EMPLOYEE SERVICE SHUTTLE ROUTING OPTIMIZATION PROBLEM

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YÜKSEK LİSANS TEZİ

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ÖZET

PERSONEL SERVİSİ ROTALAMA OPTİMİZASYONU PROBLEMİ

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İzmir Bakırçay Üniversitesi, Lisansüstü Eğitim Enstitüsü, Haziran 2022

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Bu tez çalışmasında, araç rotalama problemlerinin bir alt dalı olan okul servis rotalama probleminden yola çıkarak, üretim sektöründe faaliyet gösteren bir firmanın farklı lokasyonlarda oturan personelleri için, personel servisi rotalama problemi üzerinde çalışılmıştır. Klasik okul servis rotalama probleminden farklı olarak bu çalışmada personellerin memnuniyetini arttırmak için seyahat süresini minimize eden, hem de firmaya getireceği maliyetten ötürü otobüs sayısını da minimize eden çok amaçlı bir model ele alınmıştır. Bu iki amaç fonksiyonu, birbiri ile çelişki yarattığından dolayı problem çözümünde çok kriterli karar verme yöntemlerinin başında gelen ağırlıklı hedef programlama kullanılmıştır. Personellerin otobüste geçirdiği toplam seyahat süresi ve kullanılan toplam otobüs sayısı için hedef kriterleri belirlenmiş, bu hedeflerden sapma miktarları ise amaç fonksiyonunda minimize edilmeye çalışılmıştır. Birbiri ile çelişki yaratan her iki amaç fonksiyon değeri için de farklı ağırlıklandırmalar yapılıp, elde edilen sonuçlar, tek bir amaca yönelen doğrusal programlama modelinden elde edilen sonuçlar ile karşılaştırılmıştır. Model, İzmir Bölgesi için hem rassal olarak oluşturulan veriler ile hem de Ankara ilinde üretim yapan bir firmadan alınan yolcu ve gerçek rota verileri ile çalıştırılmıştır.

Anahtar Sözcükler: Personel servis rotalama problemi; Okul servis rotalama problemi; Araç rotalama problemi; Ağırlıklı hedef programlama.

ABSTRACT

EMPLOYEE SERVICE SHUTTLE ROUTING OPTIMIZATION PROBLEM

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İzmir Bakırçay University, Graduate Education Institute, June 2022

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In this thesis, the school bus routing problem, which is a sub-branch of vehicle routing problems, was developed and applied to the field of employee transportation instead of students. In this study, which is considered as a personnel service routing problem with different solutions are sought for the personnel living in different locations of a company operating in the production sector Different from the classical school bus routing problem is considered in this study, a multi-purpose model that minimizes the travelling time in order to increase the satisfaction of the personnel and also minimizes the number of buses due to the cost it will bring the company. Since these two objective functions conflict with each other, Weighted-Preemptive Goal Programming, which is one of the leading multi-criteria decision-making methods, was used in problem solution. Target values were determined for the total travelling time of the personnel on the bus and the total number of buses used, and the amount of deviation from these targets was tried to be minimized in the objective function. Different weights were used for both objective function values that conflict with each other, and the results obtained were compared with the results obtained from the linear programming model oriented to a single objective. The model was run with both the randomly generated data for the Izmir Region and the personnel and real route data obtained from a manufacturing company in Ankara.

Keywords: Employee service shuttle routing optimization problem; School bus routing problem; Vehicle routing problem; Weighted-preemptive goal programming.

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13/06/2022

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with Turnitin scientific plagiarism detection program used by İzmir Bakırçay University, and that "it does not have any plagiarism" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

Gaye PEKER

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LIST OF ACRONYMS

VRP : Vehicle Routing Problem

SBRP : School Bus Routing Problem

3PL : Third-Party Logistics

GP : Goal Programming

LP : Linear Programming

MILP : Mixed-Integer Linear Programming

VBA : Visual Basic for Applications

WPGP : Weighted-Preemptive Goal Programming

1. INTRODUCTION

Since ancient times, the need for transportation has a very important place in our lives due to both trade and the displacement of people for some reasons. With the rapid advancement of technology in the global world and the change of cultural and socioeconomic structures, this importance is increasing in all areas of daily life. With the rapid increase in population, transportation systems can be characterized as the heart of metropolitan cities, especially in the fields of health, airport, transportation, student and employee transportation, tourism, daily public and intercity transportation.

At a period when global competition is at the forefront, the correct design and management of transportation systems is indispensable for the firms to compete with other companies in terms of workforce in terms of efficiency, cost and to maintain their existence. With that being said, like environmental pollution, traffic, money, time, stress, comfort, quality of life, it also affects people's daily lives in a significant way with concepts. Considering all these factors, although VRP is one of the most studied problem types in the field of transportation, it is very difficult to obtain exact solutions with classical methods because it contains many constraints such as capacity, dynamically changing environmental conditions, demands, transportation costs, location differences, size of data, time etc.

It is very difficult to obtain exact solutions to VRP through a mathematical model, since these problems usually fall under the NP-hard class. This type of problem consists of different components due to its complex structure, and each component includes different roles according to the areas where VRP is applied. For example, depending on the sector it is applied, the warehouse in classic VRP can be accepted as a school, or the materials as students and customers as a bus stop. One of the most common subtypes of VRP, which has many different application areas, is the school bus routing problem (SBRP), which has been studied for many years. SBRP can be summarized as a type of problem that aims to assign students to the most appropriate stops and shuttles according to their residences, and to drop students to school by using the shortest route. In the literature, there are many studies and practices related to the SBRP, including time and capacity constraints, in which students belonging to the same or more than one school are transported together, and the time spent in the bus is discussed.

In this thesis, the SBRP model has been expanded and adapted to the employee field. The employee service routing problem can be thought of as the same, since it has a similar purpose to the SBRP. Employees, like students, are picked up from a certain point and dropped off at the company via a route and are returned to the stops where they were picked up. While doing this, objectives such as determining the most suitable route, minimizing the travelling time and the number of buses used are pursued.

In this study, the employee service routing problem of a company operating in the electromechanical sector in Ankara is considered. Since the number of employees of the company we work with is low, it was thought that this problem could be solved through linear programming, and an exact approach was preferred by setting a mathematical model. While the company wants to minimize the time its employees spend in the service, it also wants to minimize the number of buses used because of the cost. Because of that a two-stage solution method was used in this problem. For this, the mixed-integer linear programming (MILP) model was established with a multi-objective function for both purposes that the company wanted, and it was solved with real life data obtained from the company.

Since the two objectives that the company wants to minimize conflict with each other, an employee-oriented optimization model that takes into account the interests of the company has been considered and goal programming (GP) has been directed. Here, the goals were determined by gathering both objective functions under a single objective and it was aimed to minimize the deviations from these goals. In order to create a prioritization among these deviation amounts, a weight was determined for each deviation variable in the objective function. Mathematical models have been solved with real-life data, and in both models, much better results were obtained than the current solutions by the company.

