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Research Article

Employee Shuttle Bus Routing Problem: A Case Study

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Abstract

This paper describes the real-life application of a personnel service shuttle routing problem. The problem in question is a type of vehicle routing problem with special constraints. To solve the problem, a mathematical model was developed, which aims to minimize the total travel time of employees, including the walking times to the shuttle-stops and the times spent on the shuttles. These times were added in the model by considering the times between the designated stops, the times each shuttle spends on each stop and the total travel times of the shuttles from the starting points to the destination point. The goal programming model was coded and solved using the commercial solver IBM ILOG CPLEX Optimization Studio. The actual times between the shuttle bus stops and the employee walking times were calculated according to the real-life data provided by the company. The walking times of the employees to the bus stops were also regulated via the inclusion of some set covering constraints in the model. When the numerical results from the model were compared to the current practice of the company, it has been observed that the savings in total travel time were quite significant.

Keywords: Employee service shuttle routing problem, Weighted-preemptive goal programming, Mathematical modeling, Optimization.

Personel Servisi Rotalama Problemi: Bir Vaka Çalışması

Öz

Bu makale, bir personel servisi rotalama probleminin gerçek hayattaki uygulamasını açıklamaktadır. Söz konusu problem, özel kısıtlamaları olan bir tür araç rotalama problemidir. Problemi çözmek için, servis duraklarına yürüme süreleri ve servislerde geçirilen süreler de dahil olmak üzere çalışanların toplam seyahat sürelerini en aza indirmeyi amaçlayan bir matematiksel model geliştirilmiştir. Belirlenen duraklar arasındaki süreler, her bir servisin her bir durakta geçirdiği süre ve servislerin başlangıç noktalarından varış noktasına kadar geçirdiği toplam seyahat süreleri göz önünde bulundurularak, bu süreler modele dahil edilmiştir. Hedef programlama modeli, ticari çözücü IBM ILOG CPLEX Optimization Studio kullanılarak kodlanmış ve çözülmüştür. Duraklar arasındaki gerçek süreler ile çalışanların yürüme süreleri, şirket tarafından sağlanan gerçek hayat verilerine göre hesaplanmıştır. Modele küme örtüleme kısıtlamaları dahil edilerek çalışanların otobüs duraklarına yürüme süreleri de düzenlenmiştir. Modelden elde edilen sayısal sonuçlar şirketin mevcut uygulaması ile karşılaştırıldığında, toplam seyahat süresindeki tasarrufun oldukça çarpıcı olduğu gözlemlenmiştir.

Anahtar Kelimeler: Personel servisi rotalama problemi, Ağırlıklı-öncelikli hedef programlama, Matematiksel modelleme, Optimizasyon

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1. Introduction

With rapid advancement of technology in the global world and the change of cultural and socioeconomic structures, transportation systems have begun to have a very important place in every aspect of daily life. The need for transportation has begun to rise in direct proportion to the population's rapid growth, and particularly in large cities, traffic, air pollution, fuel costs, stress, and many other factors have begun to pose a severe challenge. In addition to all these, correct design and management of transportation systems is necessary for companies to survive in difficult country conditions and to compete with other companies in terms of efficiency and cost.

Considering today's conditions, the rapidly increasing economic crisis in the world, especially with the effect of the pandemic, made itself felt quite a lot in Turkey. Added to this economic crisis were the effects of the war waged by Russia, the major oil supplier, against Ukraine. Gasoline prices in the country have increased approximately 3.5 times compared to the previous year. These prices have negatively affected many people who use vehicles in daily life, as well as the companies that provide personnel transportation services to bring their personnel to work. From this point of view, it had become essential for companies with a large number of employees to perform service routing effectively. The extra distances covered turned into extra paid service rents or gas money. Considering all these, the importance of employee routing problems, which is a sub-branch of vehicle routing problems, has increased considerably. In order to resist rising gasoline prices, personnel shuttles must complete the most appropriate route using the least number of vehicles. However, the human factor should not be forgotten while doing this. Concepts such as the time that the personnel will spend in the service and the picked-up points are the factors affecting the transportation systems.

