TASK ASSIGNMENT IN HOME HEALTH CARE: A FUZZY GROUP GENETIC ALGORITHM APPROACH

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ABSTRACT

The assignment of home care tasks to nursing staff is a complex problem for decision makers concerned with optimizing home healthcare operations scheduling and logistics. Motivated by the ever-increasing home-based care needs, the design of high quality task assignments is highly essential for maintaining or improving worker moral, job satisfaction, service efficiency, service quality, and to ensure that business competitiveness remains momentous. To achieve high quality task assignments, the assigned workloads should be balanced or fair among the care givers. Therefore, the desired goal is to balance the workload of care givers while avoiding long distance travels in visiting the patients. However, the desired goal is often subjective as it involves the care givers, the management, and the patients. As such, the goal tends to be imprecise in the real world. This paper develops a fuzzy group genetic algorithm (FGGA) for task assignment in home healthcare services. The FGGA approach uses fuzzy evaluation based on fuzzy set theory. Results from illustrative examples show that the approach is promising.

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1 INTRODUCTION

Home healthcare service is an ever growing service industry concerned with the provision of coordinated and optimized healthcare services to patients in their homes [1]. In providing home care services, for instance, healthcare staff may have to attend to acute illness, post-hospitalization treatment, post-operation treatment, chronic illness, permanent disability, terminal illness, among other tasks such as drug delivery [2]. The services provided may include nursing, therapy activities, medical and social services, house cleaning, and drug deliveries. This is necessitated by the ever increasing ageing population, chronic diseases, pressure from societies to improve healthcare service quality, and pressure of governments to contain 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. 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.

The relationship between care givers and patients (clients) is often meant to be long-term, lasting for several years [1] [2]. Therefore obtaining and keeping satisfied clients is crucial for service providers. Due to intensive competition among healthcare service providers, it is so important to optimize the homecare operations, taking into account the target management goals, client satisfaction, and healthcare worker satisfaction. To satisfy the healthcare professionals, overtime work and long distance trips to clients should be minimized while providing satisfactory service to the clients, visiting them at their preferred time of the day.

Decision makers concerned with homecare operations management and logistics are often faced with complex decision problems involving care task assignment, patient assignment to care givers, as well as routing [3] [4]. In particular, the assignment of home care tasks to nursing staff is a complex but important assignment problem for improving home healthcare operations. Designing high quality task assignments or schedules is critical [5]. Poor quality schedules often lead to low worker moral, job dissatisfaction, absenteeism, inefficiency, poor service quality, and the ultimate loss of business. To achieve high quality task schedules, care workloads should be assigned in the most equitable and fair manner; a high quality schedule is balanced or fair among the care givers. In retrospect, the desired goal is to balance the workload of care givers while avoiding long distance travels in visiting the patients. However, the desired goal is often imprecise as it is subject to human judgment; the desired goal should ideally satisfy the care givers, the management, and the patients. As such, the goal tends to be imprecise or fuzzy, adding to the complexity of the problem. In addition, the problem is characterized by a number of constraints which makes it difficult to use conventional optimization methods such as linear programming. In practice, the task scheduling problem is extremely time-consuming, especially when it is performed manually. To that effect, developing robust and interactive decision support tools is necessary to assist the decision maker in designing high quality task schedules for home care services.

In view of the above issues, the design of effective and efficient decision support tools is especially essential for the home health care service provider. The provision of robust decision support tools is necessitated by the desire to improve the service quality or patient care, to improve the schedule quality, and to satisfy the expectations of the healthcare professionals and the management goals. The purpose of this research is to develop a fuzzy group genetic algorithm (FGGA) for task assignment in homecare healthcare services. The specific objectives are as follows;

1. To describe the task assignment problem for homecare operations logistics;
2. To propose a fuzzy group genetic algorithm approach for care task assignment; and,

3. To provide illustrative examples, highlighting useful managerial insights.

The proposed approach uses a fuzzy evaluation technique, based on the concepts of fuzzy set theory. The next section presents a brief description of the home healthcare task assignment problem and its underlying assumptions. Section 3 provides a brief background to fuzzy set theory. Section 4 presents the FGGA approach proposed in this study. Section 5 provides illustrative computational experiments, results and discussions. Finally, concluding remarks and further research prospects are provided in Section 6.

2 PROBLEM DISCRIPTION

Briefly, the home care task assignment problem is described as follows [1]: We are given a set of home care tasks, $T = \{1,...,n\}$, where each task i is defined by a task duration p_i and a time window $[e_i,l_i]$; e_j and l_j represent the respective earliest start and latest start times of the task. In addition, the tasks may be patient visits, drug delivery, and any other administrative duties. The tasks are to performed by an available set of workers $W = \{1,...,w\}$, each worker j having a scheduled working time of day. Furthermore, each task must be allocated to a qualified care worker, with skills indicated by q_j, according to the required competency c_i. In this study, it is required to balance the workload allocation between the staff. The implication is that the variation of individual workloads should be within acceptable limits; the objective is to limit, as much as possible, the variation of care workers' individual workloads from the average workload. Time window constraints specified by the clients should be satisfied. Overall, this will maximize the schedule quality.

