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A Multi-Objective Scheduling and Routing Problem for Home Health Care Services via Brain Storm Optimization

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Abstract: At present, home health care (HHC) has been accepted as an effective method for handling the healthcare problems of the elderly. The HHC scheduling and routing problem (HHCSRP) attracts wide concentration from academia and industrial communities. This work proposes an HHCSRP considering several care centers, where a group of customers (i.e., patients and the elderly) require being assigned to care centers. Then, various kinds of services are provided by caregivers for customers in different regions. By considering the skill matching, customers' appointment time, and caregivers' workload balancing, this article formulates an optimization model with multiple objectives to achieve minimal service cost and minimal delay cost. To handle it, we then introduce a brain storm optimization method with particular multi-objective search mechanisms (MOBSO) via combining with the features of the investigated HHCSRP. Moreover, we perform experiments to test the effectiveness of the designed method. Via comparing the MOBSO with two excellent optimizers, the results confirm that the developed method has significant superiority in addressing the considered HHCSRP.

Key words: home health care; multi-center service; multi-objective optimization; scheduling and routing problems; brain storm optimization

1 Introduction

As the improvement of living standards and the rising of life expectancy, population aging becomes a global trend. Currently, population over sixty accounts for 11% of the world, and the number will grow to 22% by 2050[1]. Along with this trend, the demand for medical resources increases, and thus the public medical systems face tremendous pressure.

Home health care (HHC) is an emerging paradigm of medical care that aims to assign caregivers to carry necessary medical equipment from a care center and go to customers' home to provide services. This condition is suitable for the elderly and the patients with chronic diseases or mobility difficulties[2].

The logistics operations of HHC service, including customer assignment among caregivers and route optimization of caregivers, motivate an optimization problem, namely, HHC scheduling and routing problems (HHCSRPs)[3]. Owing to the appearance of some constraints such as the skill matching and workload balancing, the decision-makers face tough challenges. In reality, several care centers usually have to cooperate with each other to provide services for customers. Although the problems with only one care center have been extensively studied, the attention of

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researchers paid to the HHCSRP with several care centers is rare.

As a matter of fact, the service process of HHC contains more than one participant, such as managers, customers, and caregivers. These participants possess their respective preference. In terms of managers, they hope to decrease service cost and acquire high profits. As far as customers are concerned, they wish to be served as their needs including appointment time and service level. With respect to caregivers, they expect to have a fair working regulation, i.e., workload balancing. Hence, the demands of managers, customers, and caregivers should be taken into account when addressing such problems. Consequently, it is necessary to handle a multi-objective HHCSRP.

Via comparing with the prior works, we make the following contributions:

(1) A multi-objective HHCSRP with several care centers is proposed. It considers the skill matching, customers' appointment time, and caregivers' workload balancing simultaneously.

(2) A mixed integer programming model with multiple objectives including minimizing service cost and minimizing delay cost caused by tardiness is established.

(3) A multi-objective brain storm optimization (MOBSO) method is developed to deal with the investigated problem. In it, the solution encoding and decoding, population initialization, clustering, new individual generation, and selection approaches are particularly designed by fully taking into account the problem's characteristics.

(4) Via making comparisons between the MOBSO and the nondominated sorting genetic algorithm II (NSGA-II)[4] and improved multi-objective artificial bee colony (IMOABC) algorithm[5], we confirm that MOBSO can achieve better optimization results than the comparative approaches for handling the HHCSRP.

In Section 2, a brief summarization on the related problems is made. Subsequently, in Section 3, the problem under investigation is defined and its corresponding model is formulated. Section 4 provides the framework of the designed approach. Then, Section 5 does comparison experiments and dissects the acquired results. Lastly, in Section 6, we sum up this article and provide promising topics for next work.

2 Related Work

Recently, the HHCSRP with a single care center has been widely investigated[6]. Effective management and operation of HHCs in medical systems are conducive to reducing related cost and improving service quality[7]. Additionally, multi-objective scheduling models on the HHC with complex constraints have gained popularity among scholars[8]. In terms of the existing literature on the HHCSRP, we can see that they possess the main characteristics as follows. (1) The academic field focused more on the HHCSRP with only one care center[9, 10], rarely paying attention to the cooperation of several care centers, in spite of its essential industry applications in real life[11]. (2) Concerning the recent research in the domain of HHC, scholars have explored multi-objective optimization model. For instance, Decerle et al.[12] studied a multi-objective HHCSRP considering caregivers' working time and customer satisfaction, while Goodarzian et al.[3] focused on an HHCSRP with reaching travel cost minimization and service time minimization. (3) Some researchers formulated multifarious models considering practical constraints such as the customers' and caregivers' preferences[13–15], working regulations[16, 17], time windows[18, 19], or even synchronization[20].

To deal with the HHCSRP, some studies introduced various heuristic and metaheuristic optimization methods. Fathollahi-Fard et al.[8] employed a new modified social engineering optimizer, while Lin et al.[16] utilized a harmony search algorithm. Next, considering caregivers' workload balancing, Yang et al.[5] developed an enhanced artificial bee colony approach to optimally handle the concerned HHCSRP. Later, in Ref. [21], a hybridization of ant colony optimization and memetic methods was developed for settling the given optimization model.

Via analyzing the aforementioned works, it can be found that a great many of researchers have taken advantage of metaheuristic methods to tackle the HHCSRP. As one of the metaheuristic approaches, brain storm optimization (BSO) was introduced in Ref. [22]. The BSO has many advantages such as easy implementation, strong search ability, and high solution stability[23]. Recently, it has gained great success in resolving diverse optimization problems such as flow shop scheduling problems[24, 25] and vehicle routing problems[26]. However, we can find that scholars have not yet applied the BSO to solve the scheduling and routing problems in HHC. Hence, this work is dedicated to investigate its applications for handling the HHCSRPs.

In this research, we propose a multi-objective HHCSRP having several care centers, where the skill matching, appointment time of customers, and workload balancing of caregivers are considered as limitations. Moreover, we construct a mathematical model with multiple optimization criteria to reach minimal service cost and minimal delay cost. Afterwards, the multi-objective BSO (MOBSO) is particularly designed to tackle the proposed problem.