The most important element of transportation system management is people. Employee satisfaction is important in terms of getting efficiency from the work done. Yalçındağ (Yalçındağ, 2020) indicates that companies have to examine their current processes in order to increase their profitability and reduce their costs. From these processes, he seeks a solution to the real-life problem with a mathematical model on the management of personnel services. Leksakul et al. (Leksakul, Smutkupt, Jintawiwat, & Phongmoo, 2017) work on the comparison of different solution methodologies for solving a location-routing problem of an industrial factory in Thailand. Purba et al. (Purba, Siswanto, & Rusdiansyah, 2020) emphasize that one of the ways to satisfy the employees is provide buses to pick and drop them up at different points. He uses Tabu Search with two scenarios in his study and reduce fuel costs by 8% and %7. Wanigasooriya and Fernando (Wanigasooriya & G I Fernando, 2013) work on multi objective and split delivery cases instead of a standard VRP solution and propose a solution with Genetic Algortihm. Hashi et al. (Hashi, Hasan, & Zaman, 2015) make a study able to design the bus stops according to from home to work or vice versa while finding the shortest bus route. Wolfler Calvo et al. (Wolfler Calvo, de Luigi, Haastrup, & Maniezzo, 2004) work on carpooling problem and used LS and GRASP algorithm also using with additional Information and Communication Technologies like web, GIS. Perugia et al. (Perugia, Moccia, Cordeau, & Laporte, 2011) work on a model which regarding to home-to-work bus service in the metropolitan area. Baldacci et al. (Baldacci, Maniezzo, & Mingozzi, 2004) study on carpooling problem and proposed Column-Generation-Based Algorithm based on two integer programming models.

All these studies show that businesses are evolving towards a structure that is not only focused on cost and profit, but also considers customer/employee satisfaction, sensitive environmental issues and time management, and wants to achieve many different goals at the same time. It is a clear indication that businesses are faced with multi-criteria-decision-making problems that they try to optimize these goals which are in conflict with each other, at the same time. GP is a widely used technique of multi-criteria decision models for modelling and solving multiple conflicting objectives. GP models, optimizes multiple goals by minimizing the targets or the amount of deviation from these targets. Charnes, Cooper and Ferguson (Charnes, Cooper, & Ferguson, 1955), in a study on salary analysis, see the inadequacy of linear programming (LP) in solving multi-objective problems and expressed their work as constraint regression which is a different version of LP. Afterwards, Charnes and Cooper (Charnes & Cooper, 1977) develop constraint regression and introduced a wider version, which clearly took its place in the literature as GP. With the effective work of Lee and Clayton(Lee & Clayton, 1972) and Ignizio(Ignizio, 1976), GP practices are expanded and its popularity increase. These studies lead to the emergence of many applications until today.

In the field of Goal Programming (GP), it is observed that there are also studies on vehicle routing problems. Ghoseiri and Ghannadpour (Ghoseiri & Ghannadpour, 2010) provide a mathematical and model solution for the time window multi-objective vehicle routing problem (VRPTW) using GP and genetic algorithms. Instead of solving GP directly with a commercial solver, Calvete, Galé, Oliveros and Sánchez-Valverde (Calvete, Galé, Oliveros, & Sánchez-Valverde, 2007) seek a two-step solution with a new approach they called enumeration-followed-by-optimization. Park and Koelling (Park & Koelling, 1986) minimized the traveled distance with GP and heuristic approach. On the other hand, Jozefowiez et al. (Jozefowiez, Semet, & Talbi, 2002) uses GP and Tabu Search Algorithm to minimize the distance traveled and to balance the tour lengths of the vehicles. Giannikos (Giannikos, 1998) looks for a solution for Location and routing for hazardous waste transportation and treatment using GP.

Multi-objective or bi-objective mathematical models are used not only in GP, but also by many researchers working in the field of routing. The research studies which belongs Tan et al. (Tan, Chew, & Lee, 2006), Chitty and Hernandez (Chitty & Hernandez, 2004), Sa'adah et al. (Sa'Adah, Ross, & Paechter, 2004) have multi-objectives and they are about minimizing the travel distance, the number of vehicles, the total mean transit time and the total variance in transit time. Boffey et al. (Boffey, García, Laporte, Mesa, & Pelegrín, 1995) provides a list of problems classified as multi-objective problems in the routing domain. On the contrary, Pitakaso et al. (Pitakaso, Sethanan, & Srijaroon, 2019) applies a mathematical model, to solve for small-size problems, with the three sub-problems which tries to minimize the rental, and travelling cost instead of using multi-objective.