2.1 General assumptions

For the purpose of this study, we model the task assignment problem based on the following simplifying assumptions for problem;

- The travel times involving patient visits are treated as part of the task duration, measured in minutes;
- Care giver visits always occur via the home base, as some tasks are done at the base;
- The skills of care workers are expressed as q_j in the range $[1,h]$, in which case 1 and h represent the lowest and highest skills, respectively;
- Each task has a pre-specified time window $[e_i,l_i]$ during which the assigned care giver must begin the task operation;
- Each task should only be assigned to a care worker that possesses the right skills as required by the task.
- All tasks are to be completed within the care worker's working time of day, defined by $[e_j,l_j]$ for each worker j;

2.2 Problem objective and constraints

Following the above-described problem, the main objective of care task assignment is to minimize the variation of each individual care worker's workload from the average workload. The following constraints must be observed [1];

- Each task is assigned to one and only one care giver;
- Each task must begin within its respective time window $[e_i,l_i]$;
- The total workload for each care worker must be within the lower and upper bounds, m and M, respectively; and,
- All tasks assigned to a care giver must be completed within the working time of the care giver.

3 FUZZY SET THEORY: A BACKGROUND

Fuzzy set theory models imprecision and uncertainty in a non-stochastic sense [6]. A fuzzy number represents imprecise quantities, such as "about 10," and "substantially greater than

10." Thus, a fuzzy set is a class of objects with no sharp boundary between the objects that belong to that class and those that do not. Fuzzy set theory, unlike Boolean logic, deals with degrees of membership, rather than membership or non-membership [7]. To further clarify the concept of fuzzy theory, we distinguish fuzzy sets from crisp sets 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,

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

Definition 2: *Fuzzy Set*. Let X be the universe of discourse whose elements are denoted by x. Then, the grade of membership of x in a fuzzy set A is be defined as $\mu_A(x) \in [0,1]$, where $\mu_A(x)$ is the membership function of x in A, which maps each element of X to a membership value in [0,1]. The fuzzy set A in X is a set of ordered pairs;

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

By the above definition, the closer the value of $\mu_A(x)$ is to 1.0, the more x belongs to A, and vice versa. The elements of a fuzzy set indicate the value of each element in the set and its grade of membership.

4 A FUZZY GROUP GENETIC ALGORITHM APPROACH

The FGGA approach is a development from group genetic algorithm proposed by Falkenauer [8] for addressing grouping problems [9]. The FGGA approach and its elements, including chromosome coding, initialization, and genetic operators, are presented in this section.

4.1 FGGA coding scheme

To enhance the performance of FGGA, we develop a unique coding scheme which exploits the group structure of the problem [10]. Let A = [1, 2, 3,…,n] be a chromosome representing a set of n tasks to performed by p care givers. The evaluation of C involves partitioning clients along C into m groups such that the workload is balanced, or 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.

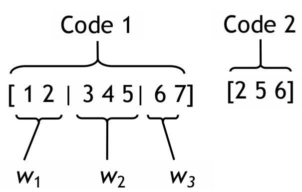

Figure 1: FGGA chromosome coding scheme

Figure 1 provides an illustration of the group structure of the chromosome code consisting of two codes: code 1 represents the assignment of care workers w_1, w_2, and w_3, to groups of clients or tasks {1,2}, {3,4,5}, and {6,7}, respectively. Code 1 is the actual group structure upon which the genetic operators act, while Code 2 denotes the last position of each client or task group, that is, it records the position of the delimiter or frontier "|" which separates client groups.

4.2 Initialization

An initial population of size p is created by random assignments of tasks to care givers. First, the care tasks are arranged in ascending order of their start times. In case of a tie, rank the duties according to their activity duration. For each care giver, assign a duty at a probability *b*, starting from the earliest. From the unassigned set of duties, assign duties beginning from the earliest. This procedure increases the likelihood of the initialization process to generate initial feasible solutions.

