Solving a multi-objective model toward home care staff planning considering cross-training and staff's preferences by NSGA-II and NRGA

Hamed Habibnejad-Ledari\textsuperscript{a}, Masoud Rabbani\textsuperscript{ab}, Nastaran Ghorbani-Kutenaie\textsuperscript{c}

\textsuperscript{ab} School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
\textsuperscript{c} Department of Industrial Engineering, School of Engineering, Alzahra University, Tehran, Iran

Abstract

Home care (HC) staff assignment problem is defined as deciding which staff to assign to each patient. In this study, a multi-objective non-linear mathematical programming model is presented to address staff assignment problem considering cross-training of caregivers for HC services. The first objective of the model minimizes costs of workload balancing, cross-training and maintenance. The second objective minimizes the number of employees for each service while the satisfaction level of caregivers is maximized through the third objective function. Several constraints including skill matching, staff preferences, regularity, synchronization, staff absenteeism and multi-functionality are considered to build a service plan. Due to NP-hardness of the problem, a non-dominated sorting genetic algorithm (NSGA-II) with a proposed who-rule heuristic initialization procedure is applied. Due to absence of benchmark available in the literature, a non-dominated ranking genetic algorithm (NRGA) is employed to validate the obtained results. The data required to run the model are gathered from a real-world HC provider. The results indicate that the proposed NSGA-II is superior to the NRGA with regard to comparison indexes. Based on the results obtained, it can be determined which staff should be cross-trained for each service and how the staff are assigned to services.

Keywords: Home care; Staff assignment; Cross-training; Optimization; NSGA-II; NRGA.

1. Introduction

Home care (HC) service which is defined as visiting, assisting, nursing and delivering medical, nonmedical and paramedical services to patients, elderly and disabled people at their homes was offered as an alternative to traditional hospitalization as well as to give opportunity to citizens to stay in their homes [1-4]. HC services consist of nonmedical services such as
cleaning, preparing meals, doing housework, bathing, dressing and shopping and medical services such as nursing, physiotherapy and occupational therapy, taking care of children, elderly, people with disabilities and conditions treated (e.g., patients suffering AIDS, cancer, neurological disorders). The main advantages of HC are considerable reduction in hospitalization rate, improving the quality of life and significant cost saving [5, 6].

Increasing health care costs and change in age distribution of population have led to an increase in the number of HC clients and HC providers are, therefore, faced with a large number of patients [7, 8]. At the same time, these providers have to reduce their resources to mitigate costs and at the same time increase their competitiveness. Moreover, demand is unpredictable and service duration is very volatile. Thus, they strive to achieve efficient workforce management which is necessary to increase service quality and reduce operational costs. However, in reality, designing an efficient workforce management policy is hard to attain [7]. In the literature, this problem is referred to as HC staff assignment problem which is concerned with deciding which staff to assign to each admitted patient [1]. HC service involves dealing with a large number of patients with rapid change in clinical and social conditions. To deal with this issue, the number of caregivers should be increased. To deal with this issue, the number of caregivers should be increased. It increases service quality and leads to high patients’ satisfaction and save their time [7]. However, increase in the number of caregivers will lead to an increase in operating and human resources costs as well as idle time of caregivers which in not economically justifiable. On the other hand, reducing number of caregivers leads to deteriorate the service quality [9, 10]. Therefore, it is recommended that instead of increasing the number of caregivers, their skills and ability be risen so that they can operate more services. This description refers, in the literature, to a concept called "cross-training".

Cross-training the staff is one of the first steps in HC staff assignment [11]. Increasing cross-trained staff leads to production flexibility and is a significant goal for today’s organizations [12, 13]. Achieving this goal at organizations or department level leads to create individual training goals [14]. Cross-trained staffs are capable of performing multiple services. Creating cross-trained staff includes three main steps [11]: (1) hiring staff with the appropriate basic skills, (2) giving them the necessary off-the-job training, and (3) assigning services to them so the required experience is acquired and maintained. Cross-training enjoys numerous advantages such as positively affecting operational performance indicators (e.g., the throughput time), dealing more
effectively with fluctuation in the supply of human resources, increasing the possibility of workload sharing, creating opportunities for job rotation, and minimizing idle time [15, 16].

Most of the above-mentioned advantages can be achieved without having to perform full cross-training. A full cross-trained system is advantageous only when the relative flexibility costs are low [17]. Achieving a full cross-trained system is, however, very costly and may lead to significant productivity loss due to the shift of staff between services. Also, there are some social reasons for limiting cross-training and labor flexibility in firms. A full cross-trained workforce makes jobs more similar which may in turn impair social identity and lead to motivational deficits. It may also cause social loafing (i.e., a situation in which no one feels exclusively responsible to do the dirty work) [18, 19]. Referring to the foregoing discussion, cross-training can be potentially motivating or demotivating based on the selected policy which suggests that it is often better not to attempt full cross-training. This raises the question “who should be cross-trained for each service?”.

In this study, we address staff assignment problem considering cross-training of caregivers in health care systems to determine which staff should be cross-trained for each service and how they should be assigned to services. We propose a multi-objective non-linear mathematical programming model where the first objective function aims to minimize workload balancing, cross-training as well as maintenance costs. Second objective function attempts to minimize the number of employees for each service, while the third objective function is concerned with maximization of caregivers’ satisfaction level. The behavior of the various elements and features of the model is evaluated in a real-world HC provider as our case study. Several constraints with respect to skill matching (SM), staff preferences (PRE), regularity (REG), synchronization (SYN), staff absenteeism, time capacity and multi-functionality level are taken into account to build a service plan. Also, we used chaining concept to balance workloads of caregivers and allow shifting jobs among caregivers. Finally, due to the cultural conditions prevailing in Iran, we supposed that services for men and women are separately performed. The problem being NP-hard, a non-dominated sorting genetic algorithm (NSGA-II) with a proposed heuristic initialization procedure is applied and the proposed model is solved based on a data set collected from our case. In the proposed initialization heuristic, a who-rule is applied to determine which staff should be assigned to services. The parameters are tuned using Taguchi method. Due to absence of benchmark available in the literature, a non-dominated ranking genetic algorithm
(NRGA) is employed to validate the obtained results. Three comparison indexes are considered and the results show the superiority of the proposed NSGA-II over the NRGA with respect to comparison indexes.