In this study, as in many publications, a solution to the employee service routing problem of a real-life company was found by using a single mathematical model by using multi-objective. Peker and Türsel Eliiyi (Peker & Eliiyi, 2022) state that most of the studies in the employee field have reached solutions to heuristic and metaheuristic methods. Although this rate has a share of almost 80%, they stated that the rate of those who reach a solution using only the exact method is 9%. This study is very important due to the fact that there are few articles in the field of employee service routing in the literature, and it is among the few publications in the literature due to the exact method to reach the solution. On the other hand, this article will make an important contribution to the literature since there is no publication that has reached a solution using Weighted-Preemptive Goal Programming (WPGP) in the field of employee service routing, with a bi-objective that takes care of both company interests and personnel satisfaction.

The rest of the paper is organized in 3 sections. In the following section, the explanation of the methodology followed is explained. Data collection steps and problem definition are clearly stated in here. The WPGP model, which is the solution approach of this problem, is also expressed in a detail. In Section 3, the computational result part is included. Here, the results obtained from the WPGP model are examined and their comparison with the real-life situation is presented. Finally, concluding remarks and future research ideas are given in Section 4.

2. Methodology

In this section, the solution method sought for the personnel service routing problem of a real-life company was explained. Real life data was used to solve this problem, and all these data such as the number of buses used, routes for the current situation, the home addresses of the personnel and the picked-up points of employees were obtained from the company. In Section 2.1, how these data are processed was given in detailed. In Section 2.2, the company's conditions, number of employees, current situation analysis and the definition of the problem were included. The multi-objective mathematical model designed to solve this problem was given in section 2.3. Since the two objectives in the objective function of mathematical model contradict each other, WPGP, a type of GP, was used in the model to provide a balance between them.

2.1. Data Collection

In the light of the information received from the company, the home addresses of 100 employees who use the service were marked on Google Maps and shown in the Figure 1. Home icons show the residence of the working personnel, and the factory icon shows the location of the factory.

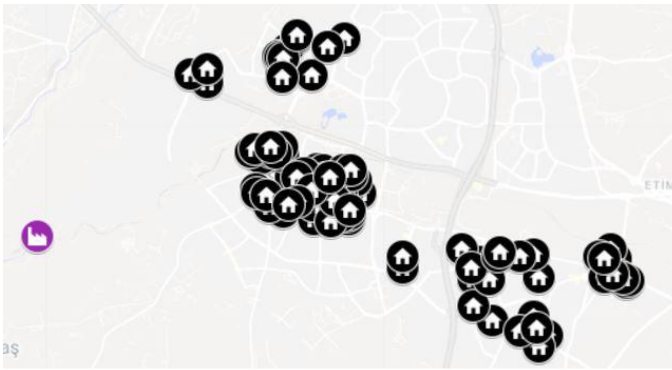

Figure 1. Employee addresses on Google maps

The stops determined by the 3PL company were supplied from the company and they were marked with a drop icon on the map in Figure 2. Bus stops and coordinates of the employees' addresses were imported from Google Maps to excel format. First, it was necessary to calculate the elapsed time to go from one stop to the next. To do this, instead of marking the stops one by one and creating the matrix manually, a Bing API key was obtained, and code was written in Visual Basic for Applications (VBA) to measure the time between two stops. Afterwards, these measured times were recorded in a matrix in excel with another code written in VBA. The same procedures were applied to calculate walking times from the employees' home to the bus stops.

