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RESEARCH PAPER

A Multi-Objective Location-Allocation-Routing Optimization With Time Window for Transferring Personnel From Residence to Work: A Case Study of Bistoon Power Plant

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Abstract
This paper presents a two-phase approach to design an optimal personnel transportation network for the Bistoon Power Plant. In the first phase, a mathematical model of location-allocation for locating bus stops and allocating staff to bus stops has been formulated with the objective of minimizing the total walking distance for staff. For the second phase, a mathematical model of location-allocation-routing with time window for selecting vehicles with the appropriate capacity for each route, locating the parking places (start nodes), vehicle routing, and trip scheduling is discussed with the two objectives of minimizing transportation costs and minimizing the maximum travel time of staff to ensure fairness among staff. One of the features of this study is the consideration of the distance between vehicle parking areas and the first demand nodes on each route in order to locate parking areas. Other expected side benefits of the implementation of this research are decreasing the total travel distances, traffic congestion, and air pollution. Despite the large number of nodes and data of the case study, the proposed mathematical models are solved by the exact solution method. In order to solve the two-objective model, the augmented epsilon constraint method has been used to find the Pareto solution set.

Keywords: location-allocation (LA), location-routing problem (LRP), personnel transportation, two-objective optimization, Epsilon constraint method.

1. Introduction

Nowadays, the optimization of systems and the creation of competitive advantage in the market are very important. They are the key success point of enterprises in the long – and even the short – run. Optimization has found wide applications in various fields of industries and services, optimization of production, logistics, and so forth. A successful sample of disaster relief logistics is presented by Bozorgi-Amiri et al. (2011), while a paper has been given in by Najafi Moghadam Gilani et al. (2020) in the field of building materials. Sometimes logistics are the costliest component in supply chains. Therefore, a special focus should be directed at the logistics optimization in the supply chains. A category of logistical outstanding issues is the transportation of passengers. One of the methods for obtaining job satisfaction and giving benefits to the personnel of a company is to provide appropriate transportation service for them. In this paper, the optimization of one transportation system is

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discussed, which supplies the personnel of the Bistoon Power Plant. The quality of passenger transportation services depends on various indicators (parameters) such as cost, travel time, efficient use of the capacity of the passenger transportation system, proper travel scheduling, considering fairness among the involved components, considering the reduction of environmental damage, etc.

Location-routing problems (LRPs) are the result of the combination and development of location problems as well as vehicle routing problems (VRPs). Locating is a strategic decision with a long-term planning horizon, while routing is essentially an operational decision with a short-term planning horizon. The purpose of the location-routing problems is to determine the location of facilities and the transit routes of vehicles that serve a number of customers within a specified period (while the demand of each customer is less than the maximum capacity of a vehicle). Each vehicle makes a route (tour) which uses one or more facilities to serve multiple customers. The first research in LRPs field was conducted by Boventer (1961) and Maranzana (1964), a basic and considerable model was presented by Perl and Daskin (1985), and a useful taxonomy and review for LRPs was presented by Lopes et al. (2013). Leksakul et al. (2017) have done a research on personnel transportation for a large-scale industrial factory. They argue that personnel transportation problems can be considered similar to the School bus routing problems (SBRPs). SBRPs consist of two sub-problems, namely bus stop location problem and vehicle routing problem. A combination of these two sub-problems is categorized as the LRP. In order to locate bus stops, two general methods are used, location-allocation-routing (LAR) and allocation-routing-location (ARL). The LAR strategy first sets the bus stops regardless of the effect of the bus stop locations on the routing determination, then assigns students to these bus stops, and finally does the routing. ARL first clusters residential areas. Then, the bus stops are determined and the routes are specified for each cluster. Leksakul and colleagues have used the ARL method in their research. On the problem of the personnel transportation, a large number of personnel are picked up from different locations in a city (bus stops) and are brought to factories and at the end of their working day, they are returned to the same initial bus stops. It is necessary that these passengers be transferred at a specific time, because the factories start working at a certain time and their personnel should arrive on time, and it is the same for students. In this type of transportation, a different collection of vehicles is used, which may be different in capacity, operational costs, and speed. Regarding the operational costs of the vehicles involved, each vehicle is rented and the costs are calculated based on their capacity. A set of bus stops are assigned to a vehicle based on its capacity and the maximum travel time (Yüceer, 2013).

Park and Kim (2010) have done a conceptual review of SBRP and have divided them into the following five sub-problems: data preparation, bus stops selection, bus routing, travel planning based on school bell (start and end time), and routes planning. In the data preparation problem, the road network has been specified. They investigated the bus routes by two exact and heuristic approaches. Azad et al. (2010) designed a two-echelon distribution network. In order to solve the problem, they considered two phases, with the first phase being an LA to locate distribution centers and the second phase being a VRP. Bahrami et al. (2016) considered a parcel distribution problem – including the hub location problem, which seeks to find optimum locations for establishing hubs and to allocate cities to them – and the vehicle routing problem – which attempts to find optimum routes to distribute parcels between cities all over the country. Both of problems are modeled in a mathematical model and solved by a meta-heuristics method.

Guo et al. (2019) considered a bus routing and the passenger assignment problem with time windows on a graph network and formulated the problem as a mixed integer problem. They attempted to optimize the use of the vehicle capacities and considered the characteristics of customized bus service problem by means of defining a group of constraints. They used branch and bound method and two heuristic methods to solve their problem. Some specifications of the problem of Guo et al. (2019) are: assumptions of homogeneity of vehicles; being identical in depot for all of the vehicles at a specific location; vehicle routing aimed at transporting passengers before returning to depot in the specific time intervals; time windows and service time are already given; quantity of travel demand from each origin to related destination and the travel time and distance of each arc are already given; the average capacity of all vehicles are constant and given; and all arcs are two-way.

