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A New Model for the Multi-Objective Multiple Allocation Hub Network Design and Routing Problem

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ABSTRACT In this paper, we propose a new model for the multi-objective multiple allocation hub network design and routing problem which contains determining the location of hubs, the design of hub network, and the routing of commodities between source-destination pairs in the given network. The selected hubs are not assumed to be fully connected, and each node and arc in the network has capacity constraints. The multiple objectives of the problem are the minimization of total fixed and transportation costs and the minimization of the maximum travel time required for routing. We propose a mathematical formulation for the multi-objective problem and present a meta-heuristic solution based on a well-known multi-objective evolutionary algorithm. Using the proposed formulation, we are able to find the optimal solution for small networks of five nodes and seven nodes. To evaluate the performance of our heuristic approach on real data, the computational experiments are conducted on Turkish postal system data set. The results demonstrate that our heuristic approach can find feasible solutions to the problem in reasonable execution time, which is less than 10 min.

INDEX TERMS Capacitated hub location problem, heuristic algorithms, mathematical model, pareto optimization, routing and network design.

I. INTRODUCTION

There are plenty of applications that need transfer of people, commodities and data between source-destination pair of nodes, such as, air transportation services, public postal services, cargo delivery systems, and telecommunication systems. The network for these applications are usually designed based on hub-and-spoke networks. In these networks, hubs are established so as to collect and distribute the flow between source-destination pairs, and spokes are the non-hub nodes that are allocated to hub nodes in the network. Hub location problem (HLP), in general, deals with the decision of hub and spoke nodes in a given network, as well as connections between hubs and spokes, i.e. the assignment of spokes to hubs, and the routing of flow between each pair of nodes.

Several variations of HLP have been studied in the literature. The problem can be modelled as single allocation HLP [1]–[3] or multiple allocation HLP [4], considering the assignment of spokes to hubs in the network. Multiple allocation HLP allows spokes to be assigned to more than one hub, whereas, in single allocation spokes can be assigned to only

one of the hubs. If capacities of hubs are considered, the HLP can be capacitated [5]–[7] or uncapacitated [8], [9]. Also, in a HLP, the number of hubs to be established can be predetermined as in p -HLP [4] or determining the number of hubs can be among the decisions that should be made. Most of the studies on HLP consider that the hubs are fully connected to each other. However, in real world applications such as less-than-truckload networks and telecommunications networks [10], it is not practical to establish a connection between each hub pair. The design of connections between hubs is referred as hub network design [11] and considered within different applications in the literature.

In this paper, a Multi-Objective Capacitated Multiple Allocation Hub Location Problem (MOCMAHLP) is addressed. The number of hubs is not known in advance and the hub network is not assumed to be fully interconnected. To the best of our knowledge, this is the first attempt that gives a mathematical model for this variation of HLP. To contribute to fill this gap, we propose a mathematical model for the MOCMAHLP with objectives of (1) minimizing transportation cost and fixed costs and (2) minimizing the maximum travel time required for routing the commodities between all node pairs. In most of the HLPs in the literature, the first objective,

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TABLE 1. Comparison of the literature on multi-objective HLP with the model in this paper.

Model in literature	Variable Number of Hubs	Capacitated	Multiple Allocation	Hub Network Design
Mirzaei and Bashiri [20]	✓	✓	✓	–
Tavakoli <i>et al.</i> [13]	✓	✓	✓	–
Köksalan and Soylu [21]	–	–	✓	–
Köksalan and Soylu [21]	–	✓	✓	–
Costa <i>et al.</i> [22]	✓	✓	–	–
Ghodratnama <i>et al.</i> [23]	✓	✓	–	–
Kaveh <i>et al.</i> [24]	–	✓	–	✓
Karimi and Setak [25]	✓	–	✓	✓
Our model	✓	✓	✓	✓

i.e., the minimization of transportation cost, is used. However, in real world applications, such as systems that transfer perishable goods, rapid transportation and delivery is required. Thus, the second objective is added to our model. The routes between each source-destination pair should be determined in order to calculate the second objective. Therefore, our proposed mathematical model includes routing of commodities through network, besides determining the location of hubs and the hub-to-hub and spoke-to-hub arcs in the whole network.

The HLP belongs to the class of NP-complete problems [12]. The computational results show that the MOCMAHLP can be solved optimally for specifically small size networks. To solve the problem for a 7-node network using brute-force method that considers every possible solution, we need approximately 3 hours, and if we increase the number of nodes to 8, the required time is more than a day. Therefore, to solve the MOCMAHLP for real size networks, a meta-heuristic is needed. Since there are numerous successful applications of genetic algorithms to solve different versions of hub location problems [13]–[18], we propose a meta-heuristic based on non-dominated sorting genetic algorithm (NSGA-II) [19]. A novel solution representation and proper genetic operators are designed as part of our solution. We conducted a set of experiments using the Turkish postal system data set considering hypervolume as comparison metric. The results of our experimental study demonstrates that our algorithm can find feasible solutions for a relatively large network containing 81 nodes in less than 10 minutes.

The rest of this paper is organized as follows. In the next section, we give a review of the related literature that emphasizes similarities, differences and deficiencies of the models presented. In Section 3, the proposed mathematical model for MOCMAHLP is given. In Section 4, we present our NSGA-II approach for the MOCMAHLP. The solution representation and the genetic operators are explained in detail. Section 5 and Section 6 include our experimental setup and a discussion about computational results, respectively. Finally, the last section highlights the conclusion and future work.

II. RELATED WORK

O’Kelly presented the first mathematical formulation on HLP [3]. Since then, the problem has received much

attention considering different variations and different solution approaches. The interested reader can refer to different surveys on HLP [26]–[28].

In this paper, we concentrate on multi-objective, capacitated, multiple allocation HLP; and in our mathematical formulation of the given problem, we consider determining the location of hubs, spoke-to-hub and hub-to-hub allocations, and routing of commodities between each pair of nodes. Although most of the models for HLP include only one objective, real-world applications of HLP require more than one objective. In Table 1, a complete comparison of models presented in literature for multi-objective HLP and the model presented in this paper is given. To the best of our knowledge, there is no study that models this variation of HLP.

In a recent study [20], Mirzaei and Bashiri present a model for multi-objective multiple allocation hub location problem. However, in their model, the hub network is assumed to be fully interconnected and no experimental result is given in the corresponding paper. The multi-objective multiple allocation hub location problem without hub network design is solved also in [13] considering sustainable development paradigm and using multi-objective differential algorithm. Köksalan and Soylu [21], present two models for multiple allocation HLP. Both models assume the fixed number of hubs and fully-interconnected hub networks. In [22]–[24], single allocation HLP is considered. Karimi and Setak [25] consider the problem similar to our assumptions except the capacities of hubs and arcs in the network.

