \\ 0 & \text{if otherwise} \end{cases} \tag{3}$$

4. Clustering Particle Swarm Optimization

The CPSO algorithm begins by randomly initializing a flock, where each bird is called a particle. Particles fly at a certain velocity, to find a global best position after a number of iterations. Iteratively, each particle adjusts its velocity according to its momentum, its best position (*pbest*) and that of its neighbors (*gbest*), which then determines its new position. Given a search space *D*, total number of particles *N*, the position of the i^{th} particle is expressed thus: $x_i = [x_{i1}, x_{i2},...,x_{iD}]$, the best position of the i^{th} particle is given by $pbest_i = [pbest_{i1}, pbest_{i2},...,pbest_{iD}]$, and the velocity of the i^{th} particle is $v_i = [v_{i1}, v_{i2},...,v_{iD}]$. Therefore, the position and velocity at iteration (t+1) are updated according to the following;

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot \eta_1 \cdot (pbest_i(t) - x_i(t)) + c_2 \cdot \eta_2 \cdot (gbest(t) - x_i(t)) \quad (6)$$

where, c_1 and c_2 are constants, η_1 and η_2 are uniformly distributed random variables in [0,1], and w is an inertia weight showing the effect of previous velocity on the new velocity vector.

Figure 3 presents a flow chart summarizing the logical of the CPSO. The algorithm consists of initialization, particle coding scheme, fitness evaluation, and velocity update.

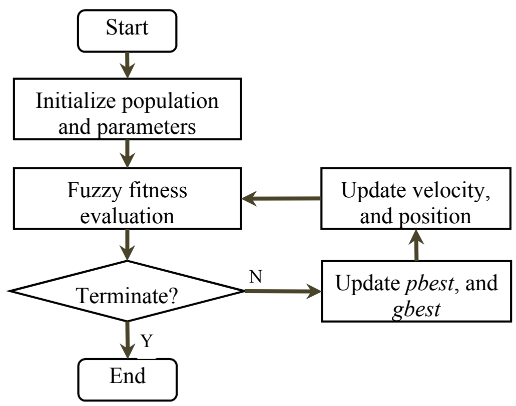

Figure 3: Proposed CPSO structure

4.1 Initialization

An initial population of size *p* is created by random assignments of tasks to care givers. The assigned tasks represent the coordinates (positions) of each particle. Each particle segment represents a group of tasks assigned to a particular healthcare staff. The CPSO assigns tasks to the care givers by generating continuous position values of using the following formula;

$$x_i = X_{\min} + round\left(\left(X_{\max} - X_{\min}\right) \times U\left(0,1\right)\right) \quad (7)$$

where, X_{min} and X_{max} are the pre-defined range of position values, $U(0, 1)$ is a uniform random number in the range [0,1]; *round*() is a rounding function that converts the continuous position values to integer positions.

4.2 CPSO Encoding

For the proposed CPSO, we develop a unique coding scheme intended to exploit the structure of the scheduling problem. Let A = [1, 2, 3,…,n] be a string representing a set of n tasks to performed by p care givers. Then the evaluation of A consists in partitioning patients along A into m groups such that the workload variation between the care givers is minimized, and the cumulative load for each group does not exceed the care giver working time limit.

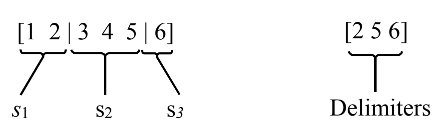

Figure 4: CPSO particle structure

Figure 4 presents an example of the structure of the particle consisting of two parts. For instance, care workers s_1, s_2, and s_3, are assigned groups of tasks {1,2}, {3,4,5}, and {6}, respectively. The second part of the structure is consists of delimiters denoting the position of the frontier "|" which separates the task or client groups.