Farzadnia and Lysgaard (2021) considered an SBRP that includes locating bus stops, allocating students to the located bus stops, and generating a route to serve them. The problem is single-school and single-route. The objective of the model is minimizing the total walking distance from student residences to the bus stops, as a quality service factor, and the model restricts the route length to an upper bound as another quality service factor. They argue that quality service factors should be considered as objective(s) or constraint(s) in formulated models. Miranda et al. (2021) considered an SBRP with adjustable school working time, which means that the time students are received to school is a decision variable, and, as a result, the transportation costs will be reduced by 9%. This policy is useful when there are multiple destinations and there is no requirement that students be present at the same time at schools, whereas we do not have these requirements in our problem.

The combination of the following items created unique research:

1. Presenting a real case study of personnel transportation from residence to work with assumptions on the aforementioned problems in the problem description section.
2. Considering different locations for vehicle parking instead of a central depot.
3. Presenting a new constraint for defining corresponding relations between vehicles and movement start stations in related research fields.
4. A solution method with the following attributes:
    - A location-allocation-problem mathematic model is formulated in order to minimize walking distances for staff.
    - A two-objective location-allocation-routing with the time window mathematical model is formulated in order to minimize the transportation cost and the maximum travel time.
    - The augmented epsilon constraint method is used to solve the two-objective problem and illustrate the efficiency of the solving method.

The rest of the article is divided as follows. Section two describes the transportation of personnel at Bistoon Power Plant and Section three presents the used mathematical models. In Section four, the multi-objective solution of the generalized ε-constraint is introduced, and in Section 5, computational results are presented. Finally, in Section 6, the conclusions and managerial insights are presented.

2. Problem Description: The Transportation Service of Bistoon Power Plant Personnel

Operating of two 320 MW steam power plants, Bistoon Power Plant produces a total of 640 MW of electricity and supplies it to Iran's national electricity network. There are about 300 personnel in Bistoon Power Plant who are working in five working shifts throughout the day. The busiest shift is a daytime working shift of the plant with a population of about 100 employees, and the other shifts have smaller populations of personnel. The personnel residence, bus stops, and transportation vehicles' start nodes are located within the city of Kermanshah, and Bistoon Power Plant, which is the destination of trips, is located 20 km off the city on the Kermanshah-Bistoon road (Figure 1). In Figure 1, the red points are the demand nodes, the yellow points are the candidate bus stops, and the green point is the Bistoon Power Plant.

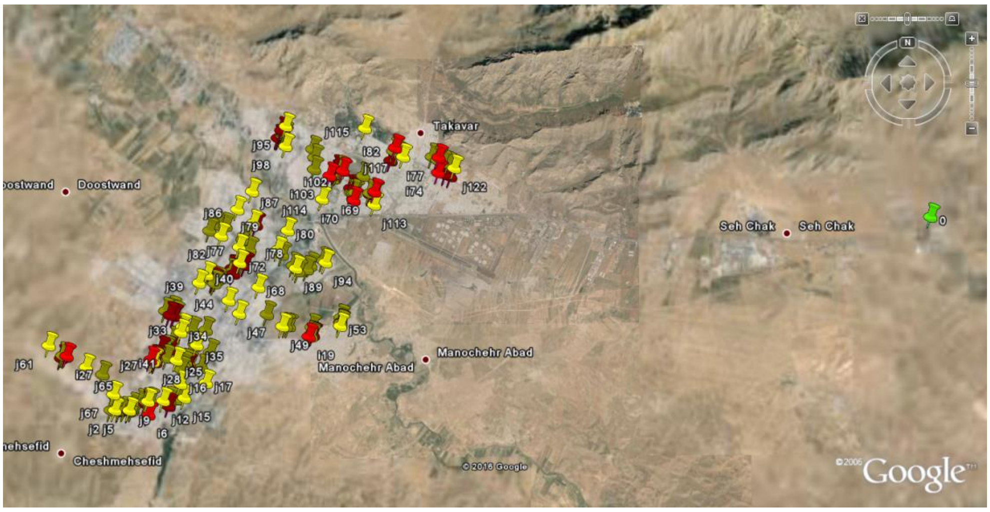

Figure 1. A View of the Map of the Location and Nodes of the Problem

Figure 2 shows a scheme of a feasible solution to the problem. The circles indicate the residence of the staff, the squares show the location of the candidate bus stops, shaded squares represent the located bus stops, the triangles point to the location of the vehicle depots, shaded triangles signify the located depots, and the hexagon expresses the destination of trips. The dotted lines show the assignment of staff to the bus stops and the arches indicate the passage of vehicles.

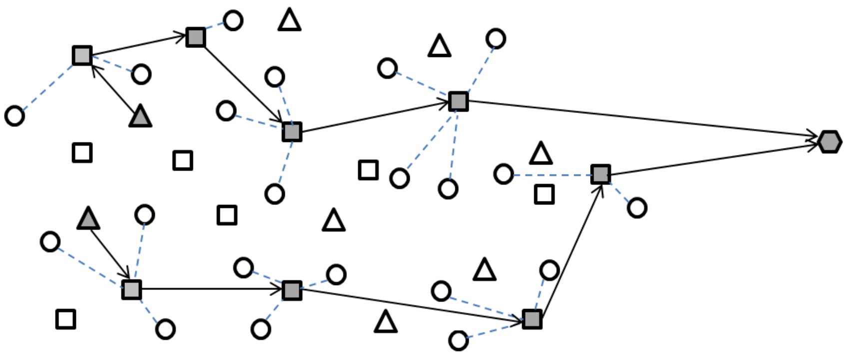

Figure 2. A Feasible Solution to the Problem

Since the transportation of each shift is independent of other shifts, and can be planned and routed independently, they can be assumed as independent problems. By gathering related data from each shift, they can be solved by similar designed mathematical models. This research has chosen the busiest shift (the daytime shift) because it is obvious that if this research can solve the problem with more data, then it is easily possible to solve problems with less data in the same way. In this problem, each route starts from the vehicle parking location (which is the drivers' residence and is called 'start node'). After serving a number of demand nodes (bus stops), finally the vehicle has to go to a specific destination (power plant). In addition, the vehicle can be used to serve other passengers out of the plant so an open path is created and there would be no closed loops.