The common objective used in most of the studies given in Table 1 is total cost minimization. Besides this, other objectives can be listed as the following:

- Minimization of maximum travel time [20]
- Minimization of environmental impacts like energy cost, noise, congestion, pollution, greenhouse gas emission [13]
- Minimization of total transportation costs [21], [22], [29]
- Minimization of the maximum delay at each hub [21]
- Minimization of total time for processing the flow collected by the hubs [22]
- Minimization of the sum of waiting times [29]
- Minimization of total gas emissions [22], [29]
- Maximization of benefits of transportation and establishment of the hub facilities [24]

- Minimization of the total transportation time [24]
- Maximization of the total amount of flow delivered in a predefined time [25]

Costa *et al.* [22] present two different mathematical models for a bi-objective capacitated single allocation HLP. In the first model, it is aimed to minimize the total costs and to minimize the total time for processing the flow collected by the hubs. In the second model, the objectives are to minimize the total costs and to minimize the maximum service time on the hubs. Two bi-criteria uncapacitated, multiple allocation p -HLPs are studied in [21]. The objectives in one of their problems are minimizing the total transportation costs and total traveling costs between hubs and source-destination points. In the other problem, the objectives are minimizing the total transportation costs and minimizing the maximum delay at each hub. Mirzaei and Bashiri [20] consider a multi-objective approach for HLP to minimize the total cost and to minimize the maximum traveling time between nodes in the network. Ghodrathnama *et al.* [23] formulate a capacitated single allocation HLP with three objectives which are minimization of total costs including the transportation and installation, minimizing the sum of service time in the hubs, and minimization of total greenhouse emission. Karimi and Setak [25] develop a flow shipment scheduling and incomplete hub location-routing problem using two conflicting objectives which are to maximize the total amount of flow delivered in a predefined time and to minimize the total costs. A hub location-allocation model considering congestion is presented in [29], with the aim of minimizing the total costs and minimizing the sum of waiting times. Tavakoli *et al.* [13] introduce a multi-objective mathematical model for multiple allocation HLP with multiple capacity levels. The problem minimizes both costs and environmental impacts.

Since HLP is NP-complete [12], optimum solutions for small-scale problems can be found by linear programming. Therefore, heuristics are used to find optimal or near optimal solutions for large-scale problems in the domain of HLP [26], [30]. In addition, meta-heuristics such as genetic algorithm [9], multi-objective differential evolution [13] and multi-objective evolutionary algorithm [15], [16], [21], [31] are successfully applied to HLPs. In addition, the non-dominated sorting genetic algorithm (NSGA-II) has been successfully applied to different multi-objective facility location problems [15], [32], [33] as well as HLPs [16], [31]. Therefore, in this paper, we propose a heuristic based on NSGA-II for the MOCMAHLP.

III. MATHEMATICAL MODEL

In this section, we present a new model for the Multi-objective Capacitated Multiple Allocation Hub Location Problem (MOCMAHLP). The basic assumptions of the problem are as follows:

- The solution space is discrete and finite
- The set of nodes is known
- The number of hubs is not fixed

- Each node has a fixed cost to be established as a hub
- Each arc in the established network has a fixed cost
- Each node can be assigned to more than one hub
- There is no direct link between spokes, i.e. two spokes can only communicate via at least one hub
- Hub network is not necessarily fully interconnected
- Each arc in the network has a flow capacity
- Each hub has a limited capacity

In the MOCMAHLP, there are three decisions to be made: (1) hub location, (2) the hub network design and (3) the routing of the flow. The first decision is to determine the number and location of hubs. The second involves decision on the allocation of spokes to hubs and then the determination of hubs that are interconnected. We consider the multiple allocation pattern, i.e. a spoke can be assigned to more than one hub. The last one is the decision on how to route the flow. Since the problem has both hub and arc capacities, the demand may be routed through separate paths going from its source and destination nodes. Therefore, the demand is divided into separate packages with different amount of flow.

Under these assumptions, we develop a mathematical model to the MOCMAHLP based on the formulation of Capacitated Multiple Allocation Hub Location Problem (CMAHLP) proposed by Rodríguez-Martín and Juan José Salazar-González [6]. To the best of our knowledge, this is the first attempt to model this variation of HLP with the specified assumptions.

First, we introduce the notation used in the model. Given a directed graph $G = (V, E)$, where V is a set of nodes and E is a set of directed edges (or arcs), each arc ($a \in E$) is associated with an ordered pair of nodes ($a = (u, v)$, $u, v \in V$). The demand from node i to node j (d_{ij}) is called *commodity* and will be denoted by a single index k where $k = (i, j)$. The amount of package p of commodity k is denoted as k_p . All edges incoming to vertex v is denoted by $V^-(v) = \{(u, v) \in E | u \in V \setminus \{v\}\}$. Besides, all edges outgoing from vertex v is denoted by $V^+(v) = \{(v, u) \in E | u \in V \setminus \{v\}\}$.

We additionally use the following notation:

- N Number of nodes ($N = |V|$)
- H Set of possible hub locations
- a_u The initial node of arc $a \in E$
- a_v The terminal node of arc $a \in E$
- T_a Time required to transfer over arc $a \in E$
- F_a Total amount of flow traversing arc $a \in E$
- C_a Unit cost of delivery on arc $a \in E$
- λ_a Fixed cost of arc $a \in E$
- Q_a Capacity of arc $a \in E$
- i_k The source node for commodity k
- j_k The destination node for commodity k
- D_k Total demand of flow for commodity k
- D_{k_p} Demand of flow for package p of commodity k
- f_a^k The flow of commodity k on arc $a \in E$
- κ_h Fixed cost of hub $h \in H$
- Q_h Capacity of hub $h \in H$
- χ Collection discount factor

- α Discount factor of hub to hub transportation
- δ Distribution discount factor

The decision variables for the MOCMAHLP are given as follows:

$$Z_a = \begin{cases} 1, & \text{if arc } a \text{ is used between nodes } a_i \text{ and } a_j \\ 0, & \text{otherwise} \end{cases}$$

$$x_i = \begin{cases} 1, & \text{if node } i \text{ is hub} \\ 0, & \text{otherwise} \end{cases}$$

$$x'_i = \begin{cases} 1, & \text{if node } i \text{ is spoke} \\ 0, & \text{otherwise} \end{cases}$$

$$A_{kp}^a = \begin{cases} 1, & \text{if the flow at package } p \text{ of commodity } k \text{ is} \\ & \text{routed via arc } a \text{ with } Z_a = 1 \\ 0, & \text{otherwise} \end{cases}$$

$$D_{k_p} = n, \quad \text{such that } 0 \leq n \leq D_k$$

$$F_a = \sum_{k_p} D_{k_p} A_{k_p}^a$$

$$f_a^k = \sum_p D_{k_p} A_{k_p}^a \quad \text{for each commodity } k$$

Here, Z_a is the decision variable used for hub network design and denotes the hub-to-hub and hub-to-spoke connections. x_i and x'_i are the decision variables used for the hub location. The remaining decision variables ($A_{k_p}^a$, D_{k_p} , F_a , and f_a^k) are used for the routing.