4.3 Fuzzy Fitness Evaluation

CPSO uses fuzzy evaluation to determine the fitness of each particle. Let x_{ij} be a binary variable that defines whether or not a task i with duration p_i is assigned to care giver j. Further, let the average workload be a. It follows that,

$$a = \sum_i \sum_j p_i x_{ij} \Big/ \sum_i \sum_j x_{ij} \tag{8}$$

The objective is to minimize the variation of individual workloads from the average workload. Let the variation be represented by f_j, then,

$$f_j = \sum_i \left| p_i x_{ij} - a \right| \quad \text{for all } j \tag{9}$$

Recall that the workload f_j should be within acceptable limits. Thus, we use a fuzzy function evaluation based on triangular functions which have widely been used as membership functions (Sakawa, 1993). Figure 5 shows a typical triangular membership function, where a fuzzy number is represented as a triangular fuzzy number with a membership function of the form μ_j: $X \rightarrow [0,1]$, which is a normalized function that shows the desirability of schedule relative to the most preferred (average) workload, f_0. Since the workload assigned to every individual care giver must be as close as possible to the most preferred workload f_0, we represent this condition by a fuzzy membership function in expression (10);

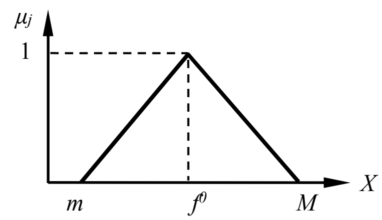

Figure 5: Preferred error as a triangular fuzzy number

$$\mu_j(x) = \begin{cases} \left(f_j - m\right) \big/ \left(f^0 - m\right) & \text{if } m \le x \le a \\ \left(f_j - M\right) \big/ \left(f^0 - M\right) & \text{if } a \le x \le M \\ 0 & \text{if otherwise} \end{cases} \tag{10}$$

Therefore, the overall objective function can be formulated as a function of the normalized functions (membership functions) as follows;

$$z = \left(\frac{\mu_1(x)}{\omega_1} \wedge 1 \right) \wedge \left(\frac{\mu_2(x)}{\omega_2} \wedge 1 \right) \wedge \ldots \wedge \left(\frac{\mu_p(x)}{\omega_p} \wedge 1 \right) \tag{11}$$

Here, ω_j denotes the weight behind schedule assignment for worker j ($j = 1,\ldots,p$), where, p is the number of care givers. This gives the modeler an opportunity to model his/her choices or preferences to reflect management and/or care givers' preferences. To evaluate the fitness of each particle, our CPSO maps the objective function to a fitness function F_k, according to the expression,

$$F_k(t) = \max\left[0, z^m(t) - z_k(t)\right] \tag{12}$$

where, $z_k(t)$ is the objective function of particle k; z^m is the maximum objective function at iteration t.

The proposed approach offers a number of practical advantages. First, its procedure is intuitively easy to follow and can be easily implemented in a number of problem situations. In addition, the algorithm is computationally efficient, being able to obtain good solutions within reasonable computation times. Notably, fuzzy evaluation allows the optimization process to accept inferior intermediate solutions which eventually yield to improved solutions. This ensures that instances of infeasible solutions are avoided during algorithm execution. Figure 6 provides a summary of proposed CPSO algorithm in terms of its pseudo code. In the next section, we present illustrative examples, computational results, together with the relevant discussions.

Algorithm 1. *Clustering particle swarm optimization algorithm*

```
Input w, η1 , η2, c1, c2, N;
Initialization
For i = 1 to N:
        Initialize particle position xi(0) and velocity vi(0);
        Initialize pbesti(0);
End For
Initialize gbest(0);
For i = 1 to N:
        Compute fitness f(x), x = (x1, x2,...,xN);
Repeat
        For i = 1 to N:
                Compute fitness fi;
                If (fi > current pbest) then
                        Set current value as new pbest;
                        If (fi > current gbest) then
                                gbest = i;
                End If
        End For;
        For i = 1 to N:
                Find neighborhood best;
                Compute particle velocity vi(t+1);
                Update particle position xi(t+1);
        End For;
Until (maximum iterations is reached);
```

Figure 6: A pseudo-code for the CPSO algorithm

5. Computational Illustrations

5.1 Computational experiments

For the purpose of illustration, we adopt a healthcare staff scheduling problem presented in Bachouch et al. (Bachouch et al., 2010). The details of task information are presented in Table 1. The task information consists of task duration p_i, time window $[e_i,l_i]$, and the competence requirement c_i. Table 2 provides information for the care worker, consisting of individual care giver working time $[e_j,l_j]$, and the corresponding qualification ranking q_j.