Each bus stop is serviced by only one vehicle. The transportation company has various types of vehicles, including minibuses, midibuses, and buses, with each having a different capacity, cost, and start node; therefore, the vehicles are assumed heterogeneous. The choice of a vehicle for each route leads to the selection of a driver and, subsequently, determining a start node and a passenger transporting capacity on that route. The reason is that each driver drives a particular vehicle that is assigned to him in advance and lives in his certain residence that is the same place as the candidate for the start node. There is not just one parking lot (depot) for all vehicles. Therefore, by selecting one of the three variables of the start node, vehicle, or driver, the other two variables, along with the route capacity, are chosen and compelled. To apply the distance between a start node and first demand node (bus stop), it is necessary to consider the above condition in the optimizing model; therefore, it is required that one define a new LRP constraint that has not been seen in previous related articles.

The reason that the solution is divided into two phases is a difference in the nature of their objective functions. Moreover, this can simplify solving the model. In the bus stop location problem, the objective is to reduce the passengers' walking distances, but in the second phase, the two objectives of reducing costs and the longest travel time are considered. Due to its importance, the objective of reducing walking distances cannot be sacrificed for the objective of reducing costs; Therefore, modeling the problem is suggested in two independent phases. The first phase has the nature of an LA problem, and the second phase has the nature of an LRP with the time window problem. The output of the first phase provides the input parameter for the second phase.

If we consider a small number of bus stops in the city, many personnel have to walk a long distance to reach the nearest bus stop certainly. On the other hand, if we consider a large number of bus stops to make it possible for staff to reach bus stops by walking a short distance, another problem is generated. That is, bus stops will mostly be single player, so a vehicle has to meet more number of bus stops along its route to reach its full capacity (to fill vehicles seats). In addition, the first passenger's travel time will be greatly increased. Therefore, there are some agreements that the walking distances for any passenger do not have to be more than 700 meters and the distance between two built bus stops do not have to be less than 200 meters.

This paper estimates a travel time for each arc based on the length of the arc and its traffic conditions. Traffic conditions are assumed fixed for each arc, separately and differently from other arcs. Traffic conditions are applied to the problem by a traffic factor for each arc based on its traffic conditions to estimate arc travel time. By multiplying the traffic factor by the arc length (km), the estimated arc travel time is gained, and by adding the arc travel times on a route to the staff riding time, the route travel time is obtained.

In the case of lower-capacity vehicles, the system's agility increases and the travel time of each person decreases, but the cost of the system increases. However, by choosing larger vehicles such as a bus, the condition is reversed. If the capacity of the vehicle is high, the vehicle must pass from more bus stops and pick up more passengers in order to reach its full capacity, which causes a longer travel time for passengers who have been picked up at the first bus stop, whereas those who are picked up at the last bus stop experience shorter travel time.

Since the present problem (the second model) seeks to reduce costs and the travel time of those who have the longest ones, the model has two objectives for minimizing transportation costs, including a) fixed costs for each vehicle unit and variable costs for a survey of every kilometer traveled by each vehicle, and b) minimizing the maximum travel time for each person to respect the fairness of the personnel.

We make the following assumptions on the problem:

1. The problem is defined through a graph network whose nodes include demand nodes, facility locations including start nodes and bus stops, and the destination node (the power plant) while nodes are connected by a set of access roads.

2. Demands are deterministic and all of them should be satisfied.
3. Each demand node is served just by one vehicle.
4. There are a number of candidate parking locations of vehicles, some of which should be established to apply their corresponding vehicles. In addition, there are several candidate bus stops, some of which should be chosen to establish and service staff. Therefore, there are two location problems.
5. All of the routes start from parking location of vehicles (start nodes), then selected vehicles service the demand nodes by passing them, and finally vehicles finish the routes by arriving at the destination node. Thus, each vehicle forms an open route.
6. Each facility is capacitated, as each bus stop is limited to the maximum vehicle capacity.
7. The vehicles are heterogeneous, with different capacity, different fixed cost on applying, and different variable cost on passing each km of access roads.
8. The duration of passing each km of a road is different from other roads due to its road width, traffic congestion, number of red lights on the road, etc.
9. Picking up the staff at the bus stops takes time based on their number.
10. The solution and the plan that is obtained from running the suggested model are always valid unless the major parameters such as the residence of staff or available vehicles change. Therefore, if the parameters do not change along the year, running the model only once is enough and running it again is not needed.

3. Mathematical Formulation

This section presents the formulation of the mentioned problems.

3.1. Formulation of the First Model

3.1.1. Sets:
P: a set of all the residential locations of the personnel
N: a set of all nodes, which are potential candidate bus stops
Subscripts:
i: residential locations index $(i \in P)$
j , *j2*: candidate bus stops index $(j, j2 \in N)$

3.1.2. Parameters:
q_i: The amount of demand at node *i*
d_{ij}: The distance between residential locations *i* and bus stop *j*
d_{jj_2}: The distance between candidate bus stops j and j_2
C_{max}: The capacity of bus stops that is equal to the capacity of the larger vehicle
l_{max}: The maximum allowed distance between residential locations and allocated bus stops

3.1.3. Decision Variable:
X_{ij}: Binary variables that set the assignment of personnel *i* to the selected bus stop in node *j*
Y_j: Binary variable for the existence of a stop in a node *j*
Z: Objective function variable that refers to the total personnel walking distance