The MOCMAHLP can be formulated as follows:

$$\begin{aligned} & \text{minimize } \sum_a F_a C_a (\chi x'_{a_u} x_{a_v} + \alpha x_{a_u} x_{a_v} + \delta x_{a_u} x'_{a_v}) \\ & \quad + \sum_a \lambda_a Z_a + \sum_{i=1}^N \kappa_i x_i \\ & \text{minimize } \max_{k_p} \sum_a T_a A_{k_p}^a \\ & \text{subject to } 1 \leq \sum_i x_i \leq N \tag{1} \\ & F_a \leq Q_a \quad \forall a \in E \tag{2} \\ & \sum_{a \in V^+(h)} F_a \leq Q_h \quad \forall h \in H \tag{3} \\ & \sum_p D_{k_p} = D_k \quad \forall k \tag{4} \\ & A_{k_p}^a \leq x_{a_v} Q_h, \quad a_v \neq j_k, \quad \forall k \tag{5} \\ & 0 \leq f_a^k \leq F_a \quad \forall a \in E \tag{6} \end{aligned}$$

for each commodity k

$$\sum_{a \in V^+(v)} f_a^k - \sum_{a \in V^-(v)} f_a^k = \begin{cases} D_k, & \text{if } v = i_k \\ -D_k, & \text{if } v = j_k \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

The first objective is to minimize the total cost including the cost of collection, transfer and distribution (the first part of the objective function), the fixed arc cost (the second part) and the fixed hub cost (the last part). The second objective

is to minimize the maximum travel time required for routing between all node pairs. Constraint (1) ensures that there is at least one hub. Constraint (2) and Constraint (3) are arc and hub capacities, respectively. Constraint (4) states that the sum of flow demand for all packages of a commodity is equal to the total flow demand for the commodity. Constraint (5) ensures that only hub is used for routing the demand (x_{a_v} become 1 if the terminal node of arc a (a_v) is selected as a hub; 0, otherwise). Constraint (6) shows that the flow of commodity k on arc a is less than total amount of flow traversing arc a . Constraint (7) states the flow balancing constraints.

IV. A HEURISTIC APPROACH FOR THE PROBLEM

The multi-objective optimization problems are problems that consist of more than one objective function that must be simultaneously optimized. A key goal in multi-objective optimization research is to find a set of optimal solutions known as Pareto optimal set instead of a single optimal solution. A set of points mapped from the Pareto optimal set is referred to as the Pareto-front.

Evolutionary algorithms have been successfully applied to the multi-objective optimization problems. The non-dominated sorting genetic algorithm (NSGA-II) [19] is one of the most well-known multi-objective evolutionary algorithms. NSGA-II uses genetic operators including binary tournament selection, crossover and mutation to generate offspring population. The individuals for the next generation is selected according to non-dominated and crowding distance sorting procedures.

Algorithm 1 The Pseudo-Code of the Proposed Approach

- 1: Create an initial population (P_0) and evaluate P_0
 - 2: Sort the population based on the non-domination
 - 3: **while** (termination criteria not satisfied) **do**
 - 4: Generate child population (Q_t)
 - 5: Apply A* algorithm for routing
 - 6: Evaluate the child population Q_t
 - 7: Merge child and parent populations ($R_t = P_t \cup Q_t$)
 - 8: Select the individuals for the next generation
 - 9: **end while**
-

In this study, since the problem is NP-complete, we propose a heuristic approach based on NSGA-II. In this section, the details of our algorithm are presented. The pseudo-code of the algorithm is given in Algorithm 1. We propose a new representation for the candidate solution and crossover and mutation operators are adapted to the solution representation. Besides, a repair function for the infeasible solutions is introduced.

A. SOLUTION REPRESENTATION

Each candidate solution is represented using two same length arrays. The length of both arrays is the same and equal to the number of nodes in the network.



FIGURE 1. An example of hub decision array for a 9-node network.

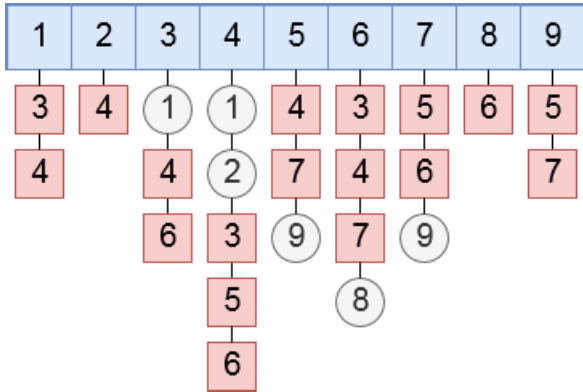


FIGURE 2. An example of link decision array for a 9-node network, with nodes 3,4,5,6, and 7 being hubs.

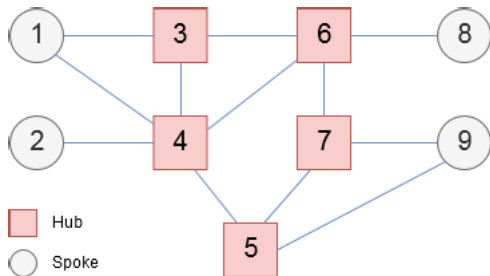


FIGURE 3. The illustration of resulting network for the hub decision and link decision arrays in Figures 1 and 2.

One of the arrays is a binary array, which is used for the hub decision, i.e. value 1 states that the corresponding node is a hub and value 0 states that it is a spoke. An example of hub decision array is illustrated in Figure 1. This solution includes five hubs out of nine nodes.

The second array, named link decision array, is just an adjacency list representation of the network design. Each element in the array contains the nodes that are connected to the corresponding node. An example of link decision array that can be generated for hub decision array in Figure 1 is illustrated in Figure 2. In this example, node 3, which is a hub, is connected to nodes 1, 4 and 6. Also, node 9, which is a spoke, is connected to nodes 5 and 7.

According to the solution representation given in Figures 1 and 2, the resulting network design can be seen in Figure 3.

B. GENETIC OPERATORS AND REPAIR FUNCTION

In our approach, binary tournament selection, one-point crossover, two different mutation operators and repair function for all infeasible solutions are applied to generate a child population (line 4 of Algorithm 1).

One-point crossover operator is applied to both hub and link decision arrays with a predefined probability. The same crossover point which is randomly selected is considered for both arrays.