The rest of the thesis is organized in five chapters. In the following chapter, other studies in the literature related to the subject studied in the thesis are presented. In Chapter 3, the definition and solution approach of the problem, how the data was collected, and the MILP and GP models established for its solution are included. The solutions obtained for these models are described in Chapter 4. In Chapter 5, the models were validated using different data sets, and the results were compared. Finally, concluding remarks and future works are given in Chapter 6.

2. LITERATURE REVIEW

Vehicle routing problem (VRP) is a type of problem included in the NP-Hard class, which is very important in material logistics and human transportation and cannot be easily solved by classical combinatorial optimization methods. In a typical VRP, vehicles start from a distribution point to a city, warehouse, school, customer, etc. stops at the distribution points and follows the most suitable route back to the distribution point (see in Figure 2.1.)

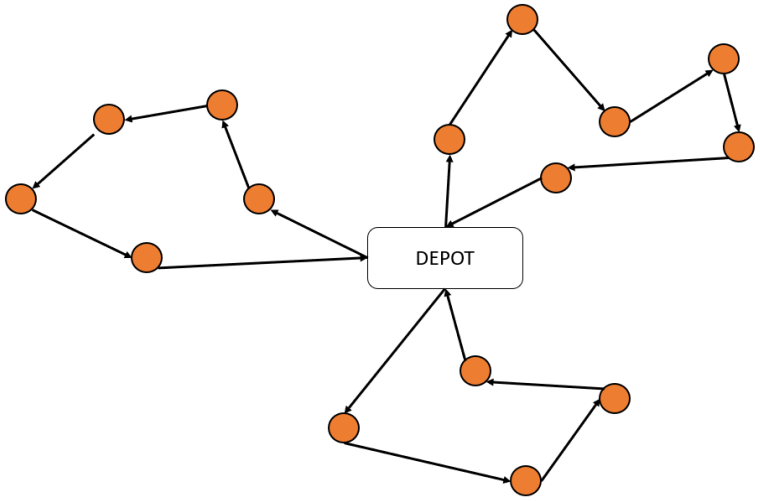


Figure 2.1. Traditional vehicle routing problem

After Dantzig and Ramser (1959) [1] introduced the first VRP, many publications have been published on this subject and on different variations of VRP. The most common VRP types in the literature are Capacitated VRP (CVRP), VRP with Time Windows (VRPTW), VRP with Pick-Up and Delivery, Asymmetrical Capacitated VRP, Open VRP, Multi-Depot VRP, VRP with Multiple Trips. According to Christofides and Eilon (1969) [2], and Braca, Bramel, Posner, Simchi-Levi (1997) [3], SBRP has been studied for many years, is a generalization of VRP. In order to contribute to the study, besides the general VRP literature, its sub-branch, SBRP, is given in this thesis. Studies in the field of SBRP were examined and based on this, the literature on the employee service shuttle routing problem, which is our main topic, was reviewed. The methods used in the articles in this field are given in the follows.

2.1. School Bus Routing Problem

SBRP is a problem type that has been studied extensively for many years since the article by Newton and Thomas (1969) [4] published in 1969. Li and Fu (2002) [5] state that most of the existing approaches for SBRP depend on a problem and there is more than one approach. Desrosiers, Ferland, Rousseau, Lapalme, Chapleau (1981) [6] stated that SBRP consists of minor sub-problems in itself and can be solved by data preparation, bus stop selection, bus route generation, school bell time adjustment, and route scheduling steps.

Newton and Thomas (1969) [4], Clarke and Wright (1964) [7], Bodin and Berman (1979) [8] preferred the school-based approach, which does not allow children going to different schools to travel on the same bus at the same time. According to Braca et al. (1997) [3], on the other hand, used the more flexible and mixed load approach. Additionally, Park, Tae, and Kim (2012) [9] argued that the collecting students from different schools in the same bus had a greater gains.

According to Bögl, Doerner, and Parragh (2015) [10] used a bi-objective function with a model that handles the penalty coefficient when it exceeds the total travelling time and the number of transfers. Oluwadare, Oguntuyi, and Nwaiwu (2018) [11] on the other hand, tried to minimize the total travel distance, the number of stops used and the number of buses using multi-objective.

In many studies in the field of SBRP, it is observed that the total travelling time, distance, number of buses and cost per km. The authors who use these objectives most in their models are Chen, Kong, Dang, Hou, and Ye (2015) [12], Diaz-Parra, Ruiz-Vanoye, Buenabad, and Cocon (2012) [13], Minocha, and Tripathi (2012) [14], Park et al. (2012) [9]. Melachrinoudis and Hokey (2011) [15] and Souza Lima, Pereira, da Conceição, and de Camargo (2016) [16] worked on a model that was not found in other publications, aiming to balance the workload between drivers.

Since VRPs are in the NP-Hard class, and optimum results cannot be obtained with a mathematical model in general, solutions are sought with heuristic or metaheuristic methods. In the literature, different types of solution methods have been used in the field of SBRP. Schittekat, Sevaux, Sörensen, and Kenneth (2006) [17] used MILP model. Then they sought a solution to SBRP by using variable neighborhood descend method. Huo, Yan, Fan, Wang, and Gao (2014) [18] developed the model they built with the ant colony algorithm. Arias-Rojas, Jiménez, and Montoya

Torres [19] worked on real-life data with the same solution method and achieved a fuel saving of 17.9% on a service network. Among these authors Uzumer and Tamer (2012) [20], Bektaş and Elmastaş (2007) [21], and Yalçındağ (2020) is one of the rare authors who achieved results using only MILP in the field of SBRP.

Riera-Ledesma, Salazar-González and José (2012) [22] introduced a generalization of the VRP. They combined bus stop selection and bus route generation together. Besides, Ngamchai and Lovell (2003) [23] proposed a model that helps to optimize the route design by combining the service frequency settings for each route using the genetic algorithm. Spada, Bierlaire, and Liebling (2005) [24] proposed insertion heuristic was used first stage for generation feasible solution and, this solution was improved with tabu search, local search and simulating annealing algorithms.

2.2. Employee Service Shuttle Routing Problem

Although a lot of work has been done in the literature in the field of SBRP, in the last 20 years, it has not been found that this study has been adapted to the employee field. This number is approximately 1/3 of the studies carried out in the field of school bus which is shown in below Figure 2.2.