The reminder of this study is organized as follows. Section 2 provides a brief review of the related literature. Section 3 presents problem definition as well as the assumptions in more detail. In Section 4, the parameters and decision variables are introduced and the mathematical model is presented. Section 5 details the solution methodology and designs the NSGA-II to solve the proposed model. Also implementation of Taguchi method and other details proposed for parameter tuning is described in this Section. Our real-world case study together with the relevant computational results are given in Section 6. Finally, Section 7 is dedicated to concluding remarks and directions for future research.

2. Literature review

2.1. HC staff assignment problem

Staff assignment problem in health care systems is an interesting topic for researchers in different fields. In the literature, optimizing different financial measures such as personnel cost, overtime cost, outsource cost, waiting cost and travel cost has been considered as objective function. Borsani, et al. [3] presented an integer linear programming (ILP) model for scheduling human resource as a HC staff planning problem, and applied it to a real data set collected from Italian HC providers. Akjiratikarl, et al. [20] addressed scheduling of home care workers in an attempt to minimize the distance traveled by workers. They used a particle swarm optimization (PSO) algorithm to deal with this problem. Hertz and Lahrichi [21] presented a mixed integer programming (MIP) model with the aim of balancing the workload of the nurses and minimizing the travelled distances. They applied a Tabu search (TS) algorithm to handle the proposed model. Rabeh, et al. [22] proposed a mixed ILP model with the objective of minimizing both the travelled and waited times, and took advantage of Lingo to solve the problem. Rasmussen, et al. [1] studied vehicle routing problem (VRP) with time windows in health care system. They formulated it as a set partitioning problem and presented a branch-and-price solution algorithm based on the soft preference constraints to solve it.

Gamst and Jensen [23] addressed the long-term home care scheduling problem and designed a branch and price algorithm to solve the proposed model in an attempt to minimizing the overall
cost and maximizing the service level. Liu, et al. [24] proposed two MIP models to address VRP in home health care logistics. They considered delivery, pickup and time windows and applied genetic algorithm and TS method to solve the presented model. Allaoua, et al. [2] presented an ILP model with the aim of establishing the optimal routes and rosters for the HC staff, and applied a metaheuristic based on decomposition to deal with this problem. A mathematical model was developed by Mankowska, et al. [25] in an attempt to optimize performance measures concerning economic and service level. They applied a heuristic based on a sophisticated solution representation to solve the problem. Duque, et al. [26] proposed a bi-objective programming model with the aim of minimizing the distance travelled by caregiver and maximizing the service level, and designed a two-stage solution strategy to deal with it.

There are a few papers considering continuity of care and demand or uncertainty in staff assignment problem in health care environment. Lanzarone and Matta [5] studied the robust HC staff assignment problem under continuity of care and proposed an analytical structural policy to tackle this problem. They believed robust staff planning is crucial for operations in home care companies to increase quality of their services. Mutingi and Mbohwa [10] designed a fuzzy simulated algorithm to address caregivers scheduling problem in home care companies. Based on the obtained results, their algorithm has capability to tackle this problem. Carello and Lanzarone [27] proposed a cardinality-constrained robust assignment problem and analyze it on a real home care company as case study. The results show capability of model to reduce nurses overtimes costs. Mutingi and Mbohwa [28] presented a fuzzy particle swarm optimization approach for staff assignment problem in healthcare environment with the aim of maximizing workload balance and minimizing violation of patients’ time window. Mutingi and Mbohwa [29] addressed caregiver planning problem and designed a fuzzy genetic algorithm to solve the problem. Their model included multiple conflicting objectives and preference constraints.

2.2. Cross-training

Recently, cross-training has become very important for the global business to deal with variations in product mix and fluctuations in the supply of human resources. Both in the literature and in practice, implementation of cross-training policies has been recognized to play a significant role in organizations. Bokhorst, et al. [30] investigated the need of incorporating the who-rule in simulation studies. They explored the flow time impacts of different who-rules on
dual resource constrained systems where workers differ from each other in terms of workload, number of skills and task proficiencies. In another paper, Bokhorst, et al. [31] presented an integer goal programming model to evaluate cross-training policies where the objective was to minimize flow time mean and standard deviation from the operation management and human resource management viewpoints. Slomp, et al. [15] proposed an integer programming model for minimizing workload and cross-training costs. They attempted to answer the question “Which worker should be cross-trained for each machine?” Yang [32] evaluated and compared a set of cross-training policies with different numbers of cross-trained workers, additional machines and additional skills per cross-trained worker in job shops.

Yue, et al. [33] studied cross-training policies in a parallel job-shop environment. They considered learning and forgetting phenomena and assumed that new part types are frequently introduced into the system. Li, et al. [34] proposed a bi-objective integer programming model in an attempt to minimize average salary and maximize satisfaction degree. They employed a NSGA-II algorithm and compared its results with those of MOPSO. Liu, et al. [35] proposed a multi-objective model aiming at balancing total processing times and minimizing total training cost in seru production systems. They also developed a three-stage heuristic algorithm to tackle the proposed model. Taking into account cross-training, the effect of worker learning and forgetting and the heterogeneity within worker pool, Feng and Fan [36] simulated a production line in car engine parts plant and compared WIP, adaption time and productivity under different cross-training policies with each other. Habibnejad, et al. [37] presented a bi-objective non-linear programming model with the aim of minimizing workload balancing, cross-training as well as maintenance and transportation costs and maximizing caregivers’ satisfaction level. They considered several constraints such as maximum allowable distance for transportation, maximum allowable consecutive shifts and budget capacity and solved the proposed problem with an exact algorithm.

Table 1 provides a summary of the researches reported on home care systems according to the most common constraints and objective functions taken into account for home care services planning in chronological order. Also, Table 2 presents the cross-training and labor assignment features and summarizes which of these features are handled in the literature review. This paper, for the first time, incorporates the cross-training concept in home care staff assignment problem based on a real-world HC provider. Also, we studied cross-training and labor allocation using
who-rule, simultaneously and considered the most common constraints taken into account for cross-training and labor allocation problem, concurrently.

[Please insert Table 1 here]

[Please insert Table 2 here]

3. Problem definition

DAM home care medical center is a non-governmental organization founded in Iranian academic center for education, culture and research (ACECR) in 1999. This 24-hour medical center provides its 11000 patients in Tehran, Iran with HC services. The process commences when a citizen applies for HC services and a preadmission is initiated. Each visit commonly takes between 1 to 5 hours. The manager decides which caregiver should be assigned to each patient by taking into account a set of factors such as the patients’ medical statue, caregivers’ skills and training level and the patients’ and caregivers’ preferences.