After crossover, two different mutation operators are considered for the arrays used in the solution representation: (1) bit-flip mutation is used for hub decision array, (2) swap mutation is used for link decision array. A repair function is applied to all the infeasible solutions generated as a result of genetic operators. Since the operators are applied to both arrays, a repair phase is also needed for both. In the repair phase for the hub decision array, only the number of hubs in the offspring is taken into account. If the offspring does not include a hub, this offspring is discarded and a random offspring is generated instead. The repair function used for the link decision array considers the five cases listed:

- 1) A link between two nodes may not be mutually included in the link decision array. In this case, the link is mutually established.
- 2) A hub has no hub connection. In this case, the hub becomes connected to the closest hub.
- 3) There is a connection between two spoke nodes. In this case, the connection is removed.
- 4) A spoke node is not assigned to a hub. In this case, it is assigned to the closest hub.
- 5) The resulting network may be disconnected. In this case, an arc is added between the closest hubs of each sub-network to make them connected.

C. ROUTING

To obtain the total amount of flow traversing each arc, the routing of demands for all the commodities must be determined (line 5 of Algorithm 1). Due to the hub and link capacities, the demand of each commodity may be divided into separate packages. Additionally, the packages may be routed through several paths since the multiple allocation pattern and the interconnected hub network are considered.

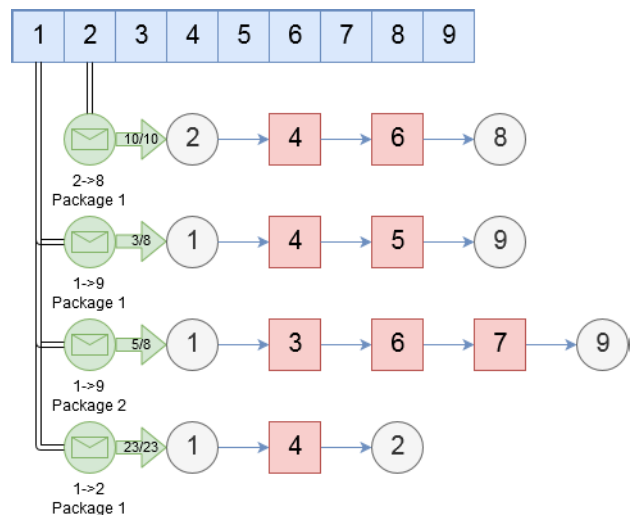


FIGURE 4. Routing example of three source-destination pairs for the given 9-node network in Figure 3.

A simple scenario for routing is given in Figure 4. As seen in the figure, the commodities from node 1 to node 2 and from node 2 to node 8 are not divided into packages and routed

through the paths $1 \rightarrow 4 \rightarrow 2$ and $2 \rightarrow 4 \rightarrow 6 \rightarrow 8$, respectively. On the other hand, the commodity from node 1 to node 9 is split into two packages. The first package, which contains three-eighth of the demand, follows the path going through two hubs (node 4 and 5). The remaining part is sent along the path: $1 \rightarrow 3 \rightarrow 6 \rightarrow 7 \rightarrow 9$.

A* algorithm which aims to find the shortest paths in a graph is employed for the routing of all the commodities. In our approach, path length is identified as the travel cost considering the discount factor of the corresponding links in the path. First, A* algorithm searches for an augmenting path in the residual network to route the demand of a commodity. If there is such a path, a portion of the flow demand with the residual capacity on this path is routed through the selected path. The residual capacity of a path is equal to the minimum available capacity considering the hub and link capacities along the path. After routing, the residual network is updated with the remaining capacities for each link and hub. If all the demand for the current commodity is not routed, a new path is examined for the remaining demand. This process is repeated for each commodity. The commodity to route next is selected randomly.

At the end of the process of routing, there may be solutions that do not route all the commodities. The total number of unrouted commodities is taken into account to select the individuals for the next generation (line 8 in Algorithm 1).

V. EXPERIMENTAL SETUP

For the experimental study, we conducted two sets of experiments. In the first set of experiments, we found the optimal solutions for the MOCMAHLP for two different small data sets with a brute-force method that searches the whole solution space. We also used the same data sets to solve the problem using our NSGA-II approach. Since our heuristic approach was able to find optimal solutions for the problem with these data sets, as a second set of experiments, we conducted parameter tuning tests to explore the influence of parameter setting on the performance of our approach. In the parameter tuning tests, we used Turkish postal system data set (will be referred as Turkish data set in the rest of this paper) introduced in [34]–[36].

To implement the proposed approach, an open source framework written in Java, MOEA,¹ is used. Tests are conducted within a computer having these hardware configurations: Intel i-7 2600K processor and 8GB ram.

A. DATA SET

Turkish data set introduced in [34]–[36] is used in the tests. It is available from OR-Library.² The data set contains 81 nodes which correspond to the 81 cities in Turkey. In the Turkish data set, travel distances, travel times, flow, and fixed link costs between these 81 cities and fixed hub costs for these cities are given. The discount factor for the hub to hub

transportation (α) is set to 0.9 as recommended in [36]. The discount factors for collection (χ) and distribution (δ) are set to 1.

Two different subsets of this large data set are generated to get optimal solutions for the problem. These subsets include 5 and 7 nodes, respectively. In the 5-node subset, we included 5 cities (Afyon, Aydın, Denizli, İzmir, Manisa) in the Aegean region of Turkey that have the largest amount of total flow demand within the region. In the 7-node subset, on the other hand, we selected the most populated cities (Ankara, Antalya, İstanbul, İzmir, Samsun, Şanlıurfa, Van) in each geographical region.

We propose a solution approach that routes each commodity considering capacity constraint on hubs and links besides location and allocation of hubs and spokes. However, there is no capacity information for hubs and links in the data set. Therefore, we generated hub and link capacities for the data set using a method explained in the next two paragraphs.

We calculated hub capacities for each city in the data set using the population size of the corresponding city declared by the Turkish Statistical Institute in 2018. To calculate the hub capacities, we propose the following formulation given in Eq. 8. In the equation, ψ denotes hub capacity multiplier and is used for scaling. To get realistic hub capacities, the ratio of city population (P_c) to total population of the country, is multiplied with total incoming and outgoing flow demand of the city (F^c) as in Eq. 8.

$$Q_c = \psi \left(\frac{P_c}{\sum_{i=1}^N P_i} \right) F^c \quad (8)$$

$$F^c = \sum_a \begin{cases} F_a, & \text{if } a_u = c \text{ or } a_v = c \\ 0, & \text{otherwise} \end{cases}$$

To calculate link (arc) capacities (Q_a), distance and travel time for the corresponding link are used. We formulated link capacity calculation as in Eq. 9. In the equation, ω used for scaling denotes link capacity multiplier. To get realistic link capacities, distance required to travel through the arc (d_a) is divided by time required to travel through the arc (T_a) and is multiplied with flow demand (F_a) between the start and end nodes of arc a .