4.3 Fitness evaluation

We use a fuzzy evaluation technique to evaluate the fitness of each chromosome. In this regard, we let A represent a feasible task assignment, and x_{ij} a binary variable that defines whether a task i is assigned to care giver j with rank k, or not. It follows that the average workload for the assignment can be expressed in the form,

$$a = \frac{\sum_i \sum_j p_i x_{ij}}{\sum_i \sum_j x_{ij}} \tag{3}$$

The main aim is to minimize a function f_j, defining the variation of each care giver's total workload from the average workload a. The function f_j is given by the expression;

$$f_j = \left| \sum_i p_{ij} x_{ij} - a \right| \qquad \text{for all } j \tag{4}$$

Nevertheless, since the workload f_j should be within acceptable limits, we use a fuzzy function evaluation. Triangular functions have widely been used as membership functions, with appreciable success [11]. Figure 2 illustrates the triangular membership function, where a fuzzy number A is a triangular fuzzy number with a membership function of the form $\mu_j : X \to [0,1]$. It is important to note that μ_A is a normalized function that shows the desirability of the task assignment relative to the most preferred (average) workload, f_0.

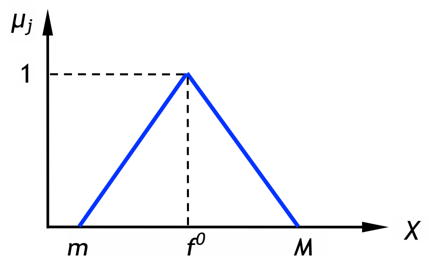

Figure 2: Preferred error as a triangular fuzzy number

Since the care givers' workloads should be as close as possible to f_0, we define the following membership function for every care worker j;

$$\mu_j(x) = \begin{cases} (f_j - m)/(f^0 - m) & \text{if } m \le x \le a \\ (f_j - M)/(f^0 - M) & \text{if } a \le x \le M \\ 0 & \text{if otherwise} \end{cases} \tag{5}$$

As a result, the final objective function can be formulated as a function of the normalized functions (membership functions) as follows;

$$z = \left(\frac{\mu_1(x)}{\omega_1} \wedge 1 \right) \wedge \left(\frac{\mu_2(x)}{\omega_2} \wedge 1 \right) \wedge \ldots \wedge \left(\frac{\mu_W(x)}{\omega_W} \wedge 1 \right) \tag{6}$$

where, ω_j denotes the weight behind task assignment of care worker j.

The weight ω_j offers the modeller an opportunity to model his/her choices or preferences to reflect management and/or care givers' preferences. This provides the FGGA an advantage over other metaheuristic approaches.

To compute fitness of each chromosome, FGGA maps the function z to a fitness function F_k,

$$F_k(t) = \max\left[0, z^m(t) - z_k(t)\right] \tag{7}$$

where, $z_k(t)$ is the objective function of chromosome k at iteration t; and z^m is the maximum objective function in the current population.

4.4 Selection

The selection operator selects the best performing chromosomes into a mating pool, *tempp*. The remainder stochastic sampling without replacement method was adopted in this study [12] [13]. Each chromosome k is selected and stored in the mating pool according to its expected count e_k,

$$e_k = \frac{F_k}{(1/p)\sum_{k=1}^{p} F_k} \tag{8}$$

where, F_k is the fitness function of the k^{th} chromosome.

In this strategy, each chromosome receives copies equal to the integer part of e_k, plus additional copies obtained by using the fractional part of e_k as a success probability of getting an additional copy of chromosome k into *tempp*. As such, the best performing candidates are selected with higher probability into the mating pool.

4.5 Crossover

Crossover is a mechanism by which selected chromosomes mate to produce new offspring, called selection pool [9]. The mechanism enables FGGA to explore unvisited regions in the solution space. Groups of genes in the selected chromosomes are exchanged at a probability *pcross*. First, a crossover point between 1 and g is randomly generated, where g is the number of groups. Second, the groups on the right of the crossover point are swapped. Third, the offspring are repaired as necessary. The process is repeated till the desired pool size, *poolsize*, is achieved. Figure 3 demonstrates the crossover mechanism using parent chromosomes P_2 and P_2. The offspring O_1 and O_2 are repaired to produce O_1' and O_2'.

Parents:	Offspring:	Repaired:
P_1: [5 2 | 4 3 1 | 6]	O_1: [5 2 | 3 1 | 6]	O_1': [5 2 | 3 1 | 4 6]
P_2: [6 5 | 3 1 | 4 2]	O_2: [6 5 | 4 3 1 | 4 2]	O_2': [6 5 | 4 3 1 | 2]

Figure 3: An example of crossover and repair mechanisms

After crossover, some genes may appear in more than one group, while others may be missing. Such offspring are repaired by eliminating duplicated genes on either side of the crossover point, and then inserting missing genes into those groups with the least loading. Thus, group coding takes advantage of the group structure to generate new offspring. Mutation follows the crossover operator.

4.6 Mutation

Mutation is applied to every new chromosome using two mutation operators: swap mutation and shift mutation [9]. Swap mutation exchanges genes between two groups in an individual chromosome, while shift mutation moves a randomly chosen frontier between two adjacent groups by one step to the right or to the left. Thus, the mutation operator provides FGGA with local search capability, a phenomenon called intensification. Figure 4 (a) and (b) provides an illustration of swap and shift mutation mechanisms, respectively.