3.1.4. Mathematical Formulation of the First Model:

$$Min\ Z = \sum_{i \in P} \sum_{j \in N} q_i d_{ij} X_{ij} \quad (1)$$

$$\sum_{j \in N} X_{ij} = 1 \qquad \forall i \in P \quad (2)$$

$$X_{ij} d_{ij} \le l_{max} \qquad \forall i \in P, \forall j \in N \quad (3)$$

$$\sum_{i \in P} q_i X_{ij} \le Y_j\ c_{max} \qquad \forall j \in N \quad (4)$$

$$Y_j + Y_{j2} \le 1 \qquad \forall j \in N, \forall j2 \in N : d_{j,j2} \le 200 \quad (5)$$

$$X_{ij} \in \{0,1\} \quad (6)$$

$$Y_j \in \{0,1\} \quad (7)$$

Equation (1) is an objective function that aims to minimize total personnel walking distances. Constraint (2) guarantees that each demand node i is assigned to only one bus stop j. It also guarantees that all the personnel who live in the neighborhood are assigned to the same bus stop. Constraint (3) ensures that maximum walking distance for each personnel is less than l_{max}(=700 meters). Constraint (4) guarantees that the number of personnel that are allocated to each bus stop j is less than the capacity of the largest vehicles (C_{max}). It also guarantees that each personnel can only be assigned to a bus stop that exists. Constraint (5) ensures that there are no two bus stops less than 200 meters apart. Constraints (6) and (7) define the domain of decision variables.

3.2. Formulation of the Second Model

3.2.1. Sets:
N: Set of all nodes, which are selected bus stops in the first model ($N = \{1,2, \dots, n\}$)
M: Set of the vehicles start nodes, which include the location of vehicle parking at nights, too ($M = \{1,2, \dots, m\}$)
K: Set of vehicles ($K = 1,2, \dots, m\}$) Note: there is one to one correspondence between set M and set K
$S = \{N \cup M\}$
$O = \{0\}$, 0 denotes the power plant location that is the destination node of all the vehicles; in fact, all routes must be finished at 0 node.
$G = \{N \cup O\}$
$Q = \{N \cup M \cup O\}$

3.2.2. Parameters:
cv_k: The cost of using the vehicle *k*
cd_k: Traveling cost of vehicle *k* per km
d_{ij}: Distance between node *i* and node *j*
t_{ij}: Average time for passing per kilometer between nodes *i* and *j* (traffic factor)
q_j: Number of personnel that are assigned to the bus stop *j* (is presented in Table 1)
c_k: The capacity of the vehicle *k*
t: Stop time of vehicle for one passenger to ride
M: A large number
et_0: Earliest arrival time to the power plant (the destination node), which is 7:25 for this problem
lt_0: Latest arrival time to the power plant, which is 7.28 for this problem

3.2.3. Decision Variables:

X_{ijk}: a binary variable that is defined as 1 if the vehicle *k* travels from *i* to *j* and serves both bus stops; it is 0 otherwise.

U_k: A binary variables that is defined as 1 if the vehicle *k* is selected; it is 0 otherwise.

H_{jk}: Departure time of the vehicle *k* from node *j*

Z: The objective function variable of the total transportation cost

Y: The objective function variable of the longest travel time for all personnel

3.2.4. Mathematical Formulation of the Second Model:

$$Min\ Z = \sum_{k\in K}\sum_{i\in S}\sum_{j\in G} cd_k\ d_{ij}\ X_{ijk} + \sum_{k\in K} U_k vc_k \quad (8)$$

$$Min\ Y \quad (9)$$

$$Y \geq \sum_{i\in S}\sum_{j\in G} t_{ij}\ d_{ij}\ X_{ijk} \qquad \forall k \in K \quad (10)$$

$$\sum_{k\in K}\sum_{i\in S} X_{ijk} = 1 \qquad \forall j \in N \quad (11)$$

$$\sum_{i\in S}\sum_{j\in N} q_j\ X_{ijk} \leq c_k\ U_k \qquad \forall k \in K \quad (12)$$

$$\sum_{i\in S} X_{ijk} - \sum_{i\in G} X_{jik} = 0 \qquad \forall k \in K, \forall j \in N \quad (13)$$

$$\sum_{j\in N}\sum_{i\in M} X_{ijk} = U_k \qquad \forall k \in K \quad (14)$$

$$\sum_{i\in Q}\sum_{j\in M} X_{ijk} = 0 \qquad \forall k \in K \quad (15)$$

$$\sum_{i\in N} X_{i0k} = U_k \qquad \forall k \in K \quad (16)$$

$$\sum_{j\in Q} X_{0jk} = 0 \qquad \forall k \in K \quad (17)$$

$$(i-k)\sum_{j\in N} X_{ijk} = 0 \qquad \forall k \in K, \forall i \in M \quad (18)$$

$$\sum_{i\in v}\sum_{j\in w}\sum_{k\in K} X_{ijk} \geq 1 \qquad \text{V is a proper subset of Q set and w is complementary of v} \quad (19)$$

$$H_{jk} \geq X_{ijk}\ d_{ij}\ t_{ij} + H_{ik} + q_j\ t - M\left(1 - X_{ijk}\right) \qquad \forall k \in K \quad (20)$$

$$H_{0k} \geq et_0 \qquad \forall k \in K \quad (21)$$

$$H_{0k} \leq lt_0 \qquad \forall k \in K \quad (22)$$

$$X_{ijk}\ ,\ U_k \in \{0,1\} \quad (23)$$

$$q_j\ ,\ c_k \in Integer \quad (24)$$

$$cd_K, vc_k, d_{ij}, t_{ij} \in \mathbb{R} \quad (25)$$

Equation (8) is the first objective function in order to minimize total transportation operational costs of the system, including fixed cost for the use of any vehicle and variable cost for traveling per kilometer. Equation (9) is the second objective function in order to minimize the longest travel time. Constraint (10) explains variable Y in the equation (9) to form the second objective. Constraint (11) guarantees that each bus stop is serviced only by one vehicle. Constraint (12) ensures that the passengers are assigned to the selected vehicle up to its maximum capacity. Constraint (13) stipulates that every node that is entered by the vehicle should be left (the continuity of flow at the intermediate bus stops). Constraint (14) guarantees that each vehicle only and only travels once from the start node (set M) to the other bus stops. Constraint (15) expresses that the vehicles are forbidden to move from a node to a start node (set M). Constraint (16) ensures that each selected vehicle only and only travels once from a node to the destination node (power plant). Constraint (17) states that it is not allowed to have any travel from the destination to other nodes. Constraint (18) guarantees that each vehicle can start traveling only from its corresponding bus stop in the starting. Constraint (19) guarantees that each bus stop reaches the destination at the end of its route. Constraint (20) determines the departure time at every bus stop. Constraint (21) ensures that the vehicles do not arrive earlier than et_0. Constraint (22) ensures that the vehicles are not arrived later than lt_0. Constraints (20), (21), and (22) apply time window to the model. Constraints (23), (24), and (25) define the domain of decision variables.