3 Problem Formulation

The HHCSRP is composed of two phases, which are assignment and scheduling phases. The assignment phase contains several care centers and a group of customers that needs to be assigned to care centers. The scheduling phase aims at providing the services for customers at their home by caregivers. Each care center has a set of caregivers, and a caregiver only belongs to a care center. For each route, caregivers carry necessary medical equipment and start from their care centers. After finishing serving all assigned customers, they must go back and put the medical equipment back into the care centers they belong to. Each customer has a definite appointment time indicated as a latest start service time.

The caregivers must arrive at the served customers earlier than their appointment time; otherwise, a delay cost occurs. In addition, the skill grade is used to represent the serviceability of a caregiver. The skill matching means that a caregiver can only provide services for those customers with skill grade requirements that are lower than or equal to the skill grade of this caregiver. To achieve the workload balancing, caregivers have the maximum allowable visiting number of customers.

Notice that if a customer is served by a caregiver with a higher skill grade than his requirement, the service cost per unit time for this customer will be higher. Because the service time is fixed, the total service cost for this customer will become higher. Besides, the following constraints for the considered problem are made: (1) Each customer must be assigned to only one care center; (2) Each customer must be provided service by only one caregiver; (3) Each customer must be served just once; (4) A caregiver can be dispatched at most once; (5) A route begins and ends at the same care center. To further clarify, Fig. 1 illustrates the investigated HHCSRP.

Indeed, the model can be viewed as a directed graph $R=(O,E)$, where O represents the set of nodes and E denotes the set of arcs. The indices, parameters, and decision variables are defined as follows.

Indices:

i, j: Node index.

k: Care center index.

l: Caregiver index.

f: Quantity of customers.

g: Quantity of care centers.

h_k: Quantity of caregivers in care center k.

F: Set of customers, $F=\{1,2,\ldots,f\}$.

G: Set of care centers, $G=\{1,2,\ldots,g\}$.

H_k: Set of caregivers belonging to care center k, $H_k=\{1,2,\ldots,h_k\}$.

O: Set of nodes, $O=F\cup G$.

E: Set of arcs, $E=\{(i,j)|i,j\in O, i\neq j\}$.

Q: Set of skill grades, $Q=\{Q_1,Q_2,Q_3\}$, there are three skill grades, $Q_1<Q_2<Q_3$.

Parameters:

s_i: Skill grade requirement of customer i.

s_{lk}: Skill grade of caregiver l in care center k.

q_i: Service time for customer i.

r_i: Service cost per unit time for customer i.

v_{ilk}: Coefficient of service cost per unit time for customer i, when caregiver l in care center k is assigned to serve customer i, $v_{ilk}=s_{lk}/s_i$.

τ_{ij}: Travel time from nodes i to j.

L_i: Appointment time of customer i.

c_k: Maximum service capacity of care center k.

ω: Maximum workload of caregivers.

η: Delay cost per unit time.

M: A large positive constant.

Decision variables:

x_{ik}: If customer i is assigned to care center k, $x_{ik}=1$; otherwise, $x_{ik}=0$.

y_{ilk}: If customer i is served by caregiver l of care center k, $y_{ilk}=1$; otherwise, $y_{ilk}=0$.

z_{ijlk}: If arc (i,j) is covered by caregiver l of care center k, $z_{ijlk}=1$; otherwise, $z_{ijlk}=0$.

a_{ilk}: Arrival time at customer i, when he is served by caregiver l of care center k.

l_{ilk}: Leave time from customer i, when he is served by caregiver l of care center k.

Then, we construct a multi-objective optimization model as below.

$$\min\left(\sum_{i\in F}\sum_{l\in H_k}\sum_{k\in G} q_i\cdot v_{ilk}\cdot r_i\cdot y_{ilk}\right) \tag{1}$$

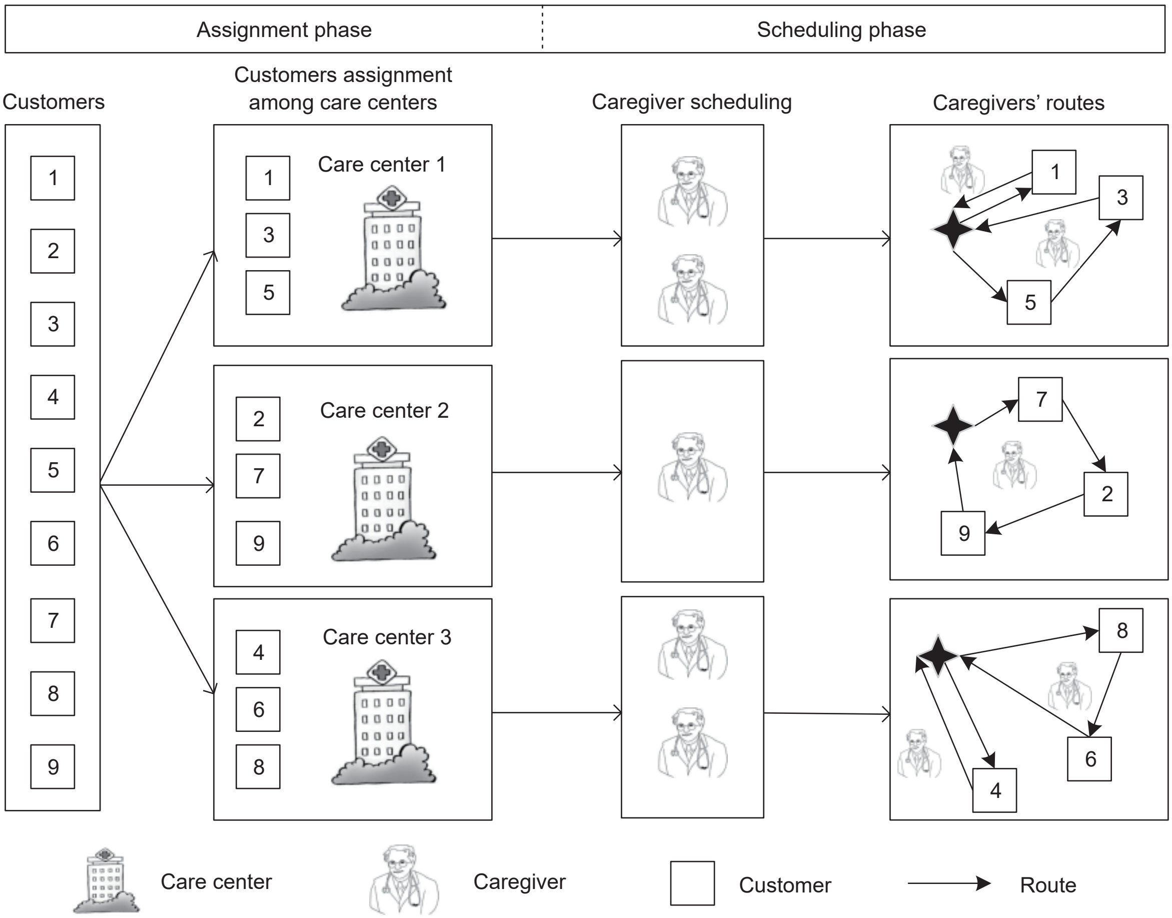

Fig. 1 Illustration of the problem under consideration.