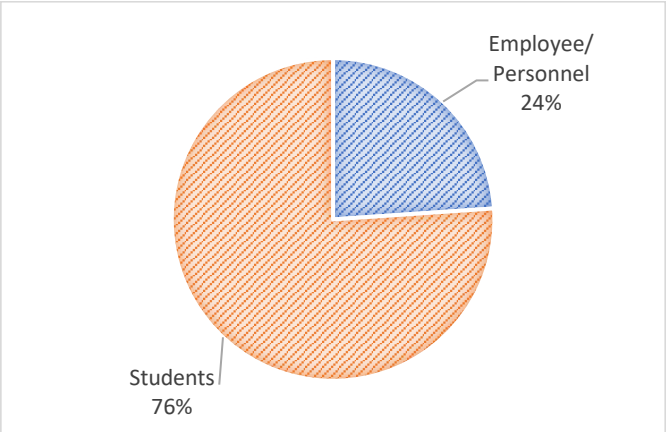


Figure 2.2. The percentages of student and employee fields in the literature

In the field of employee/personnel, there are 11 studies invastigated in the scope of this study. Yalçındağ [25] improved a mathematical model and applied an international company located in Gebze, Turkey. They set a mathematical model with multi-objective functions which are regarding to minimize the routing cost, fixed cost,

indivudual travalling cost and un-satisfaction cost. Leksakul et al. [26] worked on the comparision of different solution methodologies for solving a location-routing problem. Different then the others, to allocate the bus stops they used artificial intelligence techniques, which are Maximin, K-means, Fuzzy C-means, Competitive Learning, and two hybrids of those. This study was also applied on a large-scale industrial factory in Thailand.

Wanigasooriya and Fernando [27] have worked on multi objective and split delivery cases instead of a standard VRP solution and has proposed a solution with Genetic Algortihm. Pitakaso et al. (2019) [28] applied a mathematical model, to solve for small-size problems, with the three sub-problems which are determination of the number of bus stop ,bus assignment, and finding bus routing (shortest path), with the objective minimizing the rental, and travelling cost. And then, five Modified Differential Evolution Algorithms are developed for large-size problems.

Hashi et al. (2015) [29] did a study able to design the bus stops according to from home to work or vice versa while finding the shortest bus route. Purba et al. (2020) [6] proposed two different scenarios with two starting points for buses and a starting point other than the first stop where employees get on. Those senarios solved by the methods of Tabu Search Algorithm and Greedy Algorithm and study was applied in a coal mining company. Quadrifoglio et al. [30] developed an insertion heuristic method which regulate the slack time consumption with the control parameters. Wolfler Calvo et al. [31] worked on carpooling problem and used LS and GRASP algorithm also using with additional Information and Communication Technologies like web, GIS. Also the solved system tested on the real case. Unlike other studies in the field of employee/personnel, Deliktaş and Üstün [32] proposed Particle Swarm Optimization to determine the number of bus stops using a clustering approach. This study was also applied in a university. Perugia et al. [33] worked on a model which regarding to home-to-work bus service in the metropolitan area and This study was also applied a research center in Rome, Italy. Baldacci et al. [34] studied on carpooling problem and proposed Column-Generation-Based Algorithm based on two integer programming models.

2.3. Goal Programming

With the globalizing economic conditions, the rapid increase in population and

the expansion of consumption needs, the efficient use of scarce resources has become very important. In this context, it has become imperative for businesses to use their existing resources in the most efficient way by keeping up with rapidly advancing technological systems to maintain their existence in the world market where competition is intense. In order to achieve this, businesses need to adopt an innovative and contemporary management style instead of the old traditional management approach. With an innovative management approach, businesses should move to a structure which incorporates many different goals at the same time as not only focuses on cost and profit, but also considers customer/employee satisfaction, sensitive environmental issues, and time management. 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. In 1955, Charnes, Cooper and Ferguson [35], in a study on salary analysis, saw 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 [36] developed constraint regression and introduced a wider version in 1957, which clearly took its place in the literature asGP. With the effective work of Lee and Clayton in 1972 [37] and Ignizio in 1976 [38], GP practices were expanded and its popularity increased. These studies have led to the emergence of many applications until today.

2.3.1. Differences between linear programming and goal programming

Basically, GP is a kind of LP used in the optimization of multiple and conflicting objectives, but it shows considerable differences in itself. In LP, the goal is to get the best solution and only one goal is to be optimized. In GP, on the other hand, there is more than one goal, and the best possible solution is tried to be obtained from the determined targets to reach them. While objective function can be minimization or maximization in LP, it is only minimization as deviations from the target are looked at in GP the objective function. These two model types also differ in constraints. While hard constraints are used in LP, in addition, soft constraints that

allow deviations are also used in GP with those hard constraints. In addition to these differences, while decision variables are included in the objective function in LP, there are positive or negative deficiency variables in the objective function instead of decision variables in GP.

3. METHODOLOGY

In this section, the two-stage models established for a company's personnel service routing problem will be explained. In the first model, the classical SBRP model in the literature was expanded and designed in a line with the needs of the company. However, unlike SBRP, two different objective functions were used in this model. In the first objective, it was aimed to minimize the time employees spent on the bus, and in the other, to minimize the number of buses used. If the number of buses decreases, the time that the employees will spend in the bus will be longer, as the existing buses will go around and want to take all the employees until they fill their capacity.

Because the two objective functions conflict with each other, in order to balance between them, Weighted-Preemptive Goal Programming (WPGP), which is a type of GP, was used to set the model. In the following section, the definition of the problem and the data of the problem will be given. In Section 3.2, details about the method used to solve this problem will be given. In the following Section 3.3, the mixed-integer programming model established with two objective functions will be presented with details and in Section 3.4, the adaptation of the model established in the previous section to GP used as a solution method is explained in detail.

3.1. 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 121 personnel in total. 9 of them are in managerial positions, and the company has allocated special car to these employees. 12 of them do not prefer to use the service and provide their own transportation to the company. Therefore, this study was conducted for the remaining 100 employees.

The company works with a third-party logistics (3PL) company for the transportation of its personnel. 3PL has determined all pick-up and drop-off locations according to the regions where employees live heavily. These stop locations were accepted as fixed and the whole model was constructed in this direction. There is only one rule set by the company here about the bus stops: the stops must be within a maximum 20-minute walking distance of each personnel. If it provides this condition, the 3PL company can open as many stops wherever it wants. Under current conditions,

3PL 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, which is the last stop (see in Figure 3.1).

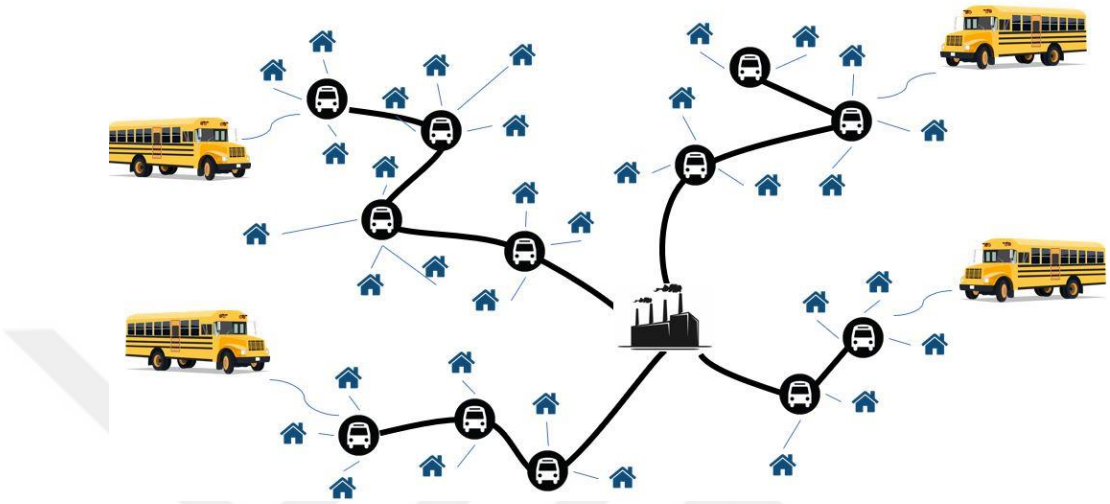


Figure 3.1. Visualized overview of the problem

Because of the agreement between the company and 3PL has been made from the first pick-up point to the final delivery point, 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. Therefore, index 0 is used for the starting point and the distances to all other stops are considered to be zero. In the evening, when the work is over, the shuttles pick up the employees assigned to them from the company and redistribute employees to the first pick up locations in the morning. The time interval for the morning services to pick up and drop off employees was taken as 06:00 - 08:00 a.m. and the time interval for picking up from work and leaving them to home in the evening is 06:00 - 08:00 p.m. 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.