$$Q_a = \omega \left(\frac{d_a}{T_a} \right) F_a \quad (9)$$

The first objective of MOCMAHLP includes summation of three different costs, namely total transportation cost, fixed arc cost, and fixed hub cost, each have different orders of magnitude. In order to bring these values to the same order of magnitude, we defined and tuned some multipliers for these cost values as *total transportation cost multiplier*, *fixed hub cost multiplier* and *fixed link cost multiplier*. In the experiments, we tested the total cost multiplier with several values between 10^{-8} and 10^{-5} and the fixed hub cost multiplier with several values between 10^{-2} and 10^1 . The fixed link cost multiplier is set to 1 in order to use the magnitude of link costs in the summation. As a result of tuning the values for these multipliers, it is experienced that;

¹<http://moeaframework.org/>

²<http://people.brunel.ac.uk/~mastjjb/jeb/orlib/phubinfo.html>

- If *total transportation cost multiplier* (ξ) is increased, more hubs and links appeared in the solutions.
- If *fixed hub cost multiplier* is increased, fewer hubs appeared in the solutions. Besides, at some point in the execution, the number of hubs decreases to 1 hub.
- If both *total transportation cost multiplier* (ξ) and *fixed hub cost multiplier* are decreased, fewer links appeared in the solutions. At some point in the execution, each spoke is assigned to only one hub.

Similar to the costs, the capacity values in the data set have different orders of magnitude. Therefore, another set of multipliers are defined for capacities (ψ for hubs, ω for links) as given in Eq. 8 and Eq. 9. ψ was tested with several values between 10^0 and 10^4 and ω was tested with several values between 10^0 and 10^3 . As a result of tuning the values of these multipliers, we conclude that:

- As ψ is decreased, hubs are mostly selected among more populated cities. When ψ is decreased further, then cities which are close to each other are selected as hubs to convey the demand through these cities.
- As ω is decreased, the number of hubs that the spokes are allocated is increasing, thereby total capacity of transportation on links is increasing.

For the first objective, i.e. minimizing the total cost, we need to calculate travel cost of each arc. The unit cost of traveling through arc a (C_a) is calculated as $C_a = \xi d_a$, where ξ denotes cost per flow per unit distance, so that by multiplying with the distance of arc gives us cost to move one unit flow through arc. Therefore, as in the first objective, multiplying C_a with total flow on arc gives the true cost of transfer through the arc.

As a result of experiments, the multipliers are set to the following values:

- *total transportation cost multiplier* (ξ) = 10^{-7} ,
- *fixed hub cost multiplier* = 0.2,
- *fixed link cost multiplier* = 1.0,
- ψ = 50,
- ω = 400.

These settings are determined empirically as a result of a set of preliminary experiments.

B. PERFORMANCE METRIC

Since the problem we study is a multi-objective problem, hypervolume indicator [37] which is the most used metric, is selected to evaluate the performance of our algorithm and to compare different test suits. Hypervolume indicates the volume between reference point in the solution space and the Pareto front found by the solution approach. The hypervolume is calculated based on the normalized objective function values. We use the hypervolume calculation provided in MOEA framework for the hypervolume of the Pareto front. Figure 5 illustrates the hypervolume indicator.

Thus, to obtain a properly chosen reference point, we executed our algorithm 5 times with the selected data set using 200000 evaluations, which is rather a long execution for the problem. At this stage, the algorithm has been converged

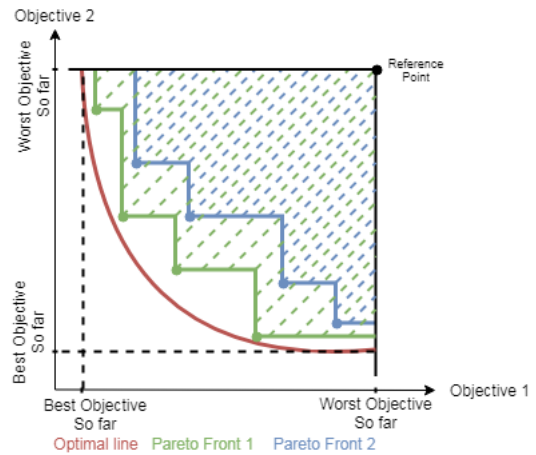


FIGURE 5. Hypervolume indicator.

(see Figure 8). The worst and the best objectives of the problem are obtained for these 5 runs to determine the reference point.

C. PARAMETER SETTING FOR OUR HEURISTIC

In the first set of tests, to evaluate the effectiveness of our heuristic approach we used the small data sets for which we obtained the optimum values. Unless stated otherwise, we consider the following parameter setting for our heuristic approach in these tests:

- Population size ($popsize$) is set to 200.
- Crossover probability (p_c) is set to 0.8.
- Bit-flip mutation probability (p_{bfm}) is set to $1/n$ where n is the number of hubs in the network.
- Swap mutation probability (p_{sm}) is set to 0.2.
- The maximum number of fitness evaluation count is set to 20000.

VI. EXPERIMENTAL EVALUATIONS

In this section, the results on two different small data sets and Turkish data set are presented.

A. RESULTS ON SMALL DATA SETS

In order to examine the correctness of our mathematical model and to observe the performance of our algorithm, first we conducted tests with the small data sets mentioned above. Optimal solutions are found with a brute-force method that evaluates every possible solution and then inserts into global non-dominated Pareto set by comparing with all solutions in the Pareto set.

The maximum number of feasible networks that can be generated for N number of nodes is given in Eq. 10. There are 3 parts in the equation; the first part calculates the permutation of i -hubs within division, the second part determines the number of spoke-to-hub connections and the last part determines the number of hub-to-hub connections.

$$\sum_{i=1}^N \binom{N}{i} (2^i - 1)^{(N-i)} (2^{i-1} - 1)^i \quad (10)$$

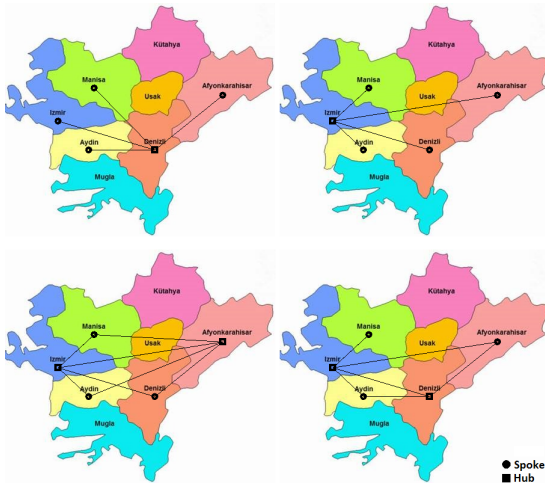


FIGURE 6. Pareto-optimal solutions obtained by brute-force method for 5-node network (Upper solutions have 1, lower solutions have 2 hubs).