$$\min\left(\eta\cdot\sum_{i\in F}\sum_{l\in H_k}\sum_{k\in G}\max(a_{ilk}-L_i,0)\right) \tag{2}$$

$$\sum_{k\in G}x_{ik}=1,\ \ \forall i\in F \tag{3}$$

$$\sum_{i\in F}x_{ik}\leqslant c_k,\ \ \forall k\in G \tag{4}$$

$$\sum_{j\in O}\sum_{l\in H_k}\sum_{k\in G}z_{ijlk}=1,\ \ \forall i\in F \tag{5}$$

$$\sum_{j\in O}z_{ijlk}=\sum_{j\in O}z_{jilk},\ \ \forall i\in F,\ \ \forall l\in H_k,\ \ \forall k\in G \tag{6}$$

$$\sum_{j\in O}\sum_{l\in H_k}z_{kjlk'}=\sum_{i\in O}\sum_{l\in H_k}z_{iklk'}=0,\ \ \forall k\in G,\ \ \forall k'\in G,\ \ k\neq k' \tag{7}$$

$$\sum_{l\in H_k}\sum_{k\in G}y_{ilk}=1,\ \ \forall i\in F \tag{8}$$

$$y_{ilk}=\sum_{j\in O}z_{ijlk},\ \ \forall i\in F,\ \ \forall l\in H_k,\ \ \forall k\in G \tag{9}$$

$$y_{jlk}=\sum_{i\in O}z_{ijlk},\ \ \forall j\in F,\ \ \forall l\in H_k,\ \ \forall k\in G \tag{10}$$

$$a_{ilk}\geqslant\tau_{ki}-(1-z_{kilk})\cdot M,\ \ \forall i\in F,\ \ \forall l\in H_k,\ \ \forall k\in G \tag{11}$$

$$\begin{gathered}a_{jlk}\geqslant l_{ilk}+\tau_{ij}-(1-z_{ijlk})\cdot M,\\ \forall i\in F,\ \ \forall j\in F,\ \ \forall l\in H_k,\ \ \forall k\in G\end{gathered} \tag{12}$$

$$l_{ilk}\geqslant a_{ilk}+q_i,\ \ \forall i\in F,\ \ \forall l\in H_k,\ \ \forall k\in G \tag{13}$$

$$\sum_{l\in H_k}\sum_{k\in G}y_{ilk}\cdot s_{lk}\geqslant s_i,\ \ \forall i\in F \tag{14}$$

$$\sum_{i\in F}y_{ilk}\leqslant\omega,\ \ \forall l\in H_k,\ \ \forall k\in G \tag{15}$$

$$\sum_{j\in F}z_{ijlk}\leqslant 1,\ \ \forall i\in F,\ \ \forall l\in H_k,\ \ \forall k\in G \tag{16}$$

$$\begin{gathered}x_{ik},y_{ilk},z_{ijlk}\in\{0,1\},\\ a_{ilk}\geqslant 0,\ \ l_{ilk}\geqslant 0,\\ i,j\in O,l\in H_k,\ \ k\in G\end{gathered} \tag{17}$$

where Formula (1) aims at minimizing service cost. Formula (2) seeks to minimize delay cost incurred by delay service. Equation (3) means that each customer must be assigned to just one care center. Formula (4) ensures that the number of customers assigned to each care center cannot surpass its service capacity. Equation (5) limits that each customer must be served just once. Equation (6) imposes the flow conservation constraint at each customer. Equation (7) guarantees that a route must begin and end at the same care center. Equation (8) implies that each customer must be visited by only one caregiver. Equations (9) and (10) describe the relationship of decision variables. Formulas (11) and (12) represent the time that a caregiver arrives at a customer. Formula (13) defines the departure time of caregivers from customers. Formula (14) implies that the skill matching between caregivers and customers must be satisfied. Formula (15) specifies that the workload of caregivers is no more than a given threshold. Formula (16) indicates that each caregiver can be dispatched at most once. Formula (17) imposes the value ranges with respect to decision variables.

4 Proposed Multi-Objective Method

The BSO has been demonstrated to be an outstanding swarm intelligence optimization algorithm in solving single-objective optimization problems[27]. Regarding the multiple objectives in the studied problem, this research employs some special strategies in the standard BSO.

4.1 Encoding method

Assume that there are m caregivers from several care centers providing services for n customers, we index customers and caregivers as $\{1,2,\ldots,n\}$ and $\{n+1,n+2,\ldots,n+m\}$, respectively. A solution (namely, an individual) consists of elements in the sets of $\{1,2,\ldots,n\}$ and $\{n+1,n+2,\ldots,n+m\}$. The customer assigned to each caregiver is between him/her and the next different caregiver. In the case that there is no customer after a caregiver, it means that this caregiver does not serve any customer.

Considering an example with 4 caregivers from two care centers providing services for 10 customers. By employing the aforementioned approach, the elements in the set of $\{1,2,\ldots,10\}$ and the set of $\{11,12,13,14\}$ are used to construct solutions. A solution [11, 1, 2, 3, 4, 12, 5, 6, 7, 13, 8, 9, 10, 14] means that Customers 1, 2, 3, and 4 are served by Caregiver 11 as their relative sequence. The remaining three routes can be decoded using the similar approach as well. Note that Caregiver 14 does not serve any customer.

4.2 Population initialization

In this work, a heuristic rule is proposed for population initialization. Its main procedure is given as follows.