In addition to the above, there are other conditions that will directly affect the solution of the problem. 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. This makes it easier to solve the routing problem within the company. Services cannot take more passengers than their capacity. In other words, it is not allowed standing travelling passengers. 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, provided that it only picks up the passengers assigned to it.

When the literature is examined, the mathematical models in the studies on employee service shuttle bus routing are mostly designed to minimize the travel distance, travelling time or total travelling cost. In this thesis, it was aimed both to minimize the number of buses used and to minimize the time spent by the personnel on the bus. Since the employees were unsatisfied with the fact that they were traveling with a few numbers of buses at high travelling times, the company wanted a solution proposal that would bring its employees to the company in a shorter time without increasing the number of buses. Considering all this, 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. Due to the fact that the MILP model established in the Section 3.3 has more than one objective function and the differences of the units in the objectives to be minimized (one is time, the other is quantity), the MILP model has been developed and the problem solution has been sought with the GP model. The objective function structure was changed by adding some targets to the established MILP model, and it was tried to minimize the deviation from the set targets. Soft constraints have been added to the model without touching the hard constraints in the MILP model. This model, which is used as a solution to the problem, is also given in detail in Section 3.4.

3.2. Solution Approach

The aim of GP is to find a solution that satisfies all the constraints and achieves as many goals as possible. The main concepts used in the GP model to reach this

solution can be found in the following section.

3.2.1. Fundamental concepts of goal programming

3.2.1.1. *Objectives*

According to Schniederjans (1984) [39] objectives is the concept that indicates the wishes of the decision makers in general. These preferences generally appear as minimizing or maximizing a goal. As an example, a company's desire to maximize its profits or to minimize the risks in an investment can be given.

3.2.1.2. *Decision variables*

Jones and Tamiz (2010) [40] defined the factors as decision variables which are under the control of the decision makers. Decision variables are an unknown quantity in an optimization problem. In other words, they are the concepts that are expected to be estimated in the problem output. These could be things like the number of personnel to be employed, the amount of money to be invested, or the amount of production quantity.

3.2.1.3. *Targets*

Türkoğlu (2017) [41] stated that the targets indicate an acceptable, sufficient, satisfactory, and realistic numerical value that the decision maker wishes to achieve. Although objective and target are similar to each other as two concepts, it can be explained the difference between them with an example. If it is expressed that it is desired to increase the daily production capacity, this is an objective, instead, if it is desired to produce at least 150 products per day, this is a goal.

3.2.1.4. *Constraints*

Constraints can be defined as an equality or an inequality that define limitations on decision variables. This concept is defined by Jones and Tamiz [40] as constraints placed on decision variables to provide a viable solution. In GP, there are two types of constraints: system constraints and goal constraints. Constraints that are rigid, must be

met exactly, and deviations are not allowed are called system constraints. It represents the scarce resources available, and these constraints must be met first. Goal constraints, on the other hand, indicate the goals that the decision makers want to achieve, and the requirements that can still be violated in viable solutions. It is more flexible than system constraints. Cinemre [42] states in her book that the target constraints were met after the system constraints were met. Rardin [43] expresses the target constraints mathematically as follows:

$$(\text{Criterion function}) - (\text{oversatisfaction deficiency variable}) + (\text{undersatisfaction deficiency variables}) = (\text{target value}) \quad (3.1)$$

3.2.1.5. *Deficiency variables*

According to Jones and Tamiz (2010) [40], variables that show the amounts that are exceeded or below the specified target are defined as deficiency variables. In classical goal programming models, undesirable deviation values from the target are minimized to reach an acceptable solution. The positive and negative amounts of divergence from the target for each target are measured using deficiency variables. While positive deficiency variables show how much the target is exceeded, negative deficiency variables show how much it falls below the determined target. These variables measure how successful the goal set by the decision maker is. Deficiency variables can never have a negative value. One of the deficiency variables is always zero because the deviation variables will take either negative or positive values.

3.2.1.6. *Objective function*

Optimal solution of GP is searched within the solution area of objective function determined by system and target constraints. Deficiency variables are included in both the objective function and the goal constraints. According to Türkoğlu (2017) [41] objective functions are functions that minimize undesirable deviations from target values in GP. The collection of these functions in a single objective function, in order of importance or weight, is also called the success function.

3.2.2. Types of goal programming

3.2.2.1. *Single objective goal programming*

Charnes and Cooper (1977) [9] said that GP is an extended version of the LP model with multiple objectives. Therefore, the LP mathematical model is quite similar to the GP model. The general GP model was defined mathematically as below:

$$min\ Z = \sum_{i=1}^{m} (d_i^+ + d_i^-) \tag{3.2}$$

Subject to

$$Ax_j - Id^+ + Id^- = b_i \tag{3.3}$$

$$x_j, d_i^+, d_i^+ \geq 0 \tag{3.4}$$

Objective function (3.2) minimizes both under satisfaction and over satisfaction values. Where *I* is defined as the unit matrix, *m* is expressed as the number of goals. The m number of column vectors are expressed by *b* ($b_1, b_2, \ldots b_m$). *A* is a mxn matrix which is shown in Figure 3.2. *x* represents variables, d^+ and d^- are deficiency variables that indicate deviation from the goals. Equation 3.3 is a soft constraint and it tries to achieve the target which is kept in the right-hand side value. If it cannot reach the target, it keeps the deviation values in the positive and negative deviation variables. Equation 2.4 is sign restrictions.

$$A_{(mxn)} = \begin{bmatrix} a11 & a12 & . & . & . & a1n \\ a21 & a22 & . & . & . & a2n \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ am1 & am2 & . & . & . & amn \end{bmatrix}$$

Figure 3.2. mxn matrix

3.2.2.2. *Preemptive (lexicographic) goal programming*

In preemptive optimization, a multi-objective optimization is performed by considering the targets one by one. Here, it is aimed to solve the other priority targets

are preserved the best value is taken from high priority target. Isermann (1982) [44] emphasized clearly that among the limited number of objective functions to be optimized, high-priority objectives are first optimized and the following low-priority objectives are solved without interfering with the optimization of high-priority objectives. Preemptive Goal Programming is used under two cases. One of them is there are no goals with equal priority between the goals to be achieved and the second one is that is a serious prioritization among these goals. Goals are given a sequential ranking, with the most important first. Here, it is aimed to solve the other priority targets are preserved the best value is taken from high priority target. Priority factors have a relationship as below:

$$P_i >>> P_{i+1} >>> P_{i+2} >>> \cdots >>> P_n$$

The P_i value, called the preemptive priority factor of the i^{th} goal, is of the highest importance level. Therefore, in practice, P_i is minimized first. The objective function of preemptive model can be stated as:

$$min\ Z = \sum_{i=1}^{m} P_i(d_i^+ + d_i^-) \tag{3.5}$$

The main difference between the objective function (3.2) and (3.5) is that the priority factor is included in the objective function of the preemptive model.