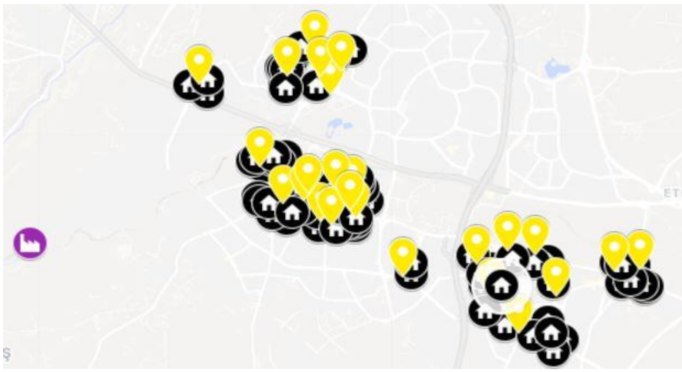

Figure 2. Bus stop points

While doing this travelling mode was only changed from driving mode to walking mode. In addition, the existing bus routes were obtained from the company. Routes for each bus passing through the current 25 stops are drawn on Google Maps and shown in Figure 3.

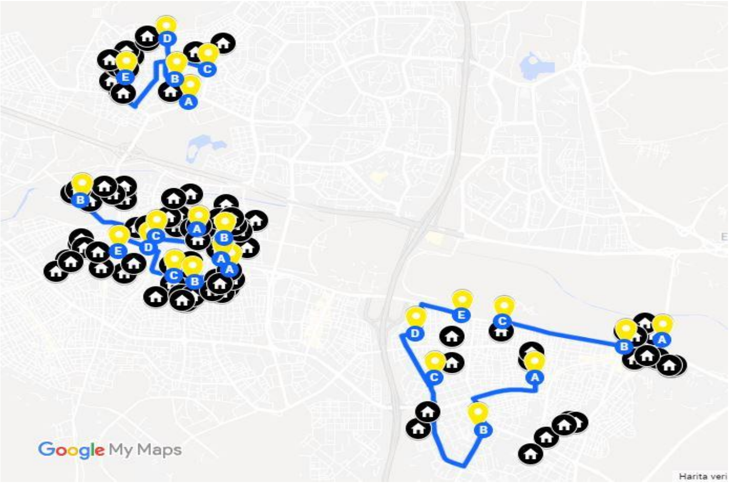

Figure 3. Bus routes of current situation

2.2. Problem Definition

In this study, a real-life application of the employee service routing optimization problem of a company operating in the electromechanical sector in Ankara is considered. The company employs 100 personnel in total. All pick-up and drop-off locations according to the regions where employees live heavily were accepted as fixed and the whole model was constructed in this direction. The company does not allow employees to walk to the bus stops for more than 20 minutes and requires that every employee using the service must be picked up. Under current conditions, company completes its route with 6 buses, each of which has a capacity of 19. Each bus starts the tour from the address where the shuttle driver lives, picks up the employees from the closest distance to their location, and completes the tour at the company (see in Figure 4).

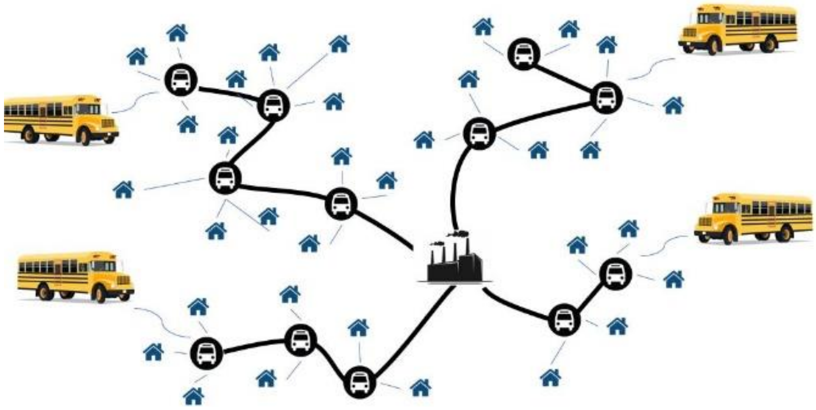

Figure 4. Visualized overwiew of the problem

It does not matter where the buses arrive at the first pick-up point. For buses, the route starts from a point where it picks up the first personnel. Considering the traffic conditions in these time intervals, the transportation times between the stops were calculated and the average of the time in the morning and evening was used. In addition, since the routes followed are considered to have symmetrical distances, buses follow the same route when bringing personnel to work and leaving them to home. Every employee must be picked up by only one service without any exception. Personnel should return to their homes in the evening with the service they were assigned in the morning. Services cannot receive employees of another company simultaneously. So, heterogenous service routing is not accepted. Services cannot take more passengers than their capacity.