Experimental results show that, the brute-force method finds 4 solutions in non-dominated Pareto set for the 5-node network, with the hubs being Denizli, İzmir, İzmir-Afyon, and İzmir-Denizli. Figure 6 shows an example optimum solution obtained for 5-node network. Also, a sample optimum solution for 7-node network is given in Figure 7. In the non-dominated Pareto set for this network, there are 6 solutions,

for which the hubs are selected as, Ankara, İstanbul, İstanbul-Samsun, İstanbul-Şanlıurfa, İstanbul-Şanlıurfa, and İstanbul-Van-İzmir.

Our NSGA-II based algorithm is also applied to these small data sets to explore its effectiveness on the problem. Our approach finds exactly the same Pareto set with linear solution for 5-node network on each run (see Figure 6). For 7-node network (see Figure 7), our approach obtains exactly the same Pareto set with linear solution in %20 of runs (i.e., in 2 out of 10 runs). For tests with 7-node network, average hypervolume ratio found with our heuristic to linear hypervolume ratio is %99, 98 and the ratio of worst hypervolume value of our heuristic to linear hypervolume value is %99, 91.

If we consider the execution times, our heuristic approach obtains the results in less than 5 seconds for 7-node network and it takes even less computation time for 5-node network. The brute-force method on the other hand, finds optimum values for 5-node network in a few seconds and for 7-node network the execution time increases to 3 hours. If we increase the network size to 81-nodes using the complete Turkish data set, it gets impossible to find a solution using brute-force method, but our heuristic finds feasible solutions in less than 10 minutes. Table 2 summarizes the approximate execution times of brute-force method and our heuristic approach for different sizes of networks. These results

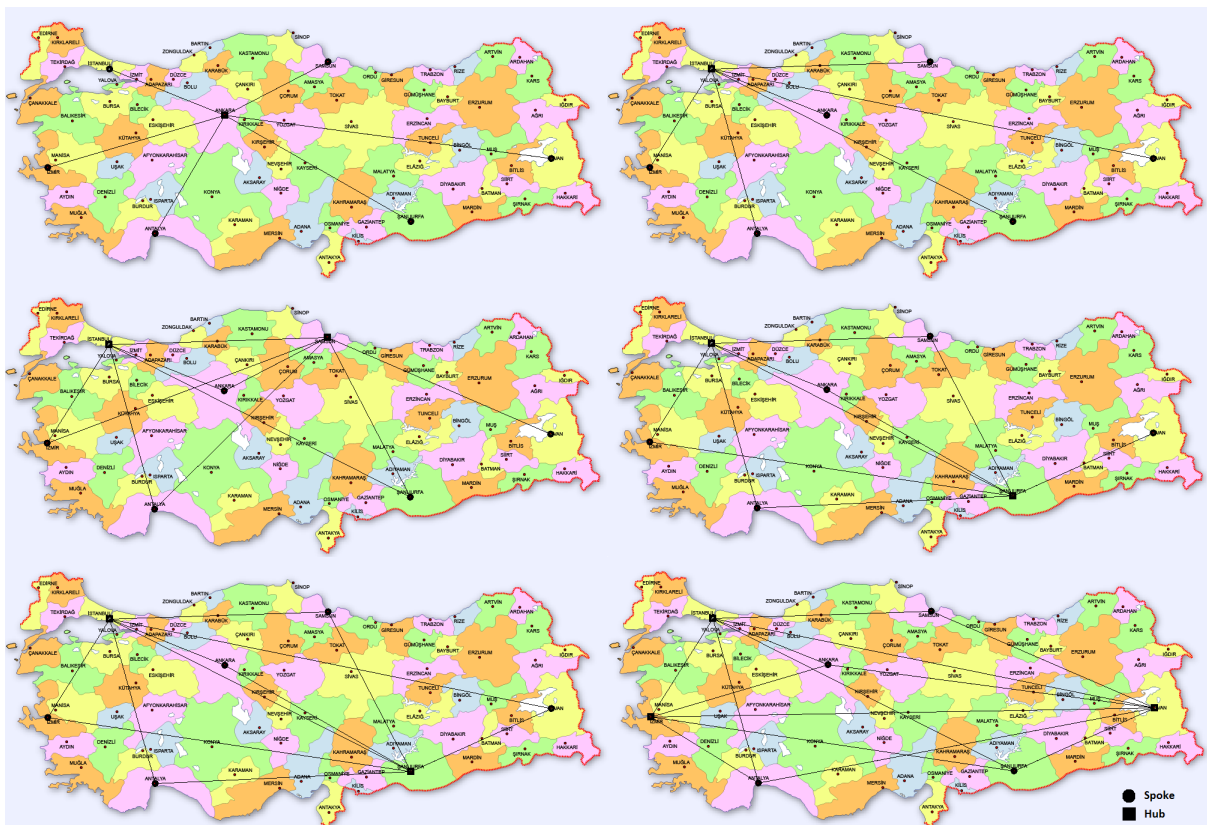


FIGURE 7. Pareto-optimal solutions obtained by brute-force method for 7-node network (From up-left corner to down-right corner the number of hubs at each case is equal to 1, 1, 2, 2, 2, and 3 hubs).

TABLE 2. Execution times of brute-force method and our heuristic for different network sizes.

# of nodes	Brute-Force	Our heuristic
5	3 sec.	2 sec.
7	11013 sec.	3 sec.
81	NA	251 sec.

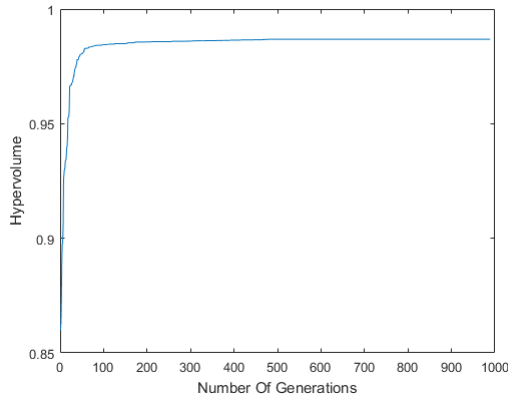


FIGURE 8. Convergence plot generated by the hypervolume values versus generation counts.

show that our heuristic approach is very effective to solve MOCMAHLP.

B. RESULTS ON TURKISH DATA SET

In order to explore the influence of the parameter settings on the performance of our approach, a set of experiments are conducted by varying values of population size (*popsiz*), crossover probability (*p_c*), bit-flip mutation probability (*p_{bfm}*), and swap mutation probability (*p_{sm}*). In the experiments, each run is repeated 10 times for the given setting. The termination condition for our heuristic is selected as number of fitness evaluations. To determine this value for the main experiments, we ran tests for our heuristic on Turkish data set for a long number of fitness evaluations. The change of fitness values is plotted in Figure 8. As it can be seen from the graph, the fitness values converge to a minimum in approximately 20000 number of evaluations which correspond to 100 generation counts. Therefore, the maximum fitness evaluation count is set to 20000 for each run in the experimental study.