3.2.2.3. *Weighted goal programming*

In general, Weighted Goal Programming is applied in cases where the deficiency variables in the goals differ in units of measure like as duration, quantity, weight, currency, etc. Rardin (1998) [43] emphasized in his book that the weighted sum of the deficiency variables in the objective function is minimized. In this way, it was stated that all goals are achieved as much as possible, instead of only one goal being achieved. The objective function of Weighted Goal Programming model can be formulated as:

$$min\ Z = \sum_{i=1}^{m} w_i^+ d_i^+ + w_i^- d_i^- \tag{3.6}$$

Objective function (3.6) is established as minimizing the total weighted deviations. Here, $w_i^+ and\ w_i^-$represent the weighting coefficients of the deviation variables. Equation $w_i^+ > w_i^-$ indicates that positive deficiency variables are more important than the negative deficiency variables. Although the importance levels of the deficiency variable are generally different from each other, when they are the same, it indicates that the deviations are of relative importance to each other. Sherali (1982) [45]stated that, it is possible to calculate the equivalent weights and it is especially preferred for some special cases and applications.

3.2.2.4. *Preemptive goal programming by weighting the objective*

Rardin [43] emphasized that Preemptive Goal Programming can be resolved under a single objective function, with the greatest weight was given to the deficiency variable which has the most important target. According to Ijiri (1965) [46], the user can achieve the targets as prioritizing the order in which the goals will be achieved. Lee and Clayton (1972) [37] explained the subject in detail through an example by giving weight to the Preemptive Goal Programming model on resource allocation. Zhou et al. (2000) [47] sought a solution to a multi-objective problem for supply chain optimization with a GP model with weighting considering the priorities of the goals.

The objective function can be defined mathematically as below:

$$min\ Z = \sum_{i=1}^{m} P_i(w_i^+ d_i^+ + w_i^- d_i^-) \tag{3.7}$$

3.3. 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 3.3. Home icons show the residence of the working personnel, and the factory icon shows the location of the factory.

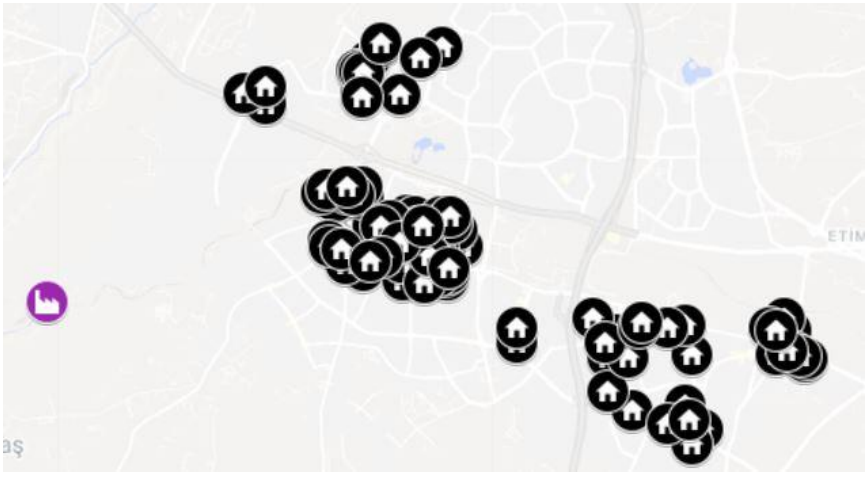


Figure 3.3. Employee addresses on Google maps

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 3.4.

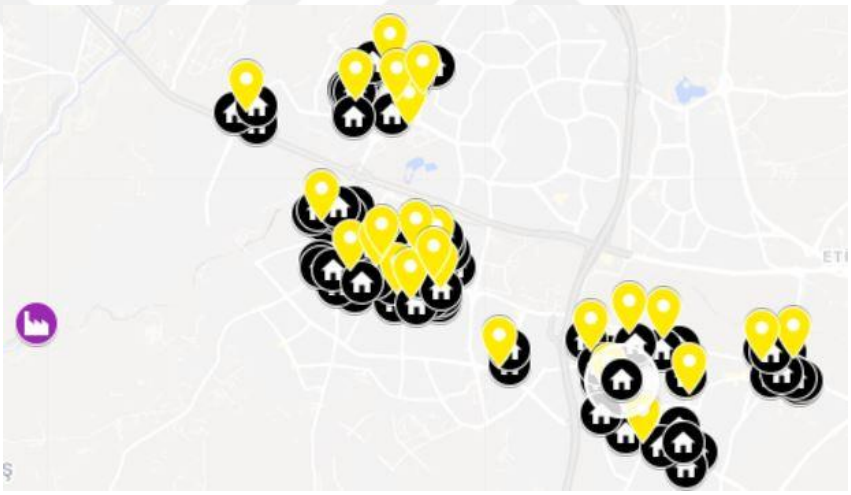


Figure 3.4. Bus stop points

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 (see in Figure 3.5).

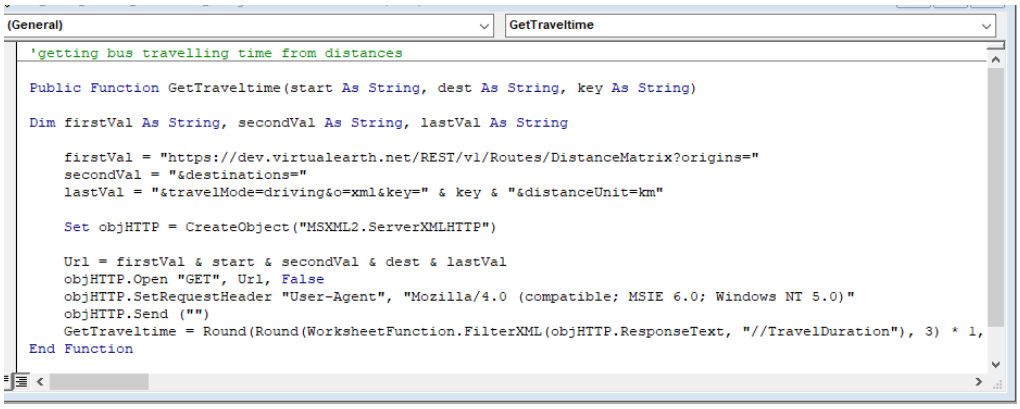


Figure 3.5. Visual Basic for Applications code of calculating travelling time between stops with Bing API key

Afterwards, these measured times were recorded in a matrix in excel with another code written in VBA (see in Figure 3.6).