The objectives of the organization are minimization of the number of employees for each service and costs associated with workload balancing, training and maintenance and maximization of staffs’ preferences so that the patients’ needs are met. Some constraints are required to build a service plan at DAM organization as follows:

1. Skill matching (SM): a service needs staffs with specific skills or training
2. Staff preferences (PRE): staff preferences respecting time and staff assignment
3. Regularity (REG): the number of employees for each service
4. Synchronization (SYN): a service needs more than one staff

Also, each caregiver can be cross-trained for a maximum number of services called multi-functionality level. A caregiver’s multi-functionality refers to the number of services who is able to deliver. The maximum number of working hours per day is another constraint that the organization has to take into account. Since there are enough regular working hours to cover all requirements, overtime and non-regular shifts are not involved. In this paper, the chaining concept is used to reallocate jobs among caregivers, leading to a more balanced workload which is desired from a social and economic viewpoint. Finally, we supposed that services for men and women are separately performed due to the cultural conditions prevailing in Iran.
4. Proposed model

In this section, our multi-objective mathematical model is presented in which the first objective aims to balance workload and minimize cross-training and maintenance costs. In the second objective function, the number of employees for each service is minimized, while the third one attempts to maximize caregivers’ preferences.

Indices

\( i \)  
Index of service type \((i = 1, \ldots, I)\).

\( j \)  
Index of caregiver \((j = 1, \ldots, J)\).

\( d \)  
Index of day \((d = 1, \ldots, D)\).

\( t \)  
Index of time slot \((t = 1, \ldots, T)\).

Parameters

\( I \)  
Number of services,

\( J \)  
Number of caregivers,

\( D \)  
Number of days,

\( T \)  
Set of time slots

\( JM \)  
Set of male caregivers,

\( JF \)  
Set of female caregivers,

\( MS \)  
Set of services that need male caregivers,

\( FS \)  
Set of services that need female caregivers,

\( A_{dt} \)  
Set of absent caregivers in day \( d \) in time slot \( t \),

\( NC_i \)  
Number of caregivers needed for service \( i \)

\( M_j \)  
Maximum multi-functionality for caregiver \( j \).

\( E_{ij} \)  
Efficiency factor for service \( i \) when performed by caregiver \( j \),

\( Time_i \)  
Normalized visit time of service \( i \),

\( C_{jt} \)  
Costs associated with caregiver \( j \)’s workload deviation from the average value in time slot \( t \),

\( TC_{ij} \)  
Costs of training caregiver \( j \) for service \( i \),

\( MC_{ij} \)  
Maintenance costs of caregiver \( j \) for service \( i \),
Demand of service \(i\) in day \(d\) in time slot \(t\),

\[ CP_{ij} \] 1, if caregiver \(j\) prefers service \(i\); 0 otherwise,

Maximum working time of caregiver \(j\) in each day,

\(\pi_1, \pi_2\) Weight factors,

\(R\) A big number.

**Decision variables**

\(S_j\) Satisfaction level of caregiver \(j\),

\(R_i\) Number of caregivers assigned to service \(i\),

\(Y_{ij}\) 1, if caregiver \(j\) is cross-trained for service \(i\); 0 otherwise,

\(Z_{ijdt}\) 1, if caregiver \(j\) is assigned to service \(i\) in day \(d\) in time slot \(t\); 0 otherwise,

\(X_{ijdt}\) Number of times caregiver \(j\) is assigned to service \(i\) in day \(d\) in time slot \(t\).

We assume that training should lead to workload balance among caregivers in various circumstances and as a result, there is always the possibility of chaining. Equally loaded caregivers can be achieved by minimizing the caregivers’ workload deviation from the average workload in different periods. Some of the services in the organization need special care due to the cultural conditions prevailing in Iran; i.e., they need either male or female caregivers. The sets of \(JM, JF, MS\) and \(FS\) are defined for this purpose. \(NC_i\) is defined due to the synchronization constraint indicating some services could possibly call for more than one caregiver. The cost of training caregiver \(j\) for service \(i\) is denoted by \(TC_{ij}\) and for a caregiver who is already qualified for a particular service is zero. \(E_{ij}\) is determined by the operational team. The smaller the value of \(E_{ij}\) is from 1, the more efficient caregiver \(j\) is for performing service \(i\). On the other hand, as \(E_{ij}\) goes higher than 1, caregiver \(j\) is assumed to become more inefficient in performing service \(i\).

4.1. **Mathematical model**

\[
\min z_1 = \pi_1 \sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} C_{jt} \left[ \sum_{l=1}^{L} \text{Time}_{i,j,d} X_{ij,d,t} - \tilde{X}_{d,l} \right] + \pi_2 \sum_{i=1}^{I} \sum_{j=1}^{J} Y_{ij} \left[ TC_{ij} + MC_{ij} \right] \tag{1}
\]

\[
\min z_2 = \sum_{i=1}^{I} R_i \tag{2}
\]

\[
\max z_3 = \sum_{j=1}^{J} S_j \tag{2}
\]
The first objective function aims to minimize two terms as follows: The first term represents costs associated with caregivers’ workload deviation from the average value. It balances workload among caregivers which in turn results in economic and behavioral benefits. The second term concerns training and maintenance costs. These two terms establish a trade-off between the balancing cost (as operating cost) and cross-training cost. The factors $\pi_1$ and $\pi_2$ are
weight factors and setting them differently leads to different arguments. A higher value of $\pi_1$ indicates that the organization emphasizes workload balancing. On the other hand, cross-training costs may lead to higher settings for the factor $\pi_2$. The second objective function attempt to minimize the number of employees for each service. Finally, the last objective function represents maximizing caregivers’ satisfaction.