Table 1: Task information (Bachouch et al., 2010)

Task i	Duration p_i	$[e_i,, l_i]$	c_i
1	19	0, 60	1
2	24	0, 60	2
3	29	60, 120	3
4	34	60, 120	4
5	39	120, 180	5
6	56	120, 180	1
7	61	180, 240	2
8	66	240, 300	3
9	71	360, 400	3
10	76	540, 600	5

Table 2: Care worker information (Bachouch et al., 2010)

Care worker	$[e_j, l_j]$	q_j
1	19, 0	4
2	24, 0	2
3	29, 60	5

Further problem examples of sizes 10, 20, and 30 tasks, with 3 to 10 care givers were generated randomly and tested using CPSO. The CPSO was implemented in JAVA on a 3.06GHz speed processor with 4GB RAM. The next section provides the computational results obtained and discussions.

5.2 Computational Results and Discussion

Table 3 provides a solution of the problem as obtained by the CPSO approach. The algorithm was able to obtain an optimal solution, similar to the solution obtained in Bachouch et al. (2010). The solution shows the start time of each task as well as the care giver assigned to each task. Interestingly, all the time windows, working hours of care workers and their competences were not violated while balancing the workload between the care workers. Here, it also noted from the given solution that care giver 2 is not assigned, meaning that, with a better utilization of resources, the care giver can be availed for other responsibilities.

Table 3: CPSO computational results

Task	Care worker	a_i	b_i
1	3	0	19
2	1	0	24
3	1	60	89
4	1	120	154
5	3	120	159
6	3	180	236
7	1	180	241
8	1	300	366
9	3	400	471
10	3	540	616

Further experimentations were conducted based on randomly generated problem instances of different sizes, ranging from 10 to 30 tasks for 3 to 10 care givers. Table 4 presents a list of the problems and their mean computation times obtained by solving the each problem 10 times. The results showed that CPSO can provide good solutions within reasonable execution times. Computations on large scale problems with large number of tasks and care givers demonstrated that the CPSO can perform large scale scheduling problems within a reasonable computation time of a few seconds or minutes, while respecting all the competence and time window constraints. From our experience, the algorithm showed potential for solving large scale problems in excess of 100 workers and 500 tasks.

Table 4: Mean computation times with varying number of care workers

Number of tasks	3 workers	5 workers	10 workers
	CPU time (sec)	CPU time (sec)	CPU time (sec)
10	5.1	5.3	4.4
20	21.7	25.3	28.2
30	48.6	53.3	61.0

6. Conclusion

The home health scheduling problem is a complex but crucial problem. As such, developing decision support tools that can handle homecare staff scheduling problems in which workload must be balanced is imperative. Task assignment or schedule quality is important for improving and maintaining high worker moral while avoiding absenteeism and attrition. In a home care environment where the preference on workload is ill-defined or imprecise, the use of fuzzy set theory concepts is beneficial. We proposed a CPSO approach that to solve staff scheduling problems in a homecare environment, given a set of tasks and a set of available care workers to perform the tasks. An example was adopted from the literature to demonstrate the effectiveness of the algorithm. The suggested approach provides useful contributions to researchers, academicians and practitioners in healthcare services.