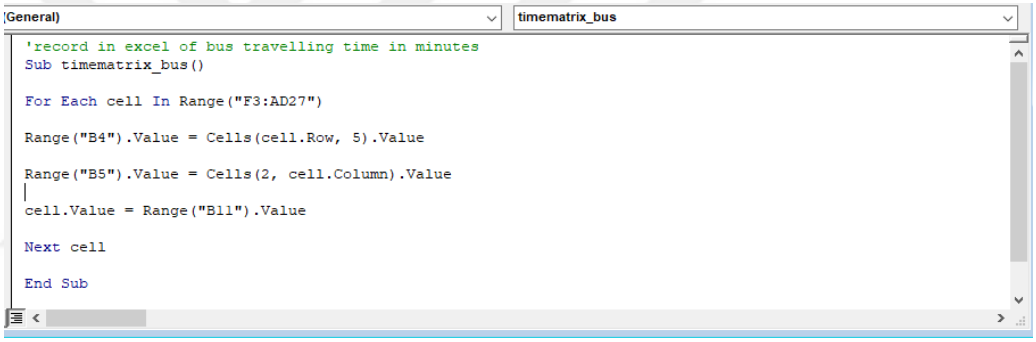


Figure 3.6. VBA code that prints the travel time between stops to Excel

The same procedures were applied to calculate walking times from the employees' home to the bus stops. 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 3.7 (The last stop, the company, is not included in the drawing.). The summary of data and route information provided by the company is shown in the table below in Table 3.1.

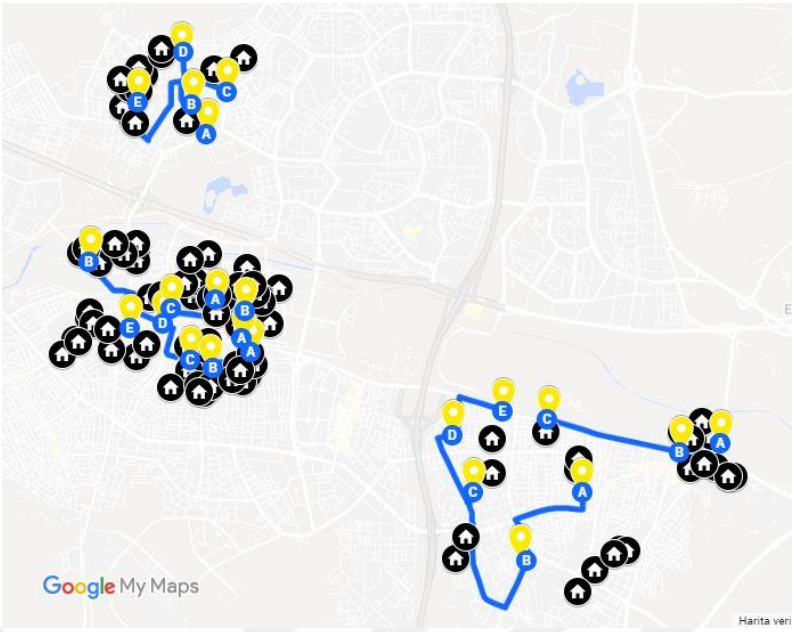


Figure 3.7. Bus routes of current situation

Table 3.1. Summary of current situation

Bus No	Visited Stops	Number of employees picked up from stop	Total travelling time of buses (min)
1	16, 17, 18, 19, 20, 21	14	64
2	8, 9	19	48
3	22, 23, 24	17	35
4	1, 2, 3, 4	19	38
5	10, 11, 12, 13, 14, 15	17	40
6	5, 6, 7	14	28
Total		100	253

In the following section, MILP was established to solve this model with the data provided above. In Section 3.4, this model was converted to GP, and targets were determined and solved by weighting under a single objective function. In the result section, the results obtained from the solution of both models were compared with the current situation.

3.4. Mixed-Integer Programming Mathematical Model

Sets of the MILP model can be defined as:

$K: Set\ of\ buses\ (k = 1, \dots, |K|)$

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

$N: Set\ of\ employees\ (n = 1, \dots, |N|)$

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

Input Parameters of the model are as:

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

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

$Q_k: Capacity\ of\ bus\ k$

$Mxd: Maximum\ walking\ time\ of\ employees\ are\ allowed\ to\ walk$

$u: unit\ processing\ time$

Decision Variables:

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

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

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

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

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

$$min \sum_{k \in K} \left[\sum_{i=1}^{L-1} \left(\sum_{j=1, j \neq i} (t_{ij}\ x_{ijk}) + x_{ijk}\ u \right) \right] \qquad (3.8)$$

$$min \sum_{k \in K} b_k \qquad (3.9)$$

$$y_{0k} = b_k \qquad \forall k \in K \qquad (3.10)$$

$$\sum_{j=1}^{L-1} x_{0jk} = b_k \qquad \forall k \in K \qquad (3.11)$$

$$\sum_{i=1}^{L-1} x_{i0k} = b_k \qquad \forall k \in K \qquad (3.12)$$

$$\sum_{j\in L\setminus\{0\},i\neq j} x_{ijk} = \sum_{j\in L,i\neq j} x_{jik} \qquad \forall i \in L\setminus\{0,|L|\}, \forall k \in K \qquad (3.13)$$

$$\sum_{j\in L\setminus\{0\},i\neq j} x_{ijk} = y_{ik} \qquad \forall i \in L\setminus\{0,|L|\}, \forall k \in K \qquad (3.14)$$

$$\sum_{j\in L\setminus\{0\},i\neq j} x_{ijk} \leq b_k \qquad \forall i \in L\setminus\{0,|L|\}, \forall k \in K \qquad (3.15)$$

$$Z_{ink} \leq y_{ik} \qquad \forall n \in N, \forall i \in L, \forall k \in K \qquad (3.16)$$

$$\sum_{i\in I_n}\sum_{k\in K} Z_{ink} = 1 \qquad \forall n \in N \qquad (3.17)$$

$$\sum_{n\in N}\sum_{i\in I_n} Z_{ink} \leq Q_k \qquad \forall k \in K \qquad (3.18)$$

$$0 \leq s_i \leq |L| \qquad \forall i \in L \qquad (3.19)$$

$$s_i - s_j + |L|\, x_{ijk} \leq |L| - 1 \qquad \forall i \in L, \forall j \in L\setminus\{0,i\}, k \in K \qquad (3.20)$$

$$x_{ijk} \in \{0,1\} \qquad \forall i \in L\setminus\{j\}, \forall j \in L\setminus\{i\}, \forall k \in K$$

$$Z_{ink} \in \{0,1\} \qquad \forall i \in L\setminus\{j\}, \forall n \in N, \forall k \in K$$