Equations (3) calculate caregiver’s workload deviation from the mean workload. Constraints (4) are related to regularity constraint. Constraints (5) guarantee that a caregiver is assigned to a given service only if he is trained for it. Constraints (6) force caregivers to be assigned to the services they have to perform. Equations (7)-(9) guarantee that the demand for different services (whether general, special or synchronization constraint) is assigned to the caregivers. Constraints (10) prevent working hours per day from exceeding maximum working time of each caregiver in each day. The maximum desired multi-functionality of each caregiver is represented by Constraints (11). The caregivers’ satisfaction level is calculated through Constraints (12). Constraints (13) ensure that no service is assigned to absent caregivers. Finally, the domain of each decision variable is denoted by Constraints (14)-(16). The presented model can be simplified by linearizing absolute term in Objective Function. The nonlinear term $\left| \sum_{i}^{l} Time_i \cdot X_{ijdt} - \bar{X}_{dt} \right|$ in the 1th term can be linearized by Equations (17) and Constraints (18). Also, the nonlinear term $\left| \sum_{i}^{l} Time_i \cdot X_{ijdt} - \bar{X}_{dt} \right|$ is replaced by term $(\eta_{jdt}^1 + \eta_{jdt}^2)$

$$\eta_{jdt}^1 - \eta_{jdt}^2 = \sum_{i}^{l} Time_i \cdot X_{ijdt} - \bar{X}_{dt} \quad \forall j, d, t \in T$$ (17)

$$\eta_{jdt}^1, \eta_{jdt}^2 \geq 0 \quad \forall j, d, t \in T$$ (18)

5. Solution methodology

NSGA-II which was first proposed by Deb, et al. [38] is one of the most famous and applicable multi-objective evolutionary algorithms. This famous rises from its capability to cope with constraint as well as to promote diversity of solutions. The efficiency and convergence of the GA has verified in the literature. In this algorithm, a non-dominance technique and a crowding distance is used to find a set of solutions ordered by fronts and select the population
fronts. The Pseudo-code of proposed NSGA-II is shown in Algorithm 1. The main components of applied NSGA-II is discussed in details in the following subsections.

Algorithm 1. NSGA-II procedure.

Generate initial solution based on the Algorithm 2.
Rank the individuals based on non-dominated sorting.

\[ I = 1 \]

Do

Apply binary tournament selection, crossover and mutation operators, respectively.
Merge all population.
Rank the individuals based on non-dominated sorting.
Truncate the population.
Rank the individuals based on non-dominated sorting.

\[ I = i + 1 \]

While \( i \) = Maximum number of iterations.

5.1. Chromosome representation

The first step in NSAG-II and many other meta-heuristic algorithms is designing a suitable chromosome to present solutions and maintain the feasibility of the generated chromosomes. Each chromosome is consisted of a sequence of real, binary or integer numbers genes and represented by two approaches: direct and indirect encoding. In this study, direct approach is used which means a chromosome totally represents a solution. The designed chromosome is shown in Figure 1. In this representation, each gene stands for a service and the chromosome shows which service is assigned to which caregiver in which time slot. Figure 1 indicates that service 3 is assigned to caregiver 2 in time slot 2 in day 1.

[Please insert Figure 1 here]

5.2. Initialization

A random population for initialization leads to produce some infeasible solutions. To deal with this issue, a heuristic approach is proposed to generate feasible initial solutions. We used
who-rule to determine which caregiver should be assigned to services. In this rule, a service is assigned to a caregiver according to the workloads of caregivers so that the workloads of caregivers are balanced [39]. The Pseudo-code of this approach is summarized in Algorithm 2.

**Algorithm 2.** Heuristic procedure for initialization.

Set the list of the available caregivers \((AC)= [1,…,J]\).

\(e\) = a pre-defined tolerance for workload balancing.

\(it=1\)

Do

for \(d=1\) to number of days, do

for \(t=1\) to number of time slots, do

Remove absent caregivers from the \(AC\).

for \(i=1\) to number of services, do

if \(i\in MS\)

Remove female caregivers form the \(AC\).

else if \(i\in FS\)

Remove male caregivers form the \(AC\).

for \(k=1\) to number of \(D_{idt}\), do

Remove a caregiver from the \(AC\), if service \(i\) has not been already assigned to him/her and the numbers of services assigned to him/her is equal to his/her maximum multi-functionality level.

Remove caregivers from the \(AC\), if they don’t have enough time to perform service \(i\).

if the workload of a caregiver in \(AC > e.\min(\text{workload of the caregivers in } AC)\)

Remove this caregiver from the \(AC\) (who-rule).

Choose \(N_i\) caregivers based on the following priorities:

1. Caregiver has already performed service \(i\).
2. Caregiver prefers to perform service \(i\).
3. Caregiver is selected randomly.

Update the decision variables according to this assignment.

end for

end for
end for
end for

\(it=it+1\)

While \(it=\) Maximum number of populations.

### 5.3. Non-dominated sorting

Non-dominated sorting algorithm assigns a rank to each individual in population based on non-domination before the selection strategy as well as after applying crossover and mutation operators [40]. To rank and select the fronts, a non-dominance technique and a crowding distance is applied. In a multi-objective model, solution \(x\) dominates solution \(y\) if:

1. \(\text{OFV}(x) \leq \text{OFV}(y)\) for all objectives.
2. \(\text{OFV}(x) < \text{OFV}(y)\) for at least one objective.

If a solution is not dominated by any other solution, it belongs to front one. Also, solutions in front tow are dominated only by solutions in front one.

After classifying the solutions in different fronts, a crowding distance is used to estimate the density of solutions and ranking the solutions in the same front. The crowding distance is computed as follows:

\[
d_i = \sum_{j=1}^{B} \left| \frac{f_{j}^{i+1} - f_{j}^{i-1}}{f_{j}^{\max} - f_{j}^{\min}} \right|
\]

(17)

where \(B\) is the number of objective functions, \(f_{j}^{i+1}\) is the \(j\)th objective function of the \((i+1)\)th solution and \(f_{j}^{i-1}\) is the \(j\)th objective function of the \((i-1)\)th solution and \(f_{j}^{\max}\) and \(f_{j}^{\min}\) are maximum and minimum values of the objective functions, respectively.

### 5.4. Genetic operators

The binary tournament selection procedure is adopted as the selection strategy in this paper. This strategy is based on the fitness value and selects two solutions of the population size, based on the non-dominance technique and crowding distance.

#### 5.4.1. Crossover

Crossover operator which combines two individuals from population to produce new offsprings is the main GA operator. In this study, two point crossover is applied to produce new
chromosomes. In two point crossover, two crossing sections are selected randomly and everything is swapped between the parents.

5.4.2. Mutation

Mutation is another GA operator which produces small random changes in chromosome to maintain the diversity of the population. Due to random changes in mutation, the solution becomes infeasible. Therefore, the mutation operator should keep the feasibility of the solutions. The basic operation of employed mutation is as follows. First, a day and a time slot is selected randomly. Second, two caregivers are selected randomly. Finally, the services of these two positions are exchanged. Figure 2 represents an example of the employed mutation.