Step 1: Assign all customers to care centers randomly under the constraint given in Formula (4).

Step 2: Randomly sort all customers at each care center, and then the obtained sequence is customer sequence (defined as Ω).

Step 3: Sort all caregivers at each care center in accordance of their skill grades as an ascending order, and the sequence is caregiver sequence (defined as Ψ).

Step 4: Assign the first customer in the Ω to the first caregiver in the Ψ, and check whether the constraints with respect to the skill matching and workload balancing are satisfied in such situation or not. If both limitations (i.e., skill grade and workload) are satisfied, the first customer is certainly assigned to the first caregiver. Otherwise, check the caregiver one by one as the caregiver sequence until a satisfied caregiver is found, then we arrange him/her to serve this customer. Following the aforementioned procedure, we can assign the rest of customers to the suitable caregivers.

4.3 Clustering

Deb et al.[4] sorted the population based on individuals' dominated relationships. The rank value of each individual is equal to its nondomination level. In the proposed MOBSO, all individuals having an identical rank value are formed as a cluster. Consequently, we can partition all individuals in the population into multiple clusters. The index of each cluster is equal to the rank values of individuals in the cluster. As a result, a cluster having a smaller index comprises of the better individuals. Noteworthily, in the case that all individuals are nondominated, there is only one cluster using the proposed method.

4.4 New individual generation

It is noted that all individuals in the same cluster are nondominated. For each cluster, this research randomly chooses an individual from it as its center, and the others are seen as its normal individuals.

The main process of the designed MOBSO is provided in Algorithm 1, in which p_g decides whether one or two clusters are chosen, while p_o and p_t represent center or normal individuals are chosen from the selected cluster(s) for generating new individuals. The binary selection approach[28] is used to choose clusters. It randomly selects two clusters and compares

Algorithm 1 Procedure of MOBSO

Input: algorithm parameters N, p_g, p_o, and p_t.
Output: external archive ε.
Begin
  set algorithm parameters, i.e., N, p_g, p_o, and p_t.
  generate a population with N individuals.
  evaluate all individuals in population.
  update ε.
  while (a given termination condition is not met) **do**
    construct clusters on the population.
    repeat
      if (there are multiple clusters) **then**
        if (rand(0, 1) < p_g) **then**
          choose a cluster by using a binary selection method.
          if (rand(0, 1) < p_o) **then**
            select its center individual and generate a new individual.
          else
            choose a normal individual and generate a new individual.
          end if
        else
          select two clusters by using a binary selection method.
          if (rand(0, 1) < p_t) **then**
            choose two clusters' center individuals and generate a new individual.
          else
            select two clusters' normal individuals and generate a new individual.
          end if
        end if
      else //there is only one cluster.
        choose two individuals randomly from this cluster.
        generate a new individual by using these two individuals.
      end if
    until (N new individuals have been generated).
    select the top N best individuals as next population.
    update ε.
  end while
  output ε.
End.

them, then reserves the cluster with a smaller index. If one individual is chosen, the mutation operation will be executed for generating a new individual. If two individuals are selected, the crossover operation will be performed for producing two new individuals and the better one will be retained. On the condition that the newly-generated individuals are nondominated, this work retains any one of them at random.

For the mutation operation, this paper designs two mutation approaches and they are chosen with equal probability. They are described in the followings: (1) Randomly swap two customers in the same route; (2) Randomly insert a customer into the other position in the same route.

The following approach is designed to execute the crossover operation. Let P_1 and P_2 be two parent individuals. Firstly, one caregiver is randomly chosen and the routes of the selected caregiver in P_1 and P_2 are marked as ρ_1 and ρ_2, respectively. Secondly, the customers in ρ_1 are compared with those in ρ_2 and the different customers are stored in λ_1 and λ_2, respectively. Thirdly, the customers in P_1 are compared with those in λ_2 and the same customers are deleted from P_1. Similarly, the same operation is performed on P_2. Fourthly, ρ_1 and ρ_2 are exchanged. Finally, the customers in λ_1 are inserted into the routes in P_1 randomly under the constraints of skill grade and workload, and the customers in λ_2 are inserted into the routes in P_2 using the same approach.

Figure 2 displays an example of generating two individuals. Looking at it, the skill grade of Caregiver 11 is Q_3, the skill grade of Caregiver 12 is Q_1, and the skill grade of Caregivers 13 and 14 is Q_2. Looking at Fig. 2, the circles with different shadows are used to distinguish the skill grades of the caregivers. The rectangles indicate customers with skill grade requirement of Q_1, the diamonds indicate customers with skill grade requirement of Q_2, and the hexagons indicate customers with skill grade requirement of Q_3.

4.5 Selection method

After generating N new individuals, we can obtain $2N$ individuals by combining the individuals in population and all the newly-generated individuals. Afterwards, this work chooses N individuals by adopting the rank and crowding distance strategies[4].

5 Experiments and Analysis

To prove the validity of the designed MOBSO in tackling the HHCSRP, NSGA-II and IMOABC are chosen for comparison. As one of the popular evolutionary methods on the basis of the Pareto rule, the NSGA-II has been employed for resolving vehicle routing problems[29–31], flow shop scheduling problems[32–38], and other multi-objective optimization problems[39]. The IMOABC was initially proposed to handle a multi-objective scheduling and routing problem having a single care center given in Ref. [5].