$$y_{ik} \in \{0,1\} \qquad \forall i \in L\setminus\{j\}, \forall k \in K$$

$$b_k \in \{0,1\} \qquad \forall k \in K$$

$$s_i, s_j \geq 0 \qquad \forall k \in K \qquad (3.21)$$

The first objective function (3.8) is to minimize the total travelling time by considering the time between the stops traveled by each bus and the unit processing time spent at the stops. The second objective function (3.9) aims to minimize the total number of buses. Constraint (3.10) tells that every bus must start from a starting point and must complete its tour in the company. Constraints (3.11) and (3.12) 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 (3.13) 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 (3.14) 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 (3.15) states that if a bus is used that bus must travel from a location i to location j. Constraint (3.16) states that if a bus doesn't visit location i, employee n is not picked up at bus stop i by bus k. Constraint (3.17) ensures that all employees can be picked up by only one bus from a stop accessible. However, unlike the 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 (3.18) indicates that the total number of employees taken by each bus from the stops cannot exceed the capacity of that bus. Constraints (3.19) and (3.20) are sub-tour elimination constraints. Constraint (3.21) are sign restrictions.

3.5. Weighted-Preemptive Goal Programming Model

In this model, instead of the objective functions (3.8) and (3.9) in the previous section, the objective function (3.22) that minimizes the deviation amounts is used. In this section, there is no changes in the hard constraints which used in the MILP model in the previous section. Given in this section, is with the newly set objective function for the GP model, the explanations of each new decision variable, parameter and soft constraint added to the model.

Added Input Parameters of the model are as:

R: $maximum\ allowed\ travelling\ time\ for\ a\ bus$

F: $maximum\ number\ of\ buses\ used$

$W1$: $the\ weightage\ coefficient\ of\ minimizing\ travelling\ time\ of\ buses$

$W2$: $the\ weightage\ coefficient\ of\ minimizing\ number\ of\ services$

Added Decision Variables:

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

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

$d3$: $number\ of\ bus\ that\ excess\ from\ the\ target$

$d4$: $number\ of\ bus\ that\ below\ the\ target\ value$

$$min\ (W1\ \times \sum_{k \in K} d1_k) + (W2\ \times\ d3) \qquad (3.22)$$

$$\sum_{i=1}^{L-1} \left(\sum_{j=1, j \neq i} \left(t_{ij}\ x_{ijk}\right) + x_{ijk}\ u \right) = R\ b_k + d1_k - d2_k \qquad \forall k \in K \qquad (3.23)$$

$$\sum_{k \in K} b_k = F + d3 - d4 \qquad \forall k \in K \qquad (3.24)$$

$$d1_k, d2_k, d3, d4 \geq 0 \qquad \forall k \in K \qquad (3.25)$$

The first part of the objective function (3.22) is to minimize the deviation in the target travelling time of a bus and the second part of the objective function (3.22) aims to minimize the deviation from the target number of buses. The first part and the second part of the objective function (3.22) create contradictions with each other. Here, it is aimed to strike a balance between this contradiction by using Weighted Goal Programming. Constraint (3.23) 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 (3.24) 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 (3.23) and Constraints (3.24) 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. The constraint (3.25) is the sign constraints added to the model.

4. 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. The MILP and GP model were coded with the run time limit of 12 hours into the commercial solver IBM ILOG CPLEX Optimization Studio 20.1.0. Then, those models have been solved by the CPLEX solver. In this section, two main solutions have been investigated where the first one is MILP model that is an exact solution approach and the second one is WPGP model by weighting the objective. Those solutions have been comprised with the real scenario. It has been observed that solutions from MILP and GP models have provided significant time saving with respect to the current situation of the company. In both models, it was observed that the solution was obtained by shortening the tour route made by the buses. Accordingly, the number of stops used by the 3PL company has been reduced and the buses have been less circulated on the route used. Therefore, with these results, it can be deduced that the cost per km that 3PL reflects on the company will also decrease significantly.

In Figure 4.1 below, the current situation and the routes followed by the buses were given, and in Figure 4.2 the route obtained after the MILP solution was shown on the map. Each zone shows all the bus stops (with the drop-shaped icon) where a bus goes and the addresses of the employees from that zone (with the house icon).