![Please insert Figure 2 here]

Some infeasible solutions may be produced by implementing crossover and mutation due to maximum working time and multi-functionality constraints. Here, to deal with this issue, the penalty function strategy is used and the values of constraint violations (Eqs. 18 and 19) with proper penalty factors are added to the first objective function.

\[
\text{constraint violation } 1 = \sum_{i=1}^{I} Time_{i} \cdot E_{ij} \cdot X_{ijdt} - K \tag{18}
\]

\[
\text{constraint violation } 2 = \sum_{i=1}^{I} Y_{ij} - M_{j} \tag{19}
\]

5.5. Parameter tuning

Due to significant effect of parameter values on the effectiveness of the algorithm, choosing appropriate parameters is necessary to preclude being trapped in local optimum and increase the search around interesting regions [41]. In this study, Taguchi method (TM) is applied to get the proper results and determine the best level of the parameters. TM is a robust approach of factorial design of experiments which introduced by Genichi Taguchi. The aim of TM is reduce the number of experiments and select a small set from all possible experiments. The NSGA-II parameters of iteration, population size, tournament size, crossover probability and mutation probability are considered in the taguchi plan. These parameters and their level are shown in Table 3.
6. Computational results

The behavior of the different elements and features of the proposed model is evaluated on a real-world HC provider called DAM organization from which all required data are collected. This information relates to three adjacent districts of Tehran with the largest caregivers and all the obtained results are solely concerned with this area. The planning horizon is a week (7 days) and about 1100 patients with 55 caregivers are assessed in this period. Table 4 presents the list of considered services in detail and also the demand for these services in the selected period. The information regarding demands are taken from the real historical data of the organization. M and F indicates male and female, respectively.

Table 5 provides information about the parameters of the model including training costs involved in learning how to perform a task. As mentioned before, these costs are zero for caregivers who are already qualified for a particular service. Moreover, the costs imposed by maintaining skills are considered to keep qualifications at a certain level. Table 5 also provides information about normalized visit time of services which indicates average visit time in a certain period as well as deviation from the average costs for workload balancing. All these parameters follow uniform distribution parameterized by specific a’s and b’s (e.g., x~U(a, b)).

6.1. Taguchi execution

In proposed TM method, 16 experiments with 4 replications are conducted and the algorithm is run under these designs. Figure 3 presents a graphical representation of the behaviour of selected parameters according to their levels.
According to Figure 3, pc and npop have the most and the least ranges (difference between the minimum and the maximum S/N ratios) and thus, have the most and the least influence on objective function value, respectively. Also, the highest S/N ratio is desired to achieve the minimum objective function value for each factor. The best values for parameters iteration, population size, tournament size, crossover probability and mutation probability are 100, 200, 5, 0.80 and 0.25, respectively.

6.2. Comparative algorithm

In this study, due to absence of benchmark available in the literature, we used a non-dominated ranking genetic algorithm (NRGA) to validate the obtained results. The Pseudo-code of NRGA is summarized in Algorithm 3.

Algorithm 3. NRGA procedure.

Generate initial solution based on the Algorithm 2.

Rank the individuals based on non-dominated sorting.

I=1

Do

Apply ranked-based roulette wheel selection, crossover and mutation operators, respectively.

Merge all population.

Rank the individuals based on non-dominated sorting.

Truncate the population.

Rank the individuals based on non-dominated sorting.

I=i+1

While i= Maximum number of iterations.

Three comparison indexes are taken into consideration to validate the proposed NSGA-II. These indexes are defined as follows:

- Quality index (QI): This index computes the percentage of the Pareto-optimal solutions for NSGA-II and NRGA. A higher value is desirable for this index [42, 43].
• Mean ideal distance index (MIDI): The distance between the best solutions and Pareto-optimal solutions. A lower value is desirable for this index [44].
• Spacing index (SI): The distribution of the spread of the non-dominated set solutions. A lower value is desirable for this index [45-47].

In order to compare these two algorithms, 25 test problems with different sizes are designed as shown in Table 6. It should be noted that test problem 15 represents the actual size of the main problem related to the case study.

[Please insert Table 6 here]

The results of comparing NSGA-II and NRGA based on the three comparison indexes for different test problems are shown in Table 7. Note that each algorithm has been run 30 times for each test problem and the average of the obtained results is reported in Table 7. NSGA-II outperformed NRGA in terms of comparative indices QI and SI for all 25 test problems. Furthermore, paired t-test at the significance level of \( \alpha = 0.05 \) is used to compare these two algorithms based on MIDI. The hypotheses of this test are as follows:

\[
\begin{align*}
H_0 &: \mu_{\text{NSGA-II}} = \mu_{\text{NRGA}} \\
H_1 &: \text{Otherwise}
\end{align*}
\] (20)

If the null hypothesis is not rejected, this means that there is no significant difference between the means of these two algorithms, in which case, the algorithm with lower average results is selected as the desired algorithm (according to MIDI). On the other hand, rejection of the null hypothesis indicates that there is a significant difference between the means of the two algorithms, in which case, in order to select the efficient algorithm according to MIDI, we use the following test:

\[
\begin{align*}
H_0 &: \mu_{\text{NSGA-II}} = \mu_{\text{NRGA}} \\
H_1 &: \mu_{\text{NSGA-II}} < \mu_{\text{NRGA}}
\end{align*}
\] (21)

If the null hypothesis of the above test is rejected, it can be concluded that NSGA-II outperforms NRGA in terms of MIDI and thus is selected as the superior algorithm. Otherwise, the algorithm with lower average result is selected. The p-value of the paired t-test is equal to
0.006 and therefore, the null hypothesis is rejected, meaning that there is no significant difference between NSGA-II and NRGA based on MIDI. In order to choose the superior algorithm, the second statistical hypothesis testing is used. The p-value for this test is equal to 0.003 according to which the null hypothesis is rejected and thus NSGA-II is selected as the superior algorithm. Based on the obtained results, the proposed NSGA-II is superior over NRGA in terms of all comparison indexes (i.e., QI, MIDI and SI) and thus is recommended for the proposed multi-objective home care problem. The remainder of the analyses and results are based on the NSGA-II for the actual size of the case study.