4. The Proposed Multi-Objective Solution Method

In order to solve the proposed multi-objective model, ε-constraint method is utilized. In this section, first the ordinary and augmented ε-constraint techniques are briefly presented in the next two subsections.

4.1. Ordinary ε-Constraint Method

Esmaili et al. (2011) illustrated that the ε-constraint is a method for solving multi-objective function problems with P objective functions in which $f_i(x)$, $(i = 1,2, \dots, P)$, where x is a vector of decision variables and $x \in S$ while S is a feasible solution space that is formed by main problem's constraints. In order to solve a multi-objective problem by ε-constraint method, it is necessary to change the structure of the problem. Thus, the main objective function of the problem is considered as the only objective function of the problem, and the rest of the objective functions are added as new constraints to the main model, and probably the feasible solution space (S) is smaller than before. To simplify, it is assumed in descriptions that all of the objective functions are for maximization. Therefore, the primary objective functions in the main model Equations are replaced with (26) and (27).

$$Max\ f_1(x) \tag{26}$$

$$subject\ to: f_i(x) \geq e_i \qquad (i = 2,\dots,P), \qquad x \in S \tag{27}$$

The Pareto solutions are available by variations on the right hand side of the newly added constraints $(e_2, \dots, e_p)$. Thus, the variation ranges for P-1 objective functions are required. These ranges usually can be obtained from a payoff table. The payoff table shows values for every objective function in the individual optimizations. Individual optimization means solving the problem at least P-1 times considering only one of the objective functions and calculating another objective function values on the basis of the obtained decision variable values. Minimum and maximum values for every objective function in the payoff table are shown by f_i^{max} and f_i^{min} , thus variation ranges for i^{th} objective function is $r_i = f_i^{max} - f_i^{min}$. After finding variation ranges for each objective function $(e_2, \dots, e_p)$, the range r_i is divided into q_i equal intervals. Then, e_i in (27) is set to $q_i + 1$ grid points as equation (28):

$$e_i^k = f_i^{max} - k \times r_i / q_i \qquad k = 0,1,\dots,q_i \tag{28}$$

Where k stands for the number of the grid points. Thus the main multi-objective function is changed to $\sum_{i=2}^{p}(q_i + 1)$ number of single objective sub-problems, where feasible solution space for every sub-problem is S while it is limited by new added constraints for $f_2, \dots, f_p$. Every composed sub-problem might have an infeasible space because of the new constraint effects on the S or maybe because the results of solving them presents a candidate solution that might be a Pareto solution for the primary multi-objective problem. Finally, decision makers are engaged in selecting the most preferred solution out of the obtained Pareto optimal solutions.

4.2. The Augmented ε-Constraint Method

This paper applies augmented ε-constraint method that was introduced by Mavrotas (2009). As previous research illustrated, it is necessary to have the range of variations for every objective function (at least for the number of P-1 objective functions) for the application of the augmented ε-constraint method. While the best value for any individual optimization is readily available, it is not easy to access the worst value (nadir value). In the ordinary ε-constraint method, the ranges are obtained from the payoff table, and the minimum value of every objective function in the corresponding column of payoff table is approximated as the worst value. However, it is necessary to be sure that the final solutions, which are obtained from the problem solution process, are Pareto solutions. However, there is not such certainty in the ordinary ε-constraint method. According to ordinary ε-constraint method, the first payoff table is formed using conventional LP optimizer at individual optimizations, while the obtained optimal solutions presented in this payoff table may be dominated by each other. However, the solutions are presented in the payoff table while there may be another solution that can dominate them. This way, the search will be finished and results will be presented as solutions.

In order to eliminate this uncertainty, Mavrotas (2009) uses the lexicographic optimization for every objective function to compose the payoff table with only Pareto optimal solutions. A simple remedy to achieve this certainty is to define the reservation values for objective functions. The reservation value is a lower bound for the objective function values (or upper bound for minimization objective functions), worse than which is not permitted. Lexicographic optimization method obtains a solution that optimizes the main objective function while other solutions could not dominate it; thus, it is a Pareto solution. The purpose of the lexicographic optimization is to find the optimum solution for the first objective function, and, at the same time, the best solution for the second objective function, and so on. Practically, lexicographic optimization implements as what follows.

Mavrotas (2009) optimizes the main (first) objective function ($\max f_1 = Z_1^*$), then adds $f_1 = Z_1^*$ as a new constraint to the S in order to make sure the first objective function remains optimal during the solution process. Next, he optimizes the second objective function. Subsequently, the third objective function optimizes the subject to $f_1 = Z_1^*$, $f_2 = Z_2^*$ and S. The next objective function becomes optimal with respect to previous objective function optimizations until objective functions are finished. With the solutions that are obtained from lexicographic optimization, the payoff table is composed and the varied ranges are divided into equal intervals like the ordinary ε-constraint method, several grid points are used as values for $e_2, \dots, e_p$, and sub problems are formed. The comparison results show that the payoff table made from the lexicographic optimization method has more meaningful grid points than the ones obtained from the ordinary payoff table. For extra description about this, see Mavrotas (2009).