In the literature, generally, one bus is assigned to each bus stop. In other words, if the bus is going to one stop, it has to pick up all the employees there. However, in this model, if the number of employee walking to one stop is more than the empty capacity of the bus, employees can be taken with another bus from the same stop. In other words, each bus can stop at the stops where other buses stop, if it only picks up the passengers assigned to it.

Considering all these aspects, it was desired to create a model that protects both company interests and employee satisfaction and the multi-objective model was used in the solution method. In following section WPGP model, which is used as a solution to the problem, was given in detail.

2.2. Weighted-Preemptive Goal Programming Model

Sets of the WPGP model can be defined as:

K: Set of buses (k=1,…,|K|)

L: Set of pickup locations (bus stops) (i,j=0,…,|L|)

N: Set of employees (n=1,…,|N|)

I: The set of stops that the employee can reach with less than the maximum walking time I:{i| $a_{in} \leq Mxd$}

Input Parameters of the model are as:

a_{in}: Walking time of employee n from home to bus stop i

t_{ij}: Time to go from location i to location j

Q_k: Capacity of bus k

Mxd: Maximum walking time of employees are allowed to walk

u: unit processing time

R: maximum allowed travelling time for a bus

F: maximum number of buses used

W1: the weight coefficient of minimizing travelling time of buses

W2: the weight coefficient of minimizing number of services

Decision Variables:

$$x_{ijk} = \begin{Bmatrix} 1, & \text{if bus k travels from location } i \text{ to } j \\ 0, & \text{otherwise} \end{Bmatrix}$$

$$Z_{ink} = \begin{Bmatrix} 1, & \text{if employee } n \text{ picked up by bus } k \text{ at bus stop } i \\ 0, & \text{otherwise} \end{Bmatrix}$$

$$y_{ik} = \begin{Bmatrix} 1, & if\ bus\ k \text{ visits location } i \\ 0, & \text{otherwise} \end{Bmatrix}$$

$$b_k = \begin{Bmatrix} 1, & \text{if bus } k \text{ is used} \\ 0, & \text{otherwise} \end{Bmatrix}$$

s_i *and* s_j: variables that define the number of points visited on a tour

$d1_k$: positive deviation in the target travelling time of a bus

$d2_k$: negative deviation in the target travelling time of a bus

d3: number of buses that excess from the target

d4: number of buses that below the target value.

$$min\ (W1 \times \sum_{k \in K} d1_k) + (W2 \times d3) \tag{1}$$

$$\sum_{i=1}^{L-1} \left(\sum_{j=1, j \neq i} (t_{ij}\ x_{ijk}) + x_{ijk}\ u \right) = R\ b_k + d1_k - d2_k \qquad \forall k \in K \tag{2}$$

$$\sum_{k \in K} b_k = F + d3 - d4 \tag{3}$$

$$y_{0k} = b_k \qquad \forall k \in K \tag{4}$$

$$\sum_{j=1}^{L-1} x_{0jk} = b_k \qquad \forall k \in K \qquad (5)$$

$$\sum_{i=1}^{L-1} x_{i0k} = b_k \qquad \forall k \in K \qquad (6)$$

$$\sum_{j \in L\backslash\{0\}, i \neq j} x_{ijk} = \sum_{j \in L, i \neq j} x_{jik} \qquad \forall i \in L\backslash\{0, |L|\}, \forall k \in K \qquad (7)$$

$$\sum_{j \in L\backslash\{0\}, i \neq j} x_{ijk} = y_{ik} \qquad \forall i \in L\backslash\{0, |L|\}, \forall k \in K \qquad (8)$$

$$\sum_{j \in L\backslash\{0\}, i \neq j} x_{ijk} \leq b_k \qquad \forall i \in L\backslash\{0, |L|\}, \forall k \in K \qquad (9)$$

$$Z_{ink} \leq y_{ik} \qquad \forall n \in N, \forall i \in L, \forall k \in K \qquad (10)$$

$$\sum_{i \in I_n} \sum_{k \in K} Z_{ink} = 1 \qquad \forall n \in N \qquad (11)$$