[Please insert Table 7 here]

6.3. Results and discussions
We run the model with different values of $\pi_1$ and $\pi_2$. Five Pareto-optimal solutions are selected randomly and are reported for objective function terms with different values of $\pi_1$ and $\pi_2$ in Table 8. The values of different terms of objective functions including workload balancing cost, training cost, the number of employees for each service (regularity) and satisfaction level are presented in Table 8 as well. Also, Figures 4 and 5 show the Pareto-optimal fronts for first and third objective function with different values of $\pi_1$ and $\pi_2$. In Table 8 and Figures 4 and 5, Type 1 means $\pi_1 = 1$ and $\pi_2 = 1$ and Type 2 means $\pi_1 = 10$ and $\pi_2 = 1$. As mentioned before, a higher level of $\pi_1$ indicates that the organizations focuses on workload balancing while cross-training costs may lead to higher value settings for the factor $\pi_2$.

[Please insert Table 8 here]

[Please insert Figure 4 here]

[Please insert Figure 5 here]
The results of the proposed model for selected Pareto-optimal solution (number 4) with \( \pi_1 = 10 \) and \( \pi_2 = 1 \) are given in Table 9. Furthermore, Table 10 provides the results of analyzing caregivers and their workloads only for 10 cases for different values of weight factors.

[Please insert Table 9 here]

[Please insert Table 10 here]

Table 9 shows the number of caregivers as well as the cross-training cost associated with each service. Based on the results obtained, the highest training cost is related to service nursing which also possesses the highest number of caregivers. Several conclusions can be drawn referring to the results provided in Table 10. First, the results reveal that the caregivers’ workload is relatively balanced and thus there is no bottleneck. Second, in case workload balance is of considerable importance, it is possible to lay great emphasis on this issue by boosting the value of \( \pi_1 \). This leads to an increase in training cost. Third, when \( \pi_1 = 10 \), the caregivers’ workload is more balanced (i.e., the caregivers’ workload deviations from the average value are less) than when \( \pi_1 = 1 \). Fourth, it is realized that the caregivers’ preferences are more satisfied and, except in a few cases, they were greater than 0.75. Finally, as the importance of the third objective function increases, caregivers’ satisfaction level rises as well.

7. Conclusions

In this study, a multi-objective non-linear mathematical programming model was presented to address staff assignment problem considering cross-training of caregivers for HC services in health care systems. The first objective function aimed to minimize the costs associated with workload balancing, cross-training as well as maintenance while the number of employees for each service was minimized in the second objective function. Also, caregivers’ satisfaction level was maximized in the third objective function. Moreover, several constraints including skill matching, staff preferences, regularity, synchronization, staff absenteeism, time capacity and multi-functionality level are taken into account to build a service plan. Also, we used chaining concept to balance workloads of caregivers and allow shifting jobs among caregivers. Finally, due to the cultural conditions prevailing in Iran, we supposed that services for men and women
are separately performed. We considered DAM home care medical center organization located in Iran as our case study, gathered required data and analyzed the behavior of varied characteristics of the model according to this case. A service plan was also built for 7 days (1 week) and the results determined which staff had to be cross-trained for each service and how the staff were assigned to services in each shift.

The problem being NP-hard, a non-dominated sorting genetic algorithm (NSGA-II) with a proposed heuristic initialization procedure is applied and the proposed model is solved based on a data set collected from our case. A who-rule was applied to determine which staff should be assigned to services. We used a NRGA and generated different test problems to validate the obtain results with respect to three comparison indexes including QI, MIDI and SI. Based on the results obtained from statistical hypothesis tests (paired t-test), the proposed NSGA-II is superior over NRGA in terms of all comparison indexes (i.e., QI, MIDI and SI) and thus is recommended for the proposed multi-objective home care problem. Analysis of caregivers showed that most of the caregivers achieved workload balance and thus there was no bottleneck which positively impacts on operational performance. Furthermore, when $\pi_1 = 10$, the caregivers’ workload was more balanced than when $\pi_1 = 1$. Finally, the caregivers’ preferences were satisfied and as the importance of the third objective function increases, caregivers’ satisfaction level rose as well.

Distance between patient and caregivers is a major issue which was not covered in this study. We believe combining cross-training with this issue would help researchers and organizations achieve a more real and precise service plan. Another issue which can affect organizations and could be of interest for researchers is uncertainty stemming from high variability of staff, material resources, etc. Furthermore, presenting an efficient algorithm which can handle all these issues particularly in various lengths of planning horizon could be another interesting topic.

**References**


**Hamed Habibnejad-Ledari** obtained his MSc certificate from School of Industrial & Systems Engineering, College of Engineering, University of Tehran. He received his BSc degree in Industrial Engineering from Babol University of Technology. His research interests include

Nastaran Ghorbani-Kutenant obtained her MSc certificate from Department of Industrial Engineering, School of Engineering, University of Alzahra. He received his BSc degree in Industrial Engineering from Babol University of Technology. His research interests include Healthcare Engineering, Performance Assessment, Customer Relationship Management, Data Envelopment Analysis and Artificial Intelligence

Table 1. Overview of the literature regarding home care

Table 2. Overview of the literature regarding cross-training and labor assignment

Figure 1. The chromosome representation for NSGA-II

Figure 2. An example of employed mutation

Table 3. NSGA-II parameters and their level values

Table 4. List of the services and corresponding demand for them

Table 5. Parameters of the proposed model
Figure 3. Main effects plot for S/N ratios

Table 6. Data of the test problems

Table 7. Comparison results between the NSGA-II and NRGA based on to the comparison indexes

Table 8. Objective function values for different values of $\pi_1$ and $\pi_2$

Figure 4. Pareto-optimal fronts for $\pi_1 = 1$ and $\pi_2 = 1$

Figure 5. Pareto-optimal fronts for $\pi_1 = 10$ and $\pi_2 = 1$

Table 9. Analysis of the results for each service considering the number of caregivers and training costs

Table 10. Analysis of caregivers and their workloads considering satisfaction level