5. Computational Results

Exact solution method and branch and cut algorithm were chosen for solving this MOMIP. Programming models have been solved using GAMS 24.1.2 modeling language. This section presents experimental results for both models.

5.1. First Phase Solution

To solve the mathematical formulation of the first model, it was coded in the GAMS and parameters were placed in it. After running the GAMS, a set of results were gained, which are shown in Table 1. From the 124 variables Y_j, only 22 of them have been numbered as 1 and the rest of them have been numbered as zero; thus, from the 124 candidate bus stops, only 22 of them are selected to be established. The first row in Table 1 is the list of selected bus stops and the second row presents demand nodes $(i \in P)$ that are assigned to each selected bus stop. The last row presents total demand of each bus stop. The results in the objective function value show 17447 meters, which is the total walking distance for all of the personnel.

Table 1. Chosen Bus Stops and Assigned Demand Nodes for Each Chosen Bus Stop

j	j5	j8	j13	j20	j28	j30	j36	j41	j59	j63	j71
i	i3	i5 i6	i8	i32	i39 i40 i41	i42 i43	i46 i47	i51	i19 i20	i26 i27	i53 i57
qi	1	2	1	1	3	2	2	1	2	2	4
j	j73	j79	j96	j97	j104	j106	j110	j112	j116	j122	j123
i	i54 i56	i60	i91 i94	i92 i95	i97 i102	i101 i103	i67 i68 i70	i69 i73	i81 i82	i75 i76	i74 i77
qi	2	28	3	2	2	2	25	3	2	3	2

5.2. Second Phase Solution

Solving the second model because of its two objectives and the use of the ε-constraint method includes some stages, as follows.

Stage 1: The objective of the first stage is finding only minimum cost of the transportation system; thus, the second objective is ignored and the model is considered as a single objective problem. Selected vehicles, considered routes and objective function values for optimized solutions for stages 1 to 4 are presented in Table 2.

Stage 2: The purpose of the second stage is to improve the second objective function value (longest travel time) while the first objective function value is fixed to the same value that is achieved from the first stage. Thus, the first objective value of the previous stage (302.99) is added to the original model 2 as a new constraint and the first objective function is eliminated from the main model. Therefore, the second objective function is applied to the model as the only objective function.

Stage 3: In the third stage, the first objective function is ignored and only the second objective function is applied as a single objective problem (as opposed to the first stage) to the original model 2.

Stage 4: The goal of the fourth stage is to improve the first objective function value, while the value of the second objective function is assumed to be a constant number obtained before the third stage of the algorithm. To find these solutions, the second objective function is eliminated, but 47 minutes for the second objective function value is added as a new constraint to the original model 2. Thus, the fourth stage solution dominates the third stage solution.

Table 2. Routes, Used Vehicles, and Objective Function Values in the Solution of Stages 1 to 4 From ε-Constraint Method

	Vehicles	Routes
First stage	Z(Cost)=302.99 , Z(Time)=111	
	V1	M1 - j96 - j97 - j79 - j104 - j112 – 0
	V3	M3 - j63 - j5 - j8 - j13 - j20 - j30 - j28 - j36 - j41 - j71 - j73 - j106 - j116 - j123 - j122 – 0
	V5	M5 - j59 - j110 – 0
Second stage	Z(Cost)=302.99 , Z(Time)=111	
	V1	M1 - j96 - j97 - j79 - j104 - j112 – 0
	V3	M3 - j63 - j5 - j8 - j13 - j20 - j30 - j28 - j36 - j41 - j71 - j73 - j106 - j116 - j123 - j122 – 0
	V5	M5 - j59 - j110 – 0
third stage	Z(Cost)=580.635 , Z(Time)=47	
	V1	M1 - j96 - j97 – j110 - j112- j116 – 0
	V2	M2 – j79 - j71 – 0
	V3	M3 – j63 – j30 – j28- 0
	V5	M5 - j36 - j41 – 0
	V7	M7- j5- j8 – j13 – j20 – 0
	V9	M9 – j59 – j122 – j123 – 0
	V10	M10 – j73 – j106 – j104 – 0
Fourth stage	Z(Cost)=562.718 , Z(Time)=47	
	V1	M1 - j96 - j97 – j116 - j122 - 0
	V2	M2 – j79 – j106-j104 – 0
	V3	M3 – j63 – j110- 0
	V6	M6 - j30 – j28 – j36 - 0
	V7	M7- j5- j8 – j13 – j20 - 0
	V9	M9 – j59 – j112 – j123 - 0
	V10	M10 – j71 – j41 – j73 - 0

Stage 5: Now the payoff table can be formed with the solutions obtained from the last four stages. Table 3 presents the problem payoff table. A range is created for the longest travel time with a minimum of 47 minutes from the third stage and a maximum of 111 minutes from the second stage; [47,111]. The range is then divided into 6 intervals and each distance sets an upper bound for the new added constraint in stage 6, which creates a new problem.

Table 3. Payoff Table of Objective Functions of Model 2

Z(Time)	Y(Cost)
111	303
47	562.72

Stage 6: To achieve Pareto solutions, the second objective function is removed and only the first objective function is applied. In addition, a new constraint is added to the original model 2 to limit the value of the second objective function to the specified intervals. Therefore, problems arise for each interval, and by solving these 6 problems, 6 Pareto solution are at hand. Table 4 presents the 6 obtained Pareto solutions.