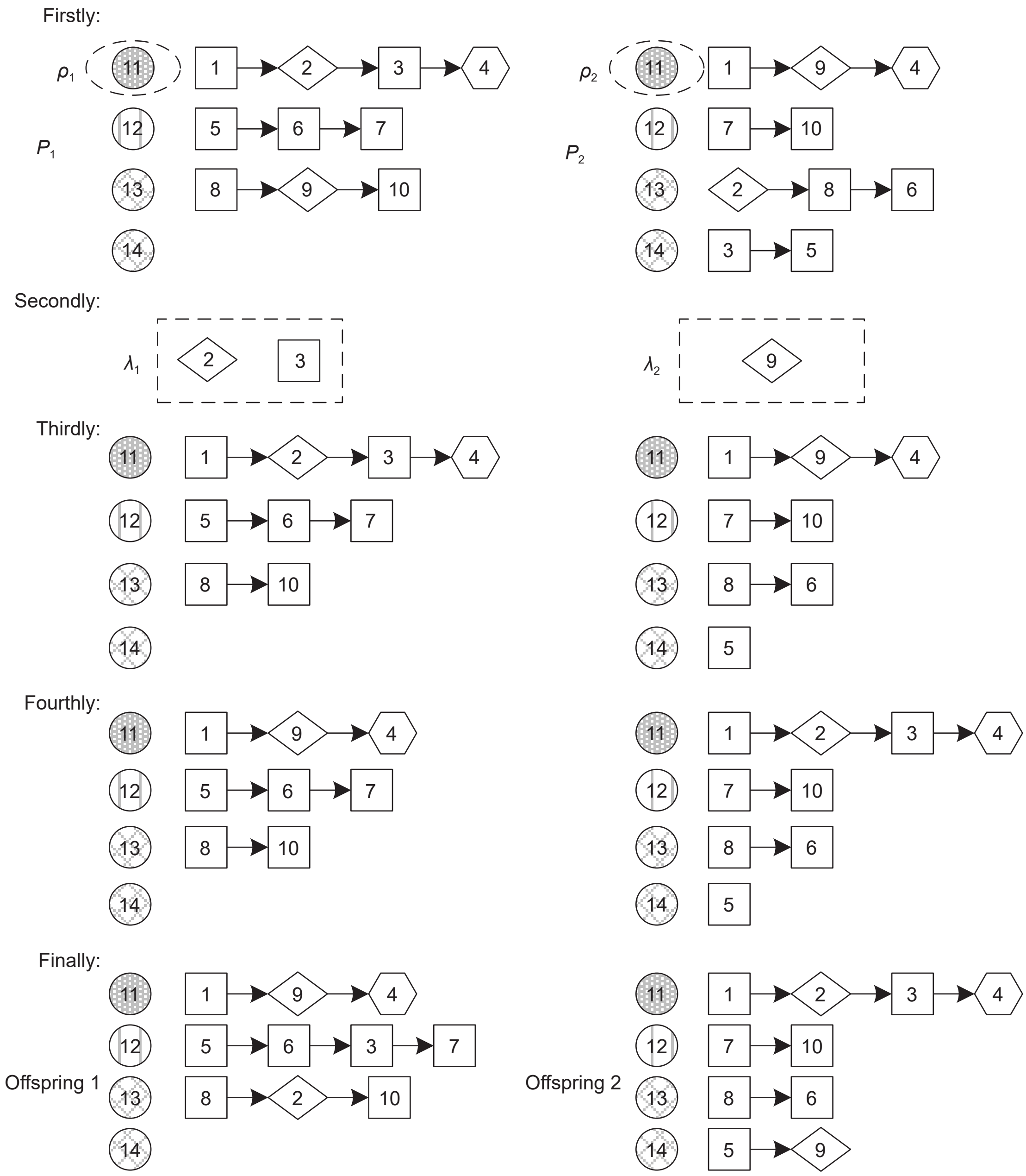

Fig. 2 Schematic view of the designed crossover method.

In this research, it is extended to deal with the HHCSRP with more than one care center.

In this work, the search processes of NSGA-II and IMOABC are described as: The NSGA-II chooses parent individuals by a binary selection strategy on the basis of their dominated relationships, and generates new individuals by performing the same crossover approach and mutation method as the MOBSO. The IMOABC includes three stages. At the employed bee stage, a swap or insert based approach is adopted. Then, the onlooker bees utilize a roulette wheel approach to select individuals and employ a swap or insert based method to create new individuals. At the scout bee stage, the worse ones in the population are replaced by randomly-generated individuals. Both the rivals implement the same encoding method as the proposed MOBSO.

The computation complexities of MOBSO, NSGA-II, and IMOABC are analyzed at each iteration in the worst case, in which N and n represent population size and the number of customers, respectively.

For the MOBSO, its basic operation and the worst case complexities are analyzed as follows. (1) The binary selection approach is used to choose $2N$

clusters, and its computation complexity is $O(4N)$. (2) The single-point crossover is employed to produce N new individuals, and its computation complexity is $O(N \cdot n^2)$. (3) The rank and crowding distance method is utilized to select N individuals, and its computation complexity is $O(2N^2)$. Therefore, the overall complexity of MOBSO in the worst case is $O(N \cdot (n^2 + 2N + 4))$, i.e., $O(N \cdot n^2)$.

For the NSGA-II, its basic operation and the worst case complexities are dissected as follows. (1) The binary selection approach is used to select N individuals, and its computation complexity is $O(2N)$. (2) The single-point crossover and the insert-based mutation operators are utilized to generate N new individuals, which have the computation complexity $O(N \cdot (n^2 + n))$. (3) The population updating process has the computation complexity $O(2N^2)$. Hence, the overall complexity of NSGA-II in the worst case is $O(N \cdot (n^2 + n + 2) + 2N^2)$, i.e., $O(N \cdot n^2)$.

For the IMOABC, its basic operation and the worst case complexities are analyzed as follows. (1) The insert-based method at the employed bee stage has the computation complexity $O(N \cdot n)$. (2) The roulette wheel and insert-based operations at the onlooker bee stage have the computation complexity $O(N \cdot (N^2 + n))$. (3) Creating a new population at the scout bee stage has the computation complexity $O(N \cdot n)$. Therefore, the overall complexity of IMOABC in the worst case is $O(N \cdot (N^2 + 3n))$, i.e., $O(N^3)$.

By analyzing their computation complexity in the worst case, we can infer that the computation complexity of MOBSO is not very large and it can be accepted as a promising method to deal with the studied problem.

5.1 Test instances and performance metrics

This section tests the performance of the MOBSO using 12 benchmark instances introduced by Vidal et al.[40] Looking at Table 1, the chosen Vidal et al.'s instances consist of four sizes, and each size contains three instances. These instances are named as: S101, S102, S103, M101, M102, M103, M201, M202, M203, L101, L102, and L103.

Table 1 Information of used instances for the considered problem.