**Table 1.** Overview of the literature regarding home care

<table>
<thead>
<tr>
<th>Paper</th>
<th>Objective Functions*</th>
<th>Constraints**</th>
</tr>
</thead>
<tbody>
<tr>
<td>Akjiratikarl, et al. [20]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hertz and Lahrichi [21]</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Trautsamwieser, et al. [48]</td>
<td>✓</td>
<td>✓  ✓</td>
</tr>
<tr>
<td>Rasmussen, et al. [1]</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Gamst and Jensen [23]</td>
<td>✓ ✓</td>
<td>✓  ✓</td>
</tr>
<tr>
<td>Liu, et al. [24]</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Mankowska, et al. [25]</td>
<td>✓ ✓</td>
<td>✓  ✓</td>
</tr>
<tr>
<td>Duque, et al. [26]</td>
<td>✓ ✓</td>
<td>✓  ✓</td>
</tr>
<tr>
<td>Habibnejad, et al. [37]</td>
<td>✓ ✓ ✓</td>
<td>✓  ✓</td>
</tr>
<tr>
<td>This study</td>
<td>✓ ✓ ✓</td>
<td>✓  ✓</td>
</tr>
</tbody>
</table>

*Note. TT: Time (travel, waiting, etc.); CC: Costs (assignment, scheduling, etc.); DD: Travelled distances; BW: Balance of the workload; SP: Staff preferences

**Note. TW: Time windows; SM: Skill matching; PRE: Staff preferences; REG: Regularity; SYN: Synchronization
Table 2. Overview of the literature regarding cross-training and labor assignment

<table>
<thead>
<tr>
<th>Paper</th>
<th>Feature*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stewart, et al. [49]</td>
<td>✓✓</td>
</tr>
<tr>
<td>Bokhorst, et al. [30]</td>
<td>✓</td>
</tr>
<tr>
<td>Slomp, et al. [15]</td>
<td>✓✓✓✓✓</td>
</tr>
<tr>
<td>Easton [50]</td>
<td>✓✓✓✓</td>
</tr>
<tr>
<td>Kim and Nembhard [51]</td>
<td>✓✓</td>
</tr>
<tr>
<td>Gnanlet and Gilland [52]</td>
<td>✓✓✓✓✓</td>
</tr>
<tr>
<td>Paul and MacDonald [53]</td>
<td>✓✓</td>
</tr>
<tr>
<td>Sammarco, et al. [54]</td>
<td>✓✓✓✓✓</td>
</tr>
<tr>
<td>Habibnejad, et al. [37]</td>
<td>✓✓✓✓✓</td>
</tr>
<tr>
<td>This study</td>
<td>✓✓✓✓✓✓✓</td>
</tr>
</tbody>
</table>

*Note. 1: Cross-training; 2: Labor assignment; 3: Absenteeism; 4: Multi period; 5: Chaining; 6: who-rule; 7: where-rule; 8: when-rule;

Figure 1. The chromosome representation for NSGA-II
Figure 2. An example of employed mutation

Table 3. NSGA-II parameters and their level values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Level</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iteration (IT)</td>
<td></td>
<td>100</td>
<td>200</td>
<td>300</td>
<td>400</td>
</tr>
<tr>
<td>Population size (npop)</td>
<td></td>
<td>100</td>
<td>150</td>
<td>200</td>
<td>250</td>
</tr>
<tr>
<td>Tournament size (TS)</td>
<td></td>
<td>5</td>
<td>15</td>
<td>25</td>
<td>35</td>
</tr>
<tr>
<td>Crossover probability (pc)</td>
<td></td>
<td>0.7</td>
<td>0.75</td>
<td>0.8</td>
<td>0.85</td>
</tr>
<tr>
<td>Mutation probability (pm)</td>
<td></td>
<td>0.2</td>
<td>0.25</td>
<td>0.3</td>
<td>0.35</td>
</tr>
</tbody>
</table>

Table 4. List of the services and corresponding demand for them

<table>
<thead>
<tr>
<th>No.</th>
<th>Service</th>
<th>Caregiver</th>
<th>Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Nursing</td>
<td>M/F</td>
<td>336</td>
</tr>
<tr>
<td>2</td>
<td>Paraclinic</td>
<td>M/F</td>
<td>121</td>
</tr>
<tr>
<td>3</td>
<td>Laser therapy</td>
<td>F</td>
<td>12</td>
</tr>
<tr>
<td>No.</td>
<td>Service</td>
<td>Gender</td>
<td>TC&lt;sub&gt;ij&lt;/sub&gt; (10&lt;sup&gt;4&lt;/sup&gt;)</td>
</tr>
<tr>
<td>-----</td>
<td>---------------------------------------------</td>
<td>--------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>1</td>
<td>Nursing</td>
<td></td>
<td>[350 500]</td>
</tr>
<tr>
<td>2</td>
<td>Paraclinic</td>
<td></td>
<td>[150 300]</td>
</tr>
<tr>
<td>3</td>
<td>Laser therapy</td>
<td></td>
<td>[820 980]</td>
</tr>
<tr>
<td>4</td>
<td>Gynaecology nursing</td>
<td></td>
<td>[480 630]</td>
</tr>
<tr>
<td>5</td>
<td>Physiotherapy</td>
<td></td>
<td>[750 900]</td>
</tr>
<tr>
<td>6</td>
<td>People with special diseases care (male)</td>
<td></td>
<td>[300 450]</td>
</tr>
<tr>
<td>7</td>
<td>People with special diseases care (female)</td>
<td></td>
<td>[300 450]</td>
</tr>
<tr>
<td>8</td>
<td>Elderly care (male)</td>
<td></td>
<td>[150 250]</td>
</tr>
<tr>
<td>9</td>
<td>Elderly care (female)</td>
<td></td>
<td>[150 250]</td>
</tr>
<tr>
<td>10</td>
<td>Child care</td>
<td></td>
<td>[150 250]</td>
</tr>
</tbody>
</table>
Figure 3. Main effects plot for S/N ratios