Table 4. Routes, Applied Vehicles, and the Objective Function Values for Each Pareto Solution

	Vehicles	Routes
First Pareto solution (98.20 , 111.000]		Z(Cost)=302.99 , Z(Time)=111
	V1	M1 - j96 - j97 - j79 - j104 - j112 - 0
	V3	M3 - j63 - j5 - j8 - j13 - j20 - j30 - j28 - j36 - j41 - j71 - j73 - j106 - j116 - j123 - j122 - 0
	V5	M5 - j59 - j110 - 0
Second Pareto solution (85.40,98.20]		Z(Cost)=305.910 , Z(Time)=95
	V2	M2 - j79 - j112 - 0
	V5	M5 – j73 – j110 - 0
	V9	M9 – j59 – j41 – j96 – j97 – j106 – j104 – j116 – j123 – j122 - 0
	V10	M10- j71 – j20 – j13 – j8 – j5 – j63 – j30 – j28 – j36 - 0
third Pareto solution (72.60,85.40]		Z(Cost)=306.479 , Z(Time)=78
	V3	M3 – j63 – j79- 0
	V5	M5 – j73 – j110 - 0
	V7	M7 – j5 – j8 – j13 – j20 – j30 – j28 – j36 – j41 – j96 – j97 – j112- 0
	V10	M10- j59 – j71 – j106 – j104 – j116 – j123 – j122 - 0
Fourth Pareto solution (89.80,72.60]		Z(Cost)=313 , Z(Time)=72
	V2	M2 – j79 – j73 – j122- 0
	V3	M3 – j63 – j20 – j36 – j110 - 0
	V9	M9 – j59 – j112 – j104 – j106 – j97 – j96 – j116 – j123- 0
	V10	M10- j13 – j8 – j5 – j30 – j28 – j41 – j71 - 0
Fifth Pareto solution (47.00,59.80]		Z(Cost)=375.127 , Z(Time)=59
	V2	M2 – j79 - 0
	V3	M3 – j63 – j41 – j73 – j110 - 0
	V7	M7 – j5 – j8 – j13 – j20 – j30 – j28 – j36- 0
	V9	M9- j59 – j112 – j116 – j123 – j122 - 0
	V10	M10- j71 – j96 – j97 – j106 – j104 - 0
Sixth Pareto solution Z(Time)=47		Z(Cost)=562.718 , Z(Time)=47
	V1	M1 – j96 – j97 – j116 –j122 - 0
	V2	M2 – j79 – j106 – j104 - 0
	V3	M3 – j63 – j110- 0
	V6	M6- j30 – j28 – j36 - 0
	V7	M7- j5 – j8 – j13 – j20 - 0
	V9	M9 – j59 – j112 – j123 - 0
	V10	M10- j71 – j41- j73 - 0

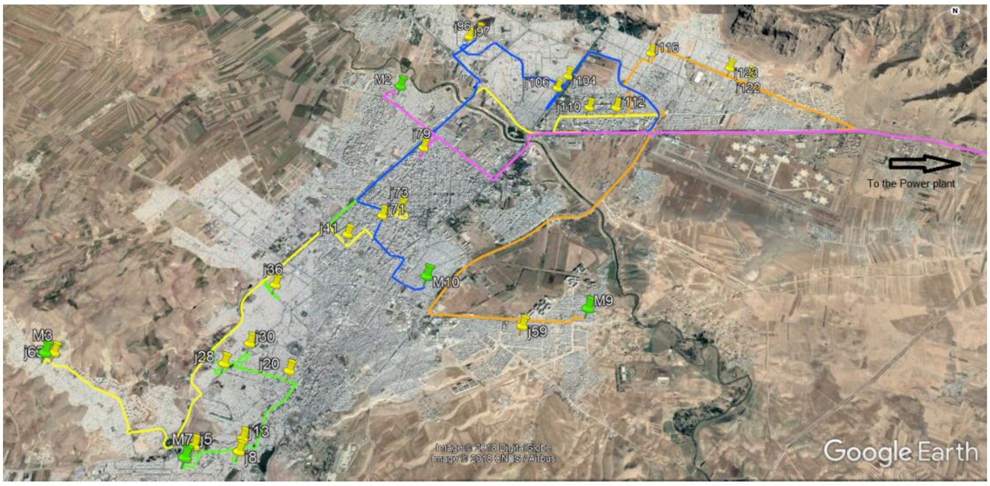

Figure 3. Nodes and Five Routes for the Fifth Pareto Solution

There are six different Pareto solutions available that vary in the total cost of transportation system, the longest travel time, the number of used vehicles, routes and the start nodes. Considering that each Pareto solution does not dominate other solutions and every solution is better than other Pareto solutions in only one objective, selecting one of the six Pareto solutions is the responsibility of the company's decision makers to choose based on the company's condition. Figure 3 shows the routes and the bus stops for the fifth Pareto solution. The figure shows the start nodes with green signs, the bus stops with yellow signs, five routes of the fifth Pareto solution with different colors, route of the vehicle V2 in pink, and in the following cases, for V3 in yellow, for V7 in Green, for V9 in orange, and for V10 in blue.

The obtained departure time of each vehicle at all of the nodes on its route, for the fifth Pareto solution, is presented in Table 5.

Table 5. Vehicle Departure Time for Each Node for the Fifth Pareto Solution

V2	Nodes on route	M2	j79	0						
	departure time	06:43	06:58	07:25						
V3	Nodes on route	M3	j63	j41	j73	j110	0			
	departure time	06:20	06:22	06:38	6:44	7:03	7:25			
V7	Nodes on route	M7	j5	j8	j13	j20	j30	j28	j36	0
	departure time	06:24	06:27	06:30	6:33	6:39	6:44	6:47	6:55	7:25
V9	Nodes on route	M9	j59	j112	j116	j123	j122	0		
	departure time	06:24	06:30	06:45	6:54	7:03	7:06	7:25		
V10	Nodes on route	M10	j71	j96	j97	j106	j104	0		
	departure time	06:22	06:32	06:49	6:51	6:58	7:02	7:25		

In order to make a comparison between the experimental method of the transportation company (experimental plan), which was performed by the company before the optimization, and six Pareto solutions, it is necessary to have data of routes as well as the objective values for the experimental plan. In the experimental plan, four vehicles are applied to serve staff through the mentioned routes at Table 6. In the experimental plan, the cost objective value is 376.2 monetary units and the longest travel time objective is 90 minutes. It is clear that in the fourth Pareto solution in comparison with the experimental plan, which applies the same number of vehicles, cost variable is decreased by 63 monetary units and the longest travel time is decreased by 18 minutes; thus, both decision variables are improved. This means that the fourth Pareto solution dominates the experimental plan completely. It is necessary to consider that the mentioned improvement is only for a one-shot implementation. We know transportation is implemented twice a day and 250 workdays per year.