$$\sum_{n \in N} \sum_{i \in I_n} Z_{ink} \leq Q_k \qquad \forall k \in K \qquad (12)$$

$$0 \leq s_i \leq |L| \qquad \forall i \in L \qquad (13)$$

$$s_i - s_j + |L|\, x_{ijk} \leq |L| - 1 \qquad \forall i \in L, \forall j \in L\backslash\{0, i\}, k \in K \qquad (14)$$

$$\left\{\begin{array}{ll} x_{ijk} \in \{0,1\} & \forall i \in L\backslash\{j\}, \forall j \in L\backslash\{i\}, \forall k \in K \\ Z_{ink} \in \{0,1\} & \forall i \in L\backslash\{j\}, \forall n \in N, \forall k \in K \\ y_{ik} \in \{0,1\} & \forall i \in L\backslash\{j\}, \forall k \in K \\ b_k \in \{0,1\} & \forall k \in K \\ s_i, s_j \geq 0 & \forall i \in L, \forall j \in L\backslash\{0, i\} \\ d1_k, d2_k, d3, d4 \geq 0 & \forall k \in K \end{array}\right\} \qquad (15)$$

The first part of the objective function (1) is to minimize the deviation in the target travelling time of a bus and the second part of the objective function (1) aims to minimize the deviation from the target number of buses. The first part and the second part of the objective function (1) create contradictions with each other. Here, it is aimed to strike a balance between this contradiction by using WPGP. Constraint (2) refers to goal 1. Here, a target value has been set for the total travel time of the buses, and d1 and d2 hold the value of positive and negative deviation from this goal. Deviations from target value in the positive or negative direction are kept separately for each bus, and it is aimed to minimize only positive deviations in the objective function. If the employee is traveling below the target value, negative deviations are not included in the objective function as this is already expected. Constraint (3) refers to goal 2. In this constraint, a goal is set for the total number of buses used, and d3 and d4 hold the values of positive and negative deviations from this goal. With this goal, company interests are protected. As the number of buses used will increase as the travel time is desired to be reduced, each bus will incur additional costs for the company. For this reason, the second target was established in order to minimize the number of buses. Both Constraints (2) and Constraints (3) are soft constraints, which are called target constraints. The system constraints in the previous section must be met exactly. Goal constraints keep the amount of deviation between the best possible result and the set target. Constraint (4) tells that every bus must start from a starting point and must complete its tour in the company. Constraints (5) and (6) ensure that each bus goes from the starting point to a location other than the last stop and arrives at the final stop only from a location except for the starting stop. In other words, buses cannot go directly to the company without stopping at least 1 of the other stops from the starting location. Constraint (7) indicates the bus entering one of the points that is between the starting point and ending point, must leave the same stop. So, the bus must continue the tour. Constraint (8) indicates that if a bus visits a location, that bus has to continue the tour with next itinerary location. This condition is not valid, if the bus at the final destination. Constraint (9) states that if a bus is used that bus must travel from a location i to location j. Constraint (10) states that if a bus doesn't visit location i, employee n is not picked up at bus stop i by bus k. Constraint (11) ensures that all employees can be picked up by only one bus from a stop accessible. However, unlike the School Bus Routing Problem (SBRP) model, more than one bus can visit the same stop to pick up the employees. In other words, the model allows employees to be picked up from the same stop by different buses. The reason for creating this difference is to allow employees to walk to the station with the shortest possible walking time and to maintain employee satisfaction with this. In the SBRP model, since the number of employees taken from the station cannot be more than the bus capacity and more than one bus cannot stop at the same stop, the model finds a solution by assigning the employees to other bus stops where they can walk. In the developed model, employee satisfaction was taken into account by allowing more than one bus to come to the same stop, instead of allowing employees to be picked up from different stops by walking more. Constraint (12) indicates that the total number of employees taken by each bus from the stops cannot exceed the capacity of that bus. Constraints (13) and (14) are sub-tour elimination constraints. Constraint (15) are sign restrictions.