Size	Number of centers	Number of caregivers	Number of customers
S1	2	10	40
M1	3	15	60
M2	4	20	80
L1	5	25	100

In the benchmark instances, we calculate the Euclidean distance between two nodes and view it as their travel time. There are totally three skill grades, i.e., $Q = \{Q_1, Q_2, Q_3\}$. In all the used instances, $R_Q = \{0.6, 0.3, 0.1\}$ is a ratio of customers with skill grade requirements of Q_1, Q_2, and Q_3. Besides, the bigger one between two randomly-generated skill grades is selected as the skill grade of a caregiver. Additionally, the maximum workload of caregivers is 5.

In this work, we utilize C-metric and IGD-metric to assess the numerical results obtained by three reported algorithms. They are defined as follows.

(1) C-metric can assess the coverage of two nondominated solution sets[41]. $C(T,U)$ represents the percentage of the quantity of solutions in U dominated by at least one solution in T, where T and U denote two solution sets acquired by two methods. Equation (18) is used to calculate $C(T,U)$.

$$C(T,U) = \frac{|\{u \in U | \exists t \in T : t \prec u\}|}{|U|} \tag{18}$$

If no solution in T can dominate the solutions in U, $C(T,U) = 0$. If the solutions in T can dominate all the solutions in U, $C(T,U) = 1$.

(2) IGD-metric is employed to assess the overall performance including approximation and distribution of solutions[42]. The suggested formulation for this metric is given in Eq. (19).

$$\mathrm{IGD}(V, V^*) = \frac{1}{|V^*|} \sum_{v \in V^*} \mathrm{dist}(v, V) \tag{19}$$

where V^* indicates an optimal solution set, and $\mathrm{dist}(v, V)$ implies the closest Euclidean distance between a solution v in V^* and solutions in V. In this work, we combine all solutions acquired by three considered approaches, and the nondominated solutions are regarded as V^*. Additionally, all objective values are standardized into $[0,1]$, then the inverted generational distance (IGD) values are calculated by Eq. (19). Evidently, a smaller IGD value implies a better performance of V.

5.2 Parameter setting

Parameter setting is of significance since it can influence the search ability of algorithms. For MOBSO, this research does numerical experiments with different parameter combinations, and subsequently uses the Taguchi method[43, 44] to determine parameter values. MOBSO contains the following pivotal parameters: N, p_g, p_o, and p_t. Table 2 lists the levels of each parameter.

In this research, the maximum number of fitness evaluations is taken as a termination criterion and it is set to $100 \cdot f$, where f is the quantity of customers. M101 is chosen as a test instance, and the MOBSO with each parameter combination is independently executed for twenty times.

Looking at Table 3, the average IGD values over twenty times are treated as average response variable (ARV) values.

Table 4 provides the effect rank of different parameters, and the effect plot of user parameters is illustrated in Fig. 3.

Table 2 Levels of parameters.

Level	N	p_g	p_o	p_t
1	20	0.2	0.2	0.2
2	40	0.4	0.4	0.4
3	60	0.6	0.6	0.6
4	80	0.8	0.8	0.8

Table 3 Orthogonal table and experimental results obtained by Taguchi method.

No.	N	p_g	p_o	p_t	ARV
1	20	0.2	0.2	0.2	0.6831
2	20	0.4	0.4	0.4	0.6134
3	20	0.6	0.6	0.6	0.5210
4	20	0.8	0.8	0.8	0.5540
5	40	0.2	0.4	0.6	0.7837
6	40	0.4	0.2	0.8	0.6147
7	40	0.6	0.8	0.2	0.5357
8	40	0.8	0.6	0.4	0.3685
9	60	0.2	0.6	0.8	0.3343
10	60	0.4	0.8	0.6	0.4997
11	60	0.6	0.2	0.4	0.6557
12	60	0.8	0.4	0.2	0.5691
13	80	0.2	0.8	0.4	0.3835
14	80	0.4	0.6	0.2	0.3055
15	80	0.6	0.4	0.8	0.5840
16	80	0.8	0.2	0.6	0.4332

Table 4 Effect rank of different parameters.

Level	N	p_g	p_o	p_t
1	0.5929	0.5461	0.5967	0.5233
2	0.5756	0.5083	0.6375	0.5053
3	0.5147	0.5741	0.3823	0.5594
4	0.4265	0.4812	0.4932	0.5217
Delta	0.1664	0.0929	0.2552	0.0541

Note: Delta is referred to the value between maximum ARV and minimum ARV in four levels. The bigger the Delta is, the more important the parameter is.

From Fig. 3, the following parameters are used in the MOBSO: $N = 80$, $p_g = 0.8$, $p_o = 0.6$, and $p_t = 0.4$.

According to Refs. [5, 45], we summarize the parameter setting of NSGA-II and IMOABC in Table 5.

In the following experiments, both of them treat the total number of fitness evaluations as a stop condition and it is set to $100 \cdot n$, where n is the number of customers.

5.3 Numerical results and analysis

Table 6 tabulates the numerical results regarding C-metric. For the sake of briefness, the MOBSO, NSGA-II, and IMOABC are indicated as the "BSO", "GA", and "ABC", respectively. For each instance, we calculate the average values over twenty independent runs in terms of C-metric. Besides, to confirm the statistical difference among the MOBSO and comparative algorithms, we adopt a statistical method, i.e., the one-tailed t-test[46]. The degree of freedom is set as 38, and the level of significance is set as 0.05. If the MOBSO is obviously worse than, statistically equivalent to, or evidently better than the comparative

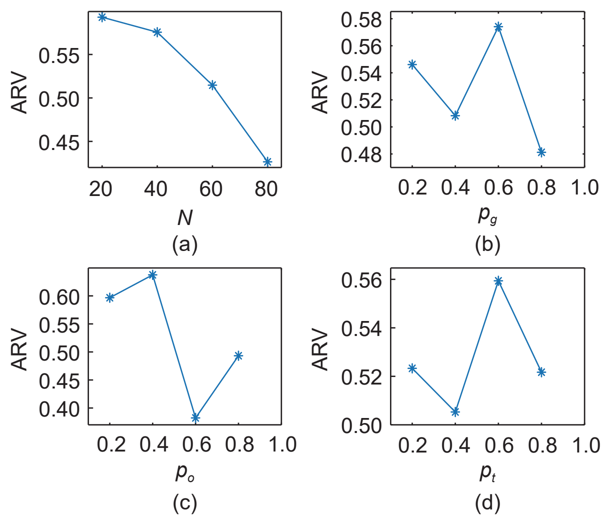

Fig. 3 Effect plot of user parameters.