Table 6. Routes, Used Vehicles, and Objective Values in Experimental Transportation Plan Performed by the Company

	Vehicles	Routes
Experimental method of transportation company	Cost=376.245 , Time =90	
	V1	M1 – j59 – j79 - 0
	V2	M2 – j110 – j112 - 0
	V3	M3 – j63 – j5 – j8 – j13 – j20 – j28 – j30 – j36 –j41 – j71 – j73- 0
	V9	M9- j96 – j97 – j104– j106 – j116 – j123 – j122 - 0

The blue points on Figure 4 are the six Pareto solutions, the blue curve that is formed by connecting the Pareto solution points presents the edge of the solution space, and the red point presents the experimental transportation plan situation rather than the Pareto solutions. Figure 4 shows the objective function values that each of the six Pareto solutions are better in (one or both of objectives) rather than the experimental transportation plan situation. Thus, it is upon decision makers to choose the best one out of the six Pareto solutions.

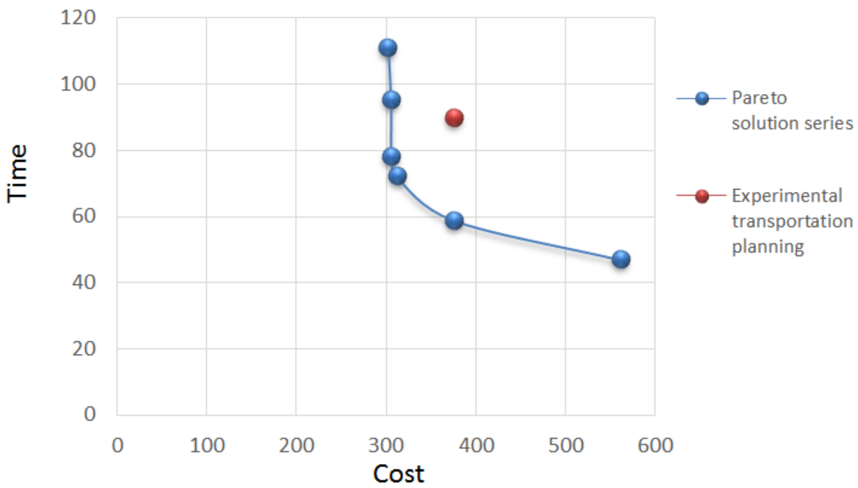

Figure 4. Objective Function Values Curve for Six Pareto Solutions and the Experimental Transportation Plan

6. Conclusion

6.1. Percentage of Improvement

In this paper a mathematical model is presented for solving the bus stop location problem with minimizing the total personnel walking distances objective and another model for routing vehicles, choosing vehicles, locating start nodes, and scheduling routes in order to minimize two objectives (cost and time), and minimizing the longest travel time for personnel in order to be fair about their travel time. The branch and cut algorithm is used for solving the problems, and the augmented ε-constraint method is applied to solve the multi-objective problem. The gained numerical result shows improvement in the objective function values. Choosing some of the Pareto solutions can improve both objective function values. The percentage of improvement in objective function values for each Pareto solution, compared with the experimental transportation plan situation, is presented in Table 7.

Table 7. Percentage of Improvement in Objective Function Values

	Percentage of improvement of the cost objective	**Percentage of improvement of the time objective**
1st Pareto solution	19.47%	-23.33%
2nd Pareto solution	18.69%	-5.56%
3th Pareto solution	18.54%	13.33%
4th Pareto solution	16.81%	20.00%
5th Pareto solution	0.30%	34.44%
6th Pareto solution	-49.56%	47.78%

6.2. Managerial Insight

The transportation system optimization results in an improvement of the functional indexes of the transportation system. Some advantages of the suggested model, for employers, transportation companies, and passengers are presented in the following lines:

- Decreasing the total traveled distances,
- Choosing appropriate vehicles for each route and optimizing the use from capacities,
- Decreasing transportation system costs and providing interests for the employer and transportation company,
- Decreasing air pollution and traffic congestion,
- Improving system efficiency,
- Preparing an accurate schedule,
- Optimizing the bus stop locations and decreasing the personnel walking distances,
- Minimizing the longest travel time and observing the fairness between personnel in terms of travel time, and
- Satisfying all the beneficiaries of the transportation system and even city inhabitants.

This paper suggests that policy makers, researchers and practitioners use this method for similar situations, in which the number of nodes is not too many and the running of the model is not frequented hourly or daily. In the similar problems that a model runs for one time and is used for many implementations, the running time of the model is not really important, whereas achieving the optimal solution is essential because a small waste of money repeats many times and creates a huge waste. Thus, applying the suggested models lead to a virtually optimal solution.

6.3. Suggestions for Future Research

LRPs are classified as NP-hard problems, so increasing the number of nodes will increase solution time exponentially and may even make the problem unsolvable. Therefore, the heuristic and meta-heuristic methods have found many applications. Nevertheless, heuristic methods only approach the optimum solution and they do not guarantee achieving the absolute optimum solution. It is then possible to conduct much research on exact and heuristic solution methodology to find faster and more efficient exact methods. Some suggestions that can expand the problem are adding stochastic assumption to personnel demands, solving this problem with the heuristic methods, adding personnel from other shifts to the problem and adding the possibility to apply one vehicle for serving several shifts, adding assumption of serving several factories concurrently in order to decrease costs (possibility of picking up personnel from several companies by a vehicle), and combining LRPs with the concept of data analyses and machine learning (a sample of using the machine learning is presented by Najafi Moghaddam Gilani et al., 2021).

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