3. Computational Results

All the programs have been run on a Windows machine equipped with CPU Intel Core i5 at 2.60 GHz and 8 GB of installed RAM. WPGP model was coded with the run time limit of 12 hours into the commercial solver IBM ILOG CPLEX Optimization Studio 20.1.0. Then, this model had been solved by the CPLEX solver. In the current situation, it is seen that company provides the transportation of a total of 100 employees by using a total of 25 stops. According to the route information received from the company, buses completed the routes with total of 193 minutes travel time with 25 stops (see in Figure 5).

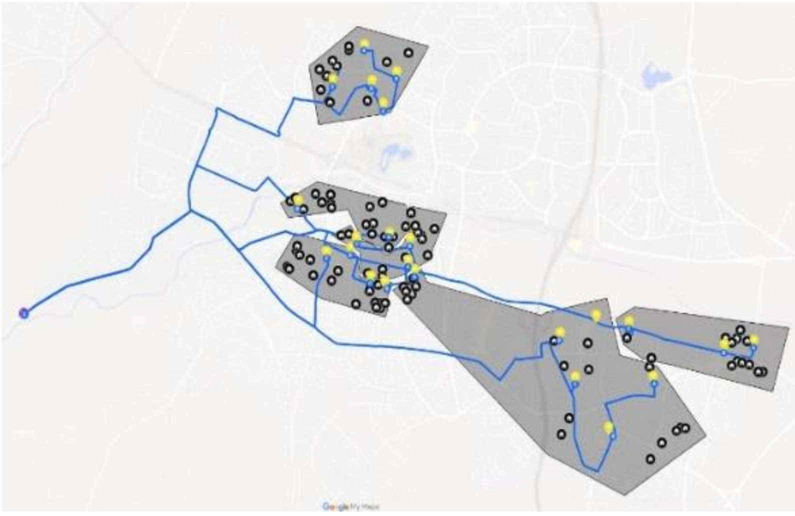

Figure 5. The map of current situation showing routes, stops and addresses.

Using same data in the WPGP model, which is a proposed solution, it has been obtained with 13 stops, a time of 164 minutes, again so that no employee is left out (see in Table 1). According to these data, it has been clearly seen that an improvement of 47,47% was achieved in the total travelling time.

Table 1. Comparison of current situation vs. proposed solution

	Total travelling time (min)	***Vehicle Population***	***Total Used Different Stops***	***Total processing time of buses (min)***
Current Situation	193	6	25	48
GP Solution (W1=10000 W2=1)	164	6	13	26

Under the conditions (goal1: 30 min traveling time and goal2: 6 buses), no matter what weight value and order of importance is given to the total travel time and the number of buses, the GP model finds the number for buses as 6. The main variable here is the total traveling time. For example, in the case where traveling time weighting is given as 10000 and number of buses is one, if objective function overestimates travelling time, it will add its value multiple by 10000. For that reason, the model tries to minimize travelling time first and then minimizes the number of buses. Considering that the number of buses has not changed, since the excess weight value is given to the travelling time, the optimal value whose travelling time closest is expected to be taken from here. However, in this scenario, since a weighting is also applied for the number of buses which must be increased in order to reduce the time spent by the personnel in the shuttles. The model obtained an optimum solution with 164 minutes by considering both weightings.

According to the results of the proposed solution, it was observed that a total of 38 employees had a better walking time compared to the current situation, while 21 employees walked more than the current situation, and 41 personnel did not have any change (see in Figure 6).

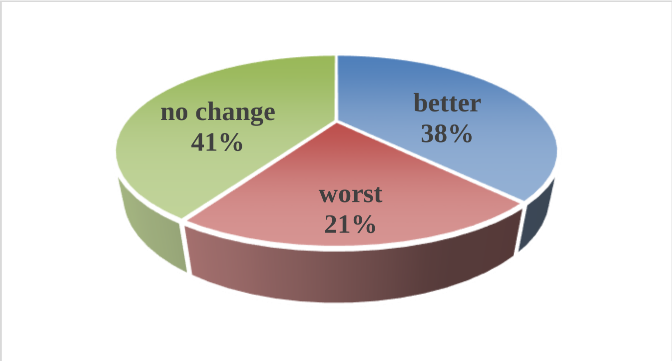

Figure 6. Comparison of employee walking time in WPGP model vs. current situation