In the result tables, the value of tested parameter(s) are given in the first one or two columns and the corresponding average and standard deviation of hypervolume values are given in the last two columns. In the rows of the tables, you can see the performance of each parameter setting. In all tables, the row with the best setting is marked in bold.

In the parameter tuning tests, we experimented with each combination of the following set of values for the parameters:

- Population size: *popsiz* ∈ {50, 100, 200}
- Crossover probability: *p_c* ∈ {0.5, 0.8, 0.9, 1.0}
- Bit-flip mutation probability: *p_{bfm}* ∈ {1/*n*, 0.5/*n*}
- Swap mutation probability: *p_{sm}* ∈ {0.005, 0.01, 0.02, 0.05}

TABLE 3. Hypervolume results and standard deviation for our approach with various population sizes *popsiz* and fixed parameter settings (*p_c* = 0.9, *p_{bfm}* = 1/*n*, *p_{sm}* = 0.01).

<i>popsiz</i>	Mean	Std. Deviation
50	0.9894	0.0088
100	0.9839	0.0090
200	0.9927	0.0046

TABLE 4. Hypervolume results and standard deviation for our approach with various crossover probabilities *p_c* and fixed parameter settings (*popsiz* = 200, *p_{bfm}* = 1/*n*, *p_{sm}* = 0.01).

<i>p_c</i>	Mean	Std. Deviation
0.5	0.9883	0.0114
0.8	0.9948	0.0005
0.9	0.9927	0.0046
1.0	0.9884	0.0090

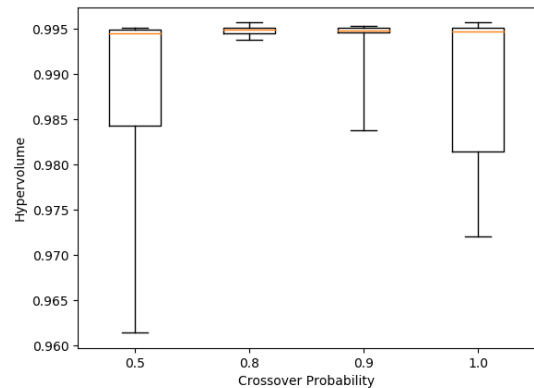


FIGURE 9. Box-plot of hypervolume values for a statistical comparison of different parameter settings for *p_c*.

TABLE 5. Hypervolume results and standard deviation for our approach with various *p_{bfm}* and *p_{sm}* and fixed values of *popsiz* = 200 and *p_c* = 0.8.

<i>p_{bfm}</i>	<i>p_{sm}</i>	Mean	Std. Deviation
1/ <i>n</i>	0.005	0.9887	0.0087
	0.01	0.9948	0.0005
	0.02	0.9906	0.0072
	0.05	0.9939	0.0042
0.5/ <i>n</i>	0.005	0.9923	0.0054
	0.01	0.9935	0.0057
	0.02	0.9922	0.0059
	0.05	0.9926	0.0055

In the remaining part, we give results of parameter tuning tests. The results are given in different tables for a better illustration of the effect of parameters. In Table 3, experimental results for various population sizes are given. We fixed the crossover probability value to *p_c* = 0.9, bit-flip mutation probability value to *p_{bfm}* = 1/*n* (*n* is the number of nodes in the network) and swap mutation probability value to *p_{sm}* = 0.01. Based on the results provided in Table 3, it can be seen that, our approach delivers a good performance with *popsiz* = 200.

In Table 4, the performance of our approach is given for different crossover probabilities, while keeping *p_{bfm}* = 1/*n*, *p_{sm}* = 0.01, and *popsiz* = 200.

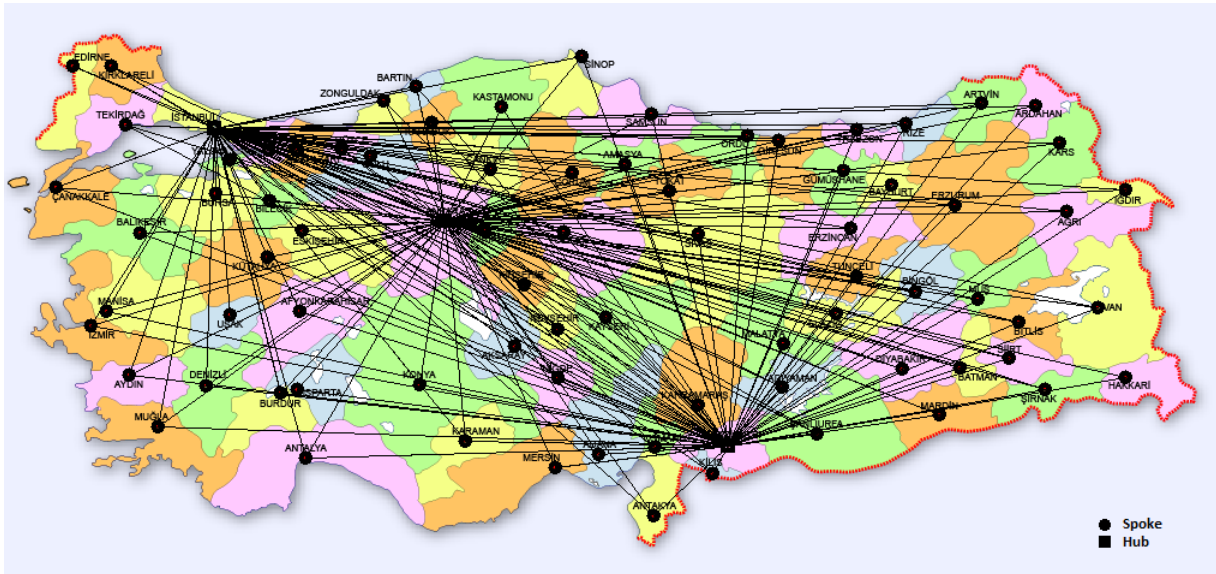


FIGURE 10. The first Pareto optimal solution that represents a hub network with all hub-to-hub and hub-to-spoke links obtained by our approach.