Before mutation :	[5 2 | **4** 3 1 | **6**]	[5 2 | 4 3 1 **|** 6]
After mutation :	[5 2 | **6** 3 1 | **4**]	[5 2 | 4 3 **|** 1 6]
	(a)	(b)

Figure 4: An illustration of swap and shift mutation

4.7 Inversion and diversification

As iterations proceed, the population may prematurely converge to a particular solution, hence, it is crucial to control the population diversity [10]. Inversion is a mechanism that probabilistically rearranges the genes of a chromosome in the reverse order. Simply put, the inversion operator transforms a chromosome [1 2 | 4 | 3 5 6] to [6 5 3 | 4 | 2 1]. To check diversity, we first define an entropic measure H_i for each client i;

$$h_i = \sum_{j=1}^{n} \frac{(x_{ij}/p) \cdot \ln(x_{ij}/p)}{\ln(n)} \tag{9}$$

where, x_{ij} is the number of chromosomes in which client i is assigned position j in the current population; n is the number of clients. Then, diversity H becomes,

$$h = \sum_{i=1}^{n} h_i / n \tag{10}$$

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

4.8 Overall FGGA algorithm

The overall algorithm incorporates the above operators, beginning with the selection of suitable input parameters. The selected input parameters were: crossover probability (0.35), mutation probability (0.01), and inversion probability (0.04). An initial population, $P(0)$, is generated randomly by random assignments of clients to care givers. The algorithm then proceeds into an iterative loop involving selection, crossover, mutation, inversion, and until termination condition is reached (maximum number of pre-specified T). Figure 5 presents the overall structure of the proposed FGGA.

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

Figure 5: Overall FGGA pseudo-code

We present illustrative examples, computational results, and relevant discussions in the next section.

5 COMPUTATIONAL EXPERIMENTS, RESULTS AND DISCUSSIONS

5.1 Computational experiments

We adopt an illustrative example from Bachouch et al. (2010) as in Table 1 and 2. The data consists of task and care worker information. Task information comprises task duration, time window and the competence requirement. The care giver information comprises working time and qualification ranking.

Table 1: Task information [1]

Task	Duration	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 [1]

Care worker	e_j	l_j	q_j
1	19	0	60
2	24	0	60
3	29	60	120
4	34	60	120
5	39	120	180
6	56	120	180
7	61	180	240
8	66	240	300
9	71	360	400
10	76	540	600

In addition to the example given, further problem examples of sizes ranging from 10, 15, 20, and 25 tasks, with 3 to 15 care givers were generated randomly and tested using the FGGA approach. We provide the results and discussion in the next section.

5.2 Results and discussions

Table 3 provides the obtained optimal solution of the problem that is presented in [1]. The task assignment solution shows the start time of each task as well as the care giver assigned to each task. Here it can be seen from the given solution that care give 2 is not assigned.

Further experimentations with large numbers of tasks and care givers demonstrated that the FGGA can perform large scale task assignment problems within a reasonable computation time of a few seconds or minutes, while respecting all the competence and time window constraints.

Table 3: FGGA 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

6 CONCLUSION

Designing decision support tools that can address the homecare task assignment problem in which workload must be balanced is a cause for concern. Task assignment or schedule quality is necessary to maintain or improve worker moral and avoid absenteeism and attrition. In an environment where the preference on workload is ill-defined or imprecise, the use of fuzzy set theory concepts is beneficial. This paper proposed a fuzzy group genetic algorithm that to solve task assignment problems in a homecare environment, given a set of tasks and a set of available care workers to perform the tasks. An illustrative example was adopted from the literature, demonstrating the effectiveness of the algorithm. The suggested approach provides useful contributions to researchers and academicians as well as practitioners in the health service sector.

6.1 Contributions to theory

The proposed algorithm is a contribution to the Industrial engineering community as it provides an approach to solve task assignment problems when the desired management goals and worker preferences are imprecise or ill-structured. Unlike other metaheuristic approaches such as genetic algorithms and simulated annealing, this approach provides more realism to the solution approach. Contrary to conventional linear programming methods, the algorithm is capable of handling large-scale problems, while 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.

6.2 Contributions to practice

The proposed fuzzy group genetic algorithm provides an opportunity to use weights, which gives a way of incorporating the decision maker's preferences and choices in an interactive manner. For the practicing Industrial Engineer (IE), it is important to appreciate the use of interactive decision support that do not prescribe the solution, but rather provide a listing of good alternative solutions, upon which the IE can make the most appropriate decision. Thus, the decision maker uses information from care givers and the management to make adjustments to the solution process in terms of weights. Overall, the fuzzy group genetic algorithm proposed in this paper is an effective and efficient approach that provides a viable platform for developing decision support tools for solving task assignment problems for the home healthcare service providers.

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