Table 6. Data of the test problems

<table>
<thead>
<tr>
<th>Test problem No.</th>
<th>Number of services</th>
<th>Number of caregivers</th>
<th>planning horizon</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4</td>
<td>30</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>35</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>40</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>40</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>35</td>
<td>3</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>40</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>6</td>
<td>45</td>
<td>3</td>
</tr>
<tr>
<td>8</td>
<td>6</td>
<td>45</td>
<td>5</td>
</tr>
<tr>
<td>9</td>
<td>8</td>
<td>45</td>
<td>5</td>
</tr>
<tr>
<td>10</td>
<td>8</td>
<td>50</td>
<td>5</td>
</tr>
<tr>
<td>11</td>
<td>8</td>
<td>55</td>
<td>5</td>
</tr>
<tr>
<td>12</td>
<td>8</td>
<td>55</td>
<td>7</td>
</tr>
<tr>
<td>13</td>
<td>10</td>
<td>45</td>
<td>7</td>
</tr>
<tr>
<td>14</td>
<td>10</td>
<td>50</td>
<td>7</td>
</tr>
<tr>
<td>Test problem No.</td>
<td>QI</td>
<td>MIDI</td>
<td>SI</td>
</tr>
<tr>
<td>-----------------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td></td>
<td>NSGA-II</td>
<td>NRGA</td>
<td>NSGA-II</td>
</tr>
<tr>
<td>1</td>
<td>0.78</td>
<td>0.64</td>
<td>0.262</td>
</tr>
<tr>
<td>2</td>
<td>0.78</td>
<td>0.69</td>
<td>0.284</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>0.415</td>
</tr>
<tr>
<td>4</td>
<td>0.82</td>
<td>0.79</td>
<td>0.236</td>
</tr>
<tr>
<td>5</td>
<td>0.85</td>
<td>0.75</td>
<td>0.197</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>0.83</td>
<td>0.512</td>
</tr>
<tr>
<td>7</td>
<td>0.72</td>
<td>0.63</td>
<td>0.298</td>
</tr>
<tr>
<td>8</td>
<td>0.83</td>
<td>0.72</td>
<td>0.230</td>
</tr>
<tr>
<td>9</td>
<td>0.87</td>
<td>0.8</td>
<td>0.259</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>1</td>
<td>0.489</td>
</tr>
<tr>
<td>11</td>
<td>0.90</td>
<td>0.75</td>
<td>0.362</td>
</tr>
<tr>
<td>12</td>
<td>0.95</td>
<td>0.75</td>
<td>0.312</td>
</tr>
<tr>
<td>13</td>
<td>1</td>
<td>1</td>
<td>0.228</td>
</tr>
</tbody>
</table>

*Table 7. Comparison results between the NSGA-II and NRGA based on the comparison indexes*
Table 8. Objective function values for different values of $\pi_1$ and $\pi_2$

<table>
<thead>
<tr>
<th>No.</th>
<th>Cross-training cost ($10^4$)</th>
<th>Workload balancing cost ($10^4$)</th>
<th>Regularity</th>
<th>Satisfaction level</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Type 1</td>
<td>Type 2</td>
<td>Type 1</td>
<td>Type 2</td>
</tr>
<tr>
<td>1</td>
<td>19111</td>
<td>22294</td>
<td>11941</td>
<td>10309</td>
</tr>
<tr>
<td>2</td>
<td>20313</td>
<td>25270</td>
<td>12961</td>
<td>11745</td>
</tr>
<tr>
<td>3</td>
<td>21436</td>
<td>27071</td>
<td>13704</td>
<td>13543</td>
</tr>
<tr>
<td>4</td>
<td>25914</td>
<td>30670</td>
<td>17069</td>
<td>14280</td>
</tr>
<tr>
<td>5</td>
<td>27864</td>
<td>33277</td>
<td>19663</td>
<td>16083</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>0.9036</td>
<td>0.8044</td>
<td>0.3248</td>
</tr>
</tbody>
</table>
Table 9. Analysis of the results for each service considering the number of caregivers and training costs
<table>
<thead>
<tr>
<th>Service</th>
<th>Caregiver</th>
<th>Training-cost (10⁶)</th>
<th>Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nursing</td>
<td>29</td>
<td>9046</td>
<td>336</td>
</tr>
<tr>
<td>Paraclinic</td>
<td>13</td>
<td>1854</td>
<td>121</td>
</tr>
<tr>
<td>Laser therapy</td>
<td>3</td>
<td>1779</td>
<td>12</td>
</tr>
<tr>
<td>Gynaecology nursing</td>
<td>6</td>
<td>2254</td>
<td>67</td>
</tr>
<tr>
<td>Physiotherapy</td>
<td>7</td>
<td>4945</td>
<td>95</td>
</tr>
<tr>
<td>People with special diseases care (male)</td>
<td>6</td>
<td>2089</td>
<td>43</td>
</tr>
<tr>
<td>People with special diseases care (female)</td>
<td>5</td>
<td>2023</td>
<td>39</td>
</tr>
<tr>
<td>Elderly care (male)</td>
<td>14</td>
<td>2234</td>
<td>120</td>
</tr>
<tr>
<td>Elderly care (female)</td>
<td>12</td>
<td>2069</td>
<td>111</td>
</tr>
<tr>
<td>Child care</td>
<td>19</td>
<td>2377</td>
<td>156</td>
</tr>
</tbody>
</table>

**Table 10.** Analysis of caregivers and their workloads considering satisfaction level

<table>
<thead>
<tr>
<th>Caregiver</th>
<th>Workload (h)</th>
<th>Deviation from average workload (h)</th>
<th>Satisfaction level</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Type 1</td>
<td>Type 2</td>
<td>Type 1</td>
</tr>
<tr>
<td>1</td>
<td>33.805</td>
<td>39.2675</td>
<td>3.1375</td>
</tr>
<tr>
<td>2</td>
<td>34.95</td>
<td>37.16</td>
<td>1.9925</td>
</tr>
<tr>
<td>3</td>
<td>41.1625</td>
<td>37.89</td>
<td>4.22</td>
</tr>
<tr>
<td>4</td>
<td>33.155</td>
<td>35.68</td>
<td>3.7875</td>
</tr>
<tr>
<td>5</td>
<td>33.1025</td>
<td>37.9075</td>
<td>3.84</td>
</tr>
<tr>
<td>6</td>
<td>35.1</td>
<td>38.355</td>
<td>1.8425</td>
</tr>
</tbody>
</table>

36
<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>36.9675</td>
<td>39.1825</td>
<td>0.025</td>
<td>1.1372</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>39.25</td>
<td>38.17</td>
<td>2.3075</td>
<td>0.1247</td>
<td>1</td>
<td>0.75</td>
</tr>
<tr>
<td>9</td>
<td>35.1125</td>
<td>36.0575</td>
<td>1.83</td>
<td>1.9877</td>
<td>0.75</td>
<td>0.66</td>
</tr>
<tr>
<td>10</td>
<td>40.7825</td>
<td>39.46</td>
<td>3.84</td>
<td>1.4147</td>
<td>1</td>
<td>0.75</td>
</tr>
</tbody>
</table>