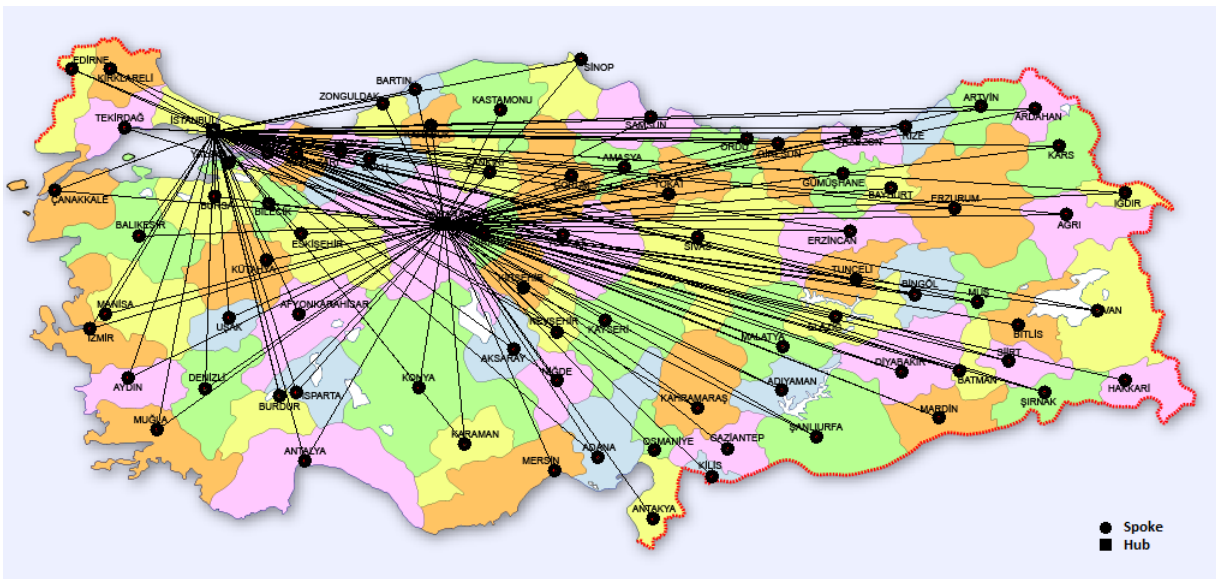


FIGURE 11. The second Pareto optimal solution that represents a hub network with all hub-to-hub and hub-to-spoke links obtained by our approach.

Figure 9 shows the box-plot for the hypervolume values of our approach with different p_c . From Table 4 and Figure 9, it can be observed that our algorithm performs well when $p_c = 0.8$.

The effect of the probability for the bit flip p_{bfm} and swap mutations p_{sm} is given in Table 5. From the table, we can conclude that, the best setting for p_{bfm} is $1/n$ and for p_{sm} , it is 0.01.

After the parameter tuning tests, we conducted main tests on Turkish data set to find solutions for the problem. Figure 10 illustrates a Pareto optimal solution that represents a hub network including all hub-to-hub and hub-to-spoke links obtained by our approach with the best

parameter settings. This network is chosen from the best hypervolume valued run and according to having the lowest crowding distance in the Pareto set. As seen in the figure, İstanbul, Ankara and Gaziantep which are among the most populated cities in Turkey are selected as hubs. Based on the results, the number of assignment of a spoke to a hub is 2.8 on average. Besides, the average number of hub to spoke connection is 73. On the other hand, Figure 11 illustrates a Pareto optimal solution from the same Pareto optimal set. In this solution, İstanbul, which is the most populated city and Ankara which is the capital of Turkey are selected as hubs. Selecting a hub at east part of Turkey, namely Gaziantep, increases the total costs while decreasing the total traveling

TABLE 6. Routing scenarios for some source-destination pairs in the given Pareto optimal solutions.

Source - Destination	Hubs (First Pareto solution - Fig. 10)	Hubs (Second Pareto Solution - Fig. 11)
Edirne - Hakkari	İstanbul → Gaziantep	İstanbul → Ankara
Hakkari - Edirne	Ankara → İstanbul	Ankara → İstanbul
Ardahan - İzmir	Ankara	Ankara
Tekirdağ - Kilis	İstanbul → Gaziantep	İstanbul → Ankara
Kırklareli - Gaziantep	İstanbul	İstanbul → Ankara
Tekirdağ - Tokat	İstanbul	İstanbul
Ordu - İzmir	Ankara	Ankara
Bilecik - Adıyaman	Ankara → Gaziantep	Ankara
Adıyaman - Bilecik	Ankara	Ankara
Ardahan - Kars	Gaziantep	Ankara
Ordu - Antakya	Gaziantep	Ankara
Mardin - Çanakkale	Gaziantep → Ankara	Ankara
Çanakkale - Mardin	Gaziantep	Ankara

time according to these solutions. In addition, most cities in the Southeastern Anatolia Region, such as Osmaniye, Kilis, Mardin, etc., are only assigned to Ankara.

In Table 6, we list some routing scenarios for some source-destination pairs with respect to the first Pareto solution given in Figure 10 and the second Pareto solution given in Figure 11. The routes for each pair may be different. For instance, the commodity from Ordu to Antakya is routed through Gaziantep for the first solution and Ankara for the second solution. While the travel time for the first path (Ordu → Gaziantep → Antakya) is 15 hours, it is 21 hours for the second path. On the other hand, the commodity from Hakkari to Edirne is routed through the same path and the traveling time between these cities is approximately 34 hours. Considering the solutions, we can conclude that routing of commodities in distant cities such as Hakkari to Edirne and Ordu to Antakya has very high impact on second objective.

VII. CONCLUSION AND FUTURE WORK

This study presents a mathematical model for a multi-objective, capacitated, multiple allocation, and incomplete HLP (MOCMAHLP). In the problem, the aim is to minimize the total cost including total transportation costs and fixed costs and to minimize the maximum travel time required for routing the demands of all commodities. We develop a multi-objective approach based on NSGA-II for decisions on the number of hubs, the location of hubs, the allocations of spokes to hubs, the hub network design, and the routing of all demands. A new solution representation and the appropriate crossover and mutation operator are proposed. The performance of our approach is tested on Turkish data set. We explore the influence of the parameters, namely population size, and crossover and mutation probabilities, on the performance of the proposed approach. The results reveal that our approach is not very sensitive to these parameters.

There are two main contributions of this study:

- To our knowledge, this is the first study that proposes a mathematical model for MOCMAHLP. In MOCMAHLP, the hub network is not fully interconnected and hubs and arcs in the network have limited capacity.

- The model includes location-allocation of hubs and spokes and routing of commodities between each pair of nodes in the network.
- Two objectives, i.e., the minimization of transportation cost and the minimization of maximum travel time of routing the commodities, are considered.
- We develop a multi-objective approach for the problem. Our approach is capable of finding good solutions on large instances of the problem.

As future work, we will experiment with other meta-heuristic algorithms, such as simulated annealing for the proposed model in order to compare the performance of our method. Besides, we will build a new model for the multi-period MOCMAHLP and design new techniques as an extension of our approach to handle the change in the environments.

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