Computational experiments were conducted to see if the model could be used in other fields and with different datasets. To conduct the computational experiments, benchmark data sets were generated. Since it is crucial to validate the model, random numbers that are close to reality were generated. First, the model was solved by changing the target value R to verify whether the targets reflect the truth, and whether the WPGP model works logically. Next, the number of locations was changed to 15, 8 different data sets were prepared for 25 different employees, and the models were run with these data. In order to make the first analysis, target data sets were created and the deviation amounts from this target were kept as a decision variable. The positive values were included in the objective function. In this data set, only the target value R was changed without altering the time matrix and the location information of 25 randomly generated employees. Accordingly, it has been observed that when the R value was reduced from 40 to 35, that is, when the target set arrows, the amount of deviation decreased as expected. The results obtained were shown in Table 2 below, which validate the WPGP model.

Table 2. Weighted-preemptive goal modeling according to different targets

	Weights	***R=40 F=2***	***R=37 F=2***	***R=36 F=2***	***R=35 F=2***
W1, W2	1, 1	90	109	89	88
# of bus	-	3	3	3	3
W1, W2	10000, 1	101	90	87	83
# of bus	-	3	3	3	3
W1, W2	1, 10000	90	90	88	88
# of bus		2	2	2	2

The last random data set was generated for 15 locations and 25 employees who reside in different places. Here, by changing the number and the location of the bus stops, it was tested whether the models work for 8 different address sets created for 25 employees. The same R and F values were used in this comparison. Accordingly, Accordingly, R value was set as 40 and F was set as 2. The results were shown in the below Table 3. With these randomly generated data sets, the results obtained from the WPGP model were found to be consistent compared to the results obtained from real-life data. While the whole table gives similar and logical results, the objective function value of the model operated with the 1st set of data gives 2 times the results of the others. Since the number of stops used in the 1st data set was higher than the other data sets, the process time was added to the objective function value for each stop visited by the buses, depending on the number of stops. This result also illustrates that the model gives correct, logical and stable results with different data sets.

Table 3. Result for 8 different random employee sets

		Employee data sets							
	Weights	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
W1, W2	1, 1	102	67	60	68	56	67	67	64
W1, W2	10000, 1	103	67	60	67	56	67	67	49
W1, W2	1, 10000	92	67	60	80	56	67	67	64
# of bus	-	3	2	2	3	2	2	2	2
Total Used Different Stops	-	6	4	3	4	2	4	4	3

Within the scope of this study, a vehicle routing problem, which minimizes the total traveling time and the number of buses used by the personnel on the way to work, was considered. Since these two goals created a conflict with each other, a solution was sought by establishing a GP model. The goals were determined for these two conflicting objectives.

For the application of the study, home addresses of the employees from an electromechanical company in Ankara, route and vehicle information were collected. According to the data, the company provided 6 vehicles, which has a capacity of 19 for this work, and it served the total number of 100 employees at 25 different stops. The result obtained from GP model was run with real-life data and the obtained results were compared with current solution. With the weighted prioritization given, both the company's interests were protected, and the satisfaction of the personnel was considered. It can be said that our method is reliable in terms of applicability and usability, since WPGP model work with both real-life data and randomly generated data sets for employees and gives reasonable results.

It can be seen from these results and comparisons, WPGP model can be used up to 200 employees and 25 locations with real life data. However, when these numbers are increased, the model run time also increases. With the given run time limit of 12-hours, the model comfortably can solve up to 200 employees and 25 locations. For larger instances of the problem, it would be more logical to either use a different solver and code structure, or tend to heuristic models and different solutions instead of exact methods.

In multi-capacity VRP, drawing routes and obtaining the optimal solution with large data sets require large processing times. It is also very difficult to reach optimal results with exact solutions methods due to the amount of data. For this reason, it may be practical to obtain good solutions in shorter times by grouping the data via a clustering algorithm. With this algorithm, small groups of employees can be routed independently, and high-quality solutions can be obtained easily. As a future study, the data can be clustered, and a solution method can be obtained using the developed WPGP model for larger instances of the problem.

As the traditional VRP is symmetrical, the distance from X location to Y location is equal to going from Y location to X location. However, this may not always be the case. In future studies, the best routes can be studied under asymmetrical distances due to road conditions and one-way streets.

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