Table 5 Parameters setting of NSGA-II and IMOABC.

Algorithm	Parameter setting
NSGA-II	Population size: 100 Crossover rate: 1.0 Mutate rate: 0.8
IMOABC	Number of food resources: 50 Maximum trial value: 2500

Table 6 Comparisons of three reported optimizers on *C*-metric.

Instance	*C* (BSO, GA)	*C* (GA, BSO)	*t*-test	*C* (BSO, ABC)	*C* (ABC, BSO)	*t*-test
S101	0.9955	0.0000	+	0.9833	0.0000	+
S102	0.6784	0.0000	+	0.7375	0.0000	+
S103	0.8862	0.0000	+	0.8708	0.0000	+
M101	0.9074	0.0000	+	0.8583	0.0000	+
M102	0.8190	0.0000	+	0.8500	0.0000	+
M103	0.9950	0.0000	+	1.0000	0.0000	+
M201	0.9850	0.0000	+	1.0000	0.0000	+
M202	0.9152	0.0000	+	0.8983	0.0000	+
M203	1.0000	0.0000	+	1.0000	0.0000	+
L101	0.9330	0.0000	+	0.9750	0.0000	+
L102	1.0000	0.0000	+	1.0000	0.0000	+
L103	0.9335	0.0000	+	0.9000	0.0000	+

algorithms, the obtained optimization results will be displayed as "–", "~", or "+".

From Table 6, we can see that almost all solutions acquired by the peer algorithms can be dominated by the nondominated solution set obtained by the proposed MOBSO, whereas no solution gained by the comparative approaches can dominate those attained by the MOBSO. On all the employed instances, the statistical results uncover that the developed MOBSO obviously exceeds both NSGA-II and IMOABC.

Table 7 provides the numerical results by three reported algorithms regarding the IGD-metric, where the variance is denoted as "var". Regarding each instance, the mean value of the MOBSO over twenty independent runs is smaller than its rivals. Therefore, we are able to declare that the overall performance (i.e., approximation and distribution) of the nondominated solution sets attained by the MOBSO is more excellent than those acquired by the NSGA-II and IMOABC. Moreover, the statistical test demonstrates that the MOBSO evidently surpasses both NSGA-II and IMOABC with respect to all the considered instances.

Furthermore, in terms of the first instance of each type, the boxplot graphs for the IGD-metric using three studied optimizers are displayed in Fig. 4. From it, we can see that the designed MOBSO algorithm is more stable for dealing with the given problem compared with NSGA-II and IMOABC.

Via summing up the given analysis and discussion on the numerical results, we can affirm that the developed MOBSO has superior performance to the comparative approaches in solving the studied problem.

5.4 Case study

To further confirm the effectiveness of the designed

Table 7 Comparisons of three considered algorithms on IGD-metric.

Instance	MOBSO		NSGA-II			IMOABC		
	Mean	Var	Mean	Var	*t*-test	Mean	Var	*t*-test
S101	0.0730	0.0008	0.8853	0.0028	+	0.9988	0.0056	+
S102	0.1110	0.0043	0.8228	0.0012	+	0.9474	0.0009	+
S103	0.1564	0.0027	0.7746	0.0024	+	0.9369	0.0031	+
M101	0.0866	0.0025	0.8994	0.0009	+	0.9982	0.0009	+
M102	0.1081	0.0062	0.8785	0.0009	+	0.9853	0.0010	+
M103	0.0654	0.0019	0.8888	0.0022	+	1.0415	0.0031	+
M201	0.0683	0.0014	0.8718	0.0017	+	1.0345	0.0054	+
M202	0.0702	0.0014	0.8691	0.0012	+	0.9912	0.0005	+
M203	0.0442	0.0003	0.8834	0.0009	+	1.0194	0.0022	+
L101	0.0875	0.0052	0.8861	0.0010	+	1.0252	0.0012	+
L102	0.0464	0.0002	0.9323	0.0013	+	1.0861	0.0036	+
L103	0.0756	0.0013	0.8939	0.0006	+	1.0078	0.0005	+

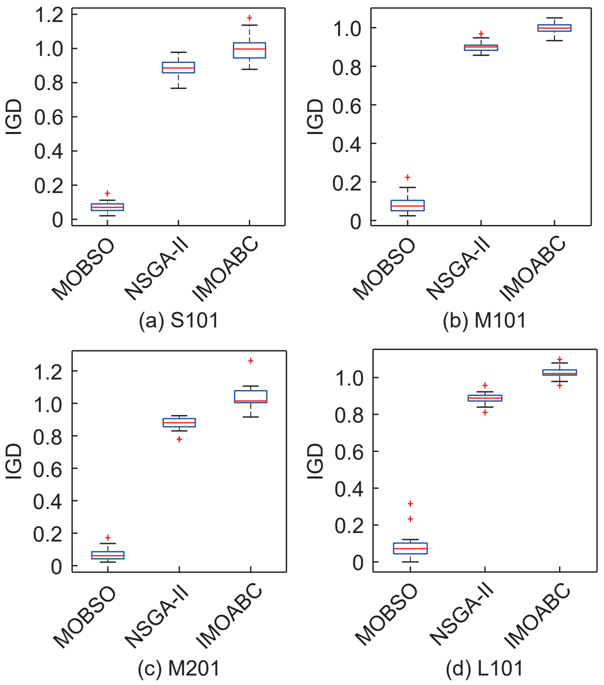

Fig. 4 Boxplot graphs of four instances obtained by three studied algorithms.

approach, this work offers a case study. There are two care centers (“A” and “B”) providing services for forty customers.

The coordinates of “A” and “B” are (53.5, 69.5) and (66, 68), respectively. Table 8 gives the basic information of customers including coordinates, service time (q_i), appointment time (L_i), and skill grade requirement (s_i). Figure 5 illustrates the location of customers.

Table 9 lists the nondominated solutions acquired by the developed method. By observing Table 9, we can infer that eight nondominated solutions are obtained by the MOBSO which can provide well-informed decisions for managers and engineers.

Table 8 Customer information for the considered case study.