The proposed algorithm is a contribution to the healthcare community as it provides an approach to solve staff scheduling problems when the desired management goals and worker preferences are imprecise or ill-structured. It provides more realism to the solution process. Unlike linear programming methods, the algorithm is capable of handling large-scale problems, providing useful solutions in a reasonable computation time. Therefore the proposed approach is an invaluable solution approach for further development of decision support systems for the home healthcare institutions. The method also provides useful contributions to the practicing decision maker.

The proposed approach provides an opportunity to use weights; this provides an opportunity for incorporating the decision maker's preferences and choices in an interactive manner. In practice, decision makers appreciate using interactive decision support that do not prescribe the solution, but rather provide a listing of good alternative solutions. Thus, the decision maker uses information from care givers and the management to make adjustments to the solution process in terms of weights. Overall, CPSO is an effective approach that provides a viable platform for developing decision support tools for solving staff scheduling problems for the home healthcare service providers.

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References

Akjiratikarl, C., Yenradee, P., Drake, P.R. PSO-based algorithm for home care worker scheduling in the UK. *Computers & Industrial Engineering*, vol. 53, pp. 559-583, 2007.

Bachouch, R.B., Liesp, A.G., Insa, L. and Hajri-Gabouj, S. An optimization model for task assignment in home healthcare. *IEEE Workshop on Health Care Management (WHCM)*, pp. 1-6, 2010.

Begur, S.V., Miller, D.M., Weaver, J.R. An integrated spatial decision support system for scheduling and routing home health care nurses, *Technical report, Institute of operations research and the management science*, 1997.

Bellman, R.E. and Zadeh, L.A. Decision making in a fuzzy environment. *Management Science*, vol. 17, pp. 141–164, 1970.

Bertels, S. and Fahle, T. Hybrid setup for a hybrid scenario: combining heuristics for the home health care problem, *Computers & Operations Research*, vol. 33, no. 10, pp. 2866-2890, 2006.

Bezdek, J.C. Editorial: fuzzy models-what are they and why? *IEEE Trans. on Fuzzy Sys*, vol. 1, no. 1, pp. 1–6, 1993.

Borsani, V., Matta, A., Beschi, G. and Sommaruga, F. A home care scheduling model for human resources. *International Conference on Service Systems and Service Management*, pp. 449–454, 2006.

Cheng, E. and Rich, J.L. A home care routing and scheduling problem. Technical Report, TR98-04, *Department of Computational and Applied Mathematics*, Rice University, 1998.

Delgado, M., Herrera, F., Verdegay, J.L. and Vila, M.A. Post optimality analysis on the membership functions of a fuzzy linear problem, *Fuzzy Sets and Systems*, vol. 53, pp. 289-297, 1993.

Drake, P., Davies, B.M. Home care outsourcing strategy, *Journal of Health Organization and Management*, vol. 20, no. 3, pp. 175–193, 2006.

Eveborn, P., Flisberg, P. and Ronnqvist. M. LAPS CARE-an operational system for staff planning of home care. *European Journal of Operational Research*, vol. 171, pp. 962–976, 2006.

Hertz, A. and Lahrichi, N. A patient assignment algorithm for home care services, *The Journal of the Operational Research Society*, vol. 60, no. 4, pp. 481-495, 2009.

Kennedy, J., Eberhart, R.C. Particle swarm optimization, *In IEEE International Conference on Neural Networks*, Seoul, Korea, vol. 4, pp. 1942-1948, 1995.

Mutingi, M. and Mbohwa, C. Complicating features in home healthcare, Working paper, 2013.

Mutingi, M. and Mbohwa, C. Task assignment in home health care: A fuzzy group genetic algorithm approach, *The 25th Annual Conference of the Southern African Institute of Industrial Engineering* 2013, Stellenbosch, South Africa, 9-11 July, pp. 1-10, 2013.

Sakawa, M. *Fuzzy sets and interactive multi-objective optimization*, Plenum Press, New York, 1993.

Shi, Y. and Eberhart R.C. A modified particle swarm optimizer, *In IEEE International Conference on Evolutionary Computation*, pp. 69-73, 1998.

Biography

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