No.	Coordinate	q_i	L_i	s_i	No.	Coordinate	q_i	L_i	s_i
1	(53.8, 66.8)	20	48	Q_1	21	(56.0, 61.6)	30	36	Q_1
2	(49.4, 65.9)	20	64	Q_1	22	(67.0, 62.3)	30	53	Q_1
3	(70.6, 69.8)	20	39	Q_1	23	(52.6, 61.5)	30	39	Q_1
4	(57.9, 69.0)	20	32	Q_1	24	(55.1, 71.3)	30	62	Q_1
5	(66.1, 63.4)	20	43	Q_1	25	(63.1, 66.3)	30	43	Q_2
6	(50.8, 72.0)	20	50	Q_1	26	(62.8, 62.9)	30	49	Q_2
7	(65.6,72.2)	20	57	Q_1	27	(67.7, 64.7)	30	65	Q_2
8	(47.1, 63.3)	20	61	Q_1	28	(62.0, 69.4)	30	48	Q_2
9	(57.4, 65.7)	20	62	Q_1	29	(66.2, 76.0)	30	59	Q_2
10	(71.2, 64.8)	20	47	Q_1	30	(70.4, 75.8)	30	66	Q_2
11	(70.0, 68.2)	30	55	Q_1	31	(67.5, 75.7)	40	49	Q_2
12	(60.7, 69.5)	30	58	Q_1	32	(63.5, 75.9)	40	55	Q_2
13	(68.1, 69.8)	30	43	Q_1	33	(68.2, 72.5)	40	62	Q_2
14	(51.0, 68.4)	30	59	Q_1	34	(57.5, 72.6)	40	58	Q_2
15	(48.1, 68.7)	30	44	Q_1	35	(55.2, 65.0)	40	52	Q_2
16	(70.3, 72.6)	30	59	Q_1	36	(59.0, 66.5)	40	69	Q_2
17	(60.9, 72.7)	30	58	Q_1	37	(49.9, 74.4)	40	47	Q_3
18	(53.0, 65.2)	30	39	Q_1	38	(70.9, 60.0)	40	36	Q_3
19	(70.5, 63.5)	30	43	Q_1	39	(50.6, 61.7)	40	52	Q_3
20	(59.9, 61.7)	30	48	Q_1	40	(53.5, 75.8)	40	43	Q_3

Fig. 5 Location map for the customers and care centers.

6 Conclusion

To be more realistic, this article considered multiple care centers and presented a multi-objective HHCSRP. To ensure customers’ and caregivers’ satisfaction simultaneously, the skill matching, appointment time of customers, and workload balancing of caregivers were taken into account. Moreover, this research formulated an optimization model with multiple objectives to minimize service cost and delay cost. To handle the two conflicting objectives, a multi-objective brain storm optimization method was introduced. Finally, this study implemented numerous experiments and the analysis of the obtained optimization results suggested that the better solutions can be attained by the designed approach in tackling the HHCSRP compared with two prominent algorithms.

Future research will consider the following two directions: (1) To achieve sustainability, green objectives can be added into our HHC scheduling and routing model[47−50]; (2) To improve the performance of the designed MOBSO, machine learning approaches can be developed[51−54].

Table 9 Nondominated solutions.

No.	Caregiver	Route	Service cost	Delay cost	No.	Caregiver	Route	Service cost	Delay cost
1	1	A-24-18-23-20-15-A	2415	1548.16	5	1	A-24-18-23-20-15-A	2445	1468.5
	2	A-1-9-7-16-3-A				2	A-1-12-9-17-22-A		
	3	A-8-2-28-31-A				3	A-8-2-28-31-A		
	4	A-25-36-39-37-A				4	A-25-36-39-37-A		
	5	A-14-29-32-A				5	A-14-29-32-A		
	6	B-17-12-13-11-22-B				6	B-13-3-11-7-16-B		
	7	B-5-10-19-21-6-B				7	B-5-10-19-21-6-B		
	8	B-4-35-30-B				8	B-4-35-30-B		
	9	B-38-34-40-B				9	B-38-34-40-B		
	10	B-26-27-33-B				10	B-26-27-33-B		
2	1	A-18-23-20-24-15-A	2430	1478.95	6	1	A-1-9-20-24-15-A	2505	1328.13
	2	A-1-6-2-8-9-A				2	A-6-18-2-23-8-A		
	3	A-28-3-16-31-A				3	A-28-12-17-31-A		
	4	A-25-36-39-37-A				4	A-25-36-39-37-A		
	5	A-14-29-32-A				5	A-14-29-32-A		
	6	B-22-11-13-17-12-B				6	B-13-3-11-7-16-B		
	7	B-7-5-10-19-21-B				7	B-5-10-19-21-22-B		
	8	B-4-35-30-B				8	B-4-35-30-B		
	9	B-34-40-38-B				9	B-38-34-40-B		
	10	B-26-27-33-B				10	B-26-27-33-B		
3	1	A-24-18-23-20-15-A	2475	1393.57	7	1	A-21-24-17-12-14-A	2400	1611.2
	2	A-2-1-9-6-8-A				2	A-4-1-2-8-23-A		
	3	A-28-12-17-31-A				3	A-6-34-29-33-31-A		
	4	A-25-36-39-37-A				4	A-39-36-A		
	5	A-14-29-32-A				5	A-40-32-A		
	6	B-13-3-11-7-16-B				6	B-11-13-16-22-20-B		
	7	B-5-10-19-21-22-B				7	B-9-18-15-19-10-B		
	8	B-4-35-30-B				8	B-5-25-26-B		
	9	B-38-34-40-B				9	B-27-28-7-35-37-B		
	10	B-26-27-33-B				10	B-30-3-38-B		
4	1	A-1-9-20-24-15-A	2460	1449.88	8	1	A-14-18-21-19-16-A	2490	1378.98
	2	A-6-18-8-2-23-A				2	A-9-1-8-15-24-A		
	3	A-28-3-16-31-A				3	A-4-7-32-34-A		
	4	A-25-36-39-37-A				4	A-37-39-A		
	5	A-14-29-32-A				5	A-28-30-31-A		
	6	B-13-22-11-17-12-B				6	B-11-12-17-22-B		
	7	B-7-5-10-19-21-B				7	B-20-23-2-6-10-B		
	8	B-4-35-30-B				8	B-3-13-33-38-B		
	9	B-38-34-40-B				9	B-5-27-29-40-B		
	10	B-27-26-33-B				10	B-25-26-35-36-B		

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