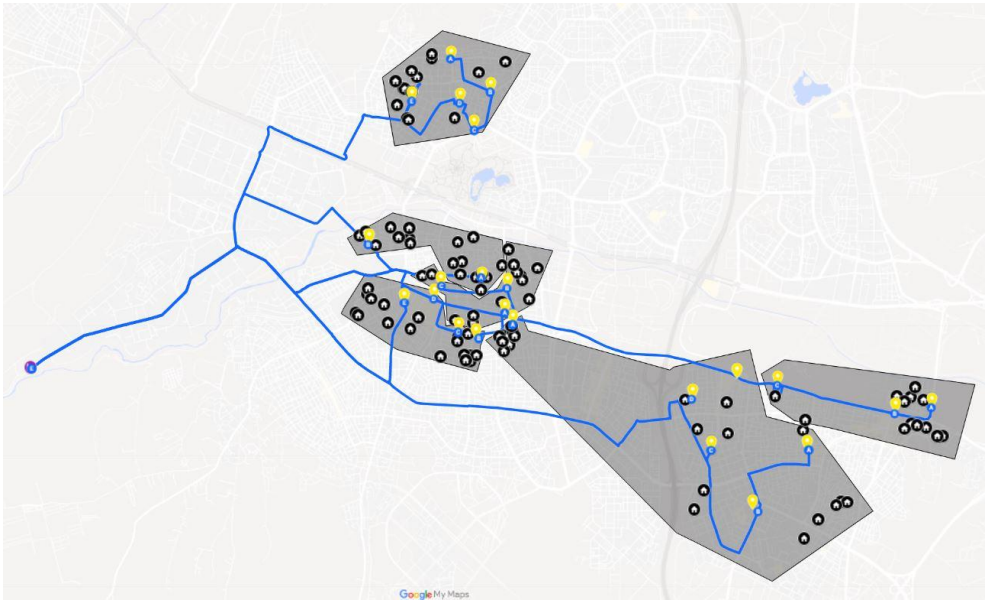


Figure 4.1. The map of current situation showing routes, stops and addresses

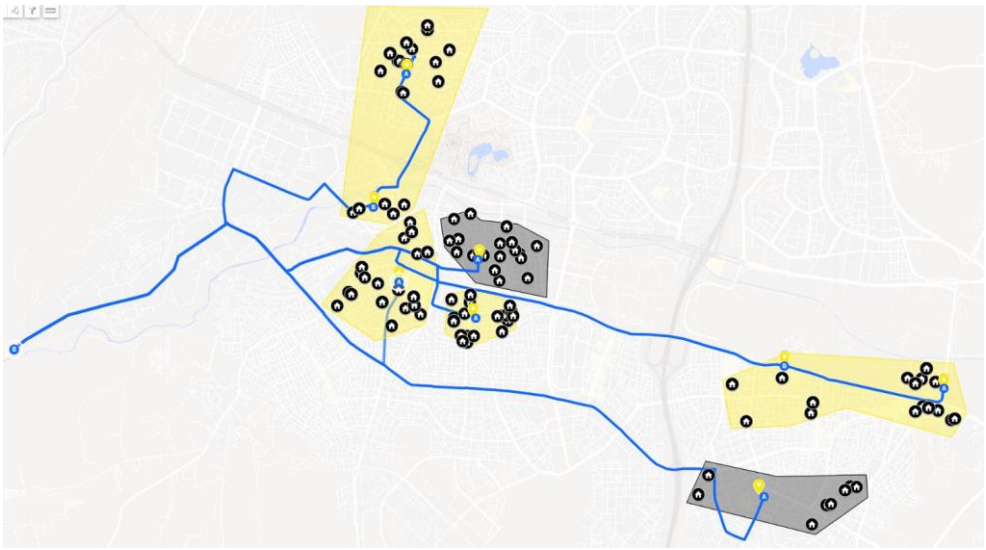


Figure 4.2. Map showing routes, stops and addresses derived from the MILP model

In all three cases, it was observed that there was no change in the number of buses and six buses were used. However, it can be said that there are serious differences in terms of the number of stops used, the distance traveled and the duration. First, the differences between the current situation and MILP model solution will be discussed (see in Table 4.1).

Table 4.1. Comparison of current situation with MILP Solution

	Total distance (m)	Total travelling time (min)	Bus No	Routes	Bus Capacity	Processing time of buses (min)	# of employees are picked up with that bus
Current Situation	12800	54	1	0 --> 16 --> 17 --> 18 --> 19 --> 20 --> 21 --> 25	19	12	14
	7500	38	2	0 --> 8 --> 9 --> 25	19	4	19
	9100	25	3	0 --> 22 --> 23 --> 24 --> 25	19	6	17
	10600	28	4	0 --> 1 --> 2 --> 3 --> 4 --> 25	19	8	19
	9900	30	5	0 --> 10 --> 11 --> 12 --> 13 --> 14 --> 15 --> 25	19	12	17
	15200	18	6	0 --> 5 --> 6 --> 7 --> 25	19	6	14
MILP Solution	8300	15	1	0 --> 1 --> 25	19	2	19
	5700	12	2	0 --> 9 --> 25	19	2	8
	7000	15	3	0 --> 8 --> 25	19	2	19
	7700	16	4	0 --> 3 --> 25	19	2	19
	13300	24	5	0 --> 7 --> 4 --> 25	19	4	19
	13900	29	6	0 --> 6 --> 5 --> 25	19	4	16

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. 3PL completes its tour by stopping by all the stops so that no employee is left out. According to the route information received from the company, it completes the 65100m with a total of 193 minutes travel time with 25 stops. Using this data in the MILP model we have established, it has been obtained with 8 stops, a total of 55900m and a time of 111 minutes, again so that no employee is left out. According to these data, it has been clearly seen that an improvement of 73,87% was achieved in the total travelling time.

One of the main reasons for this difference is the maximum walking time of 20 minutes determined by the company for its employees. While the company is considering the satisfaction of its employees, on the other hand, it also has to consider 3PL's wage due to the increasing fuel prices in the country. For this reason, the number of buses used is also very important for the company. For this reason, the company has imposed a fair limitation on the distances which employees can walk in a way that will not make its employees unhappy. According to the new results, it was observed that a total of 18 employees had a better walking time compared to the previous situation, while 36 employees walked more than the current situation, and 46 personnel did not have any change (see in Figure 4.3).

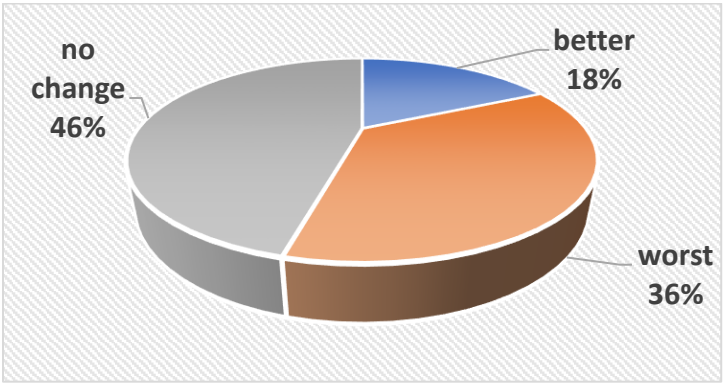


Figure 4.3. Comparison of employee walking time in current status vs. MILP model

The personnel whose walking time increased according to the current situation were also evaluated within themselves, and only 3 of the 36 personnel who walked more than the current situation had a walking time of more than 10 minutes (see in Table 4.2).

Table 4.2. Change in walking time of employees after MILP model compared to current situation

Time in minutes	# of employee with worse walking time than the current situation	# of employee with better walking time than the current situation
1	7	2
2	4	1
3	4	7
4	9	1
5	3	3
6	1	0
7	3	1
8	1	0
9	1	0
13	0	1
14	1	2
15	1	0
16	1	0

Another reason is the processing time of buses, which additionally affects the total travel time when the services stop at each stop. Processing times are determined as 2 min for each stop. This time was included in the total travel time by multiplying by the number of stops in both the current situation and the proposed situation. Currently, while there is a 50-minute processing time due to the use of 25 stops, in the recommended case, a 16-minute processing time is added to the travel time by using 8 stops. Although the walking time of the personnel decreases when the number of stops increases, the time spent by the personnel on the bus increases in direct proportion to the number of stops.

By comparing real life scenario with the results from MILP model, it was observed that employees walked more while getting better travelling time. In order to establish a balance between those, a solution was sought in WPGP. The result obtained by running the first objective function (3.8) of the MILP model in Section 3.4 as a single objective was determined as the traveling time target in the GP. Likewise, by running the second objective function (3.9) of the MILP model in Section 3.4 as a single objective function, the number of target buses in the GP was determined with the result obtained. Accordingly, these target values were determined as 6 for the number of buses and 30 minutes for the traveling time. These targets were added to

the model as soft constraints. Each positive or negative deviation from these values has been kept in a decision variable and only positive deviations have been designed to be minimized in the objective function. The weights and the degree of importance were given in different ways and the change in the results was compared (see in Table 4.3).

Table 4.3. Results from the weighted-preemptive goal programming model

W1	W2	# of bus	total travelling time (min)
1	1	6	164
10000	1	6	164
1	10000	6	149

Under these 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 solutionwith164 minutes by considering both weightings. The route and duration information, which changes according to weights and prioritization, was shown in detail in Table 4.4.

Table 4.4. GP model solution according to different weights and prioritization

	Total travelling time (min)	Bus No	Routes	Bus Capacity	Processing time of buses (min)	Number of employees are picked up with that bus
GP Solution W1=1 W2=1	20	1	0 --> 22 --> 2 --> 25	19	4	16
	31	2	0 --> 6 --> 5 --> 16 --> 25	19	6	15
	34	3	0 --> 9 --> 8 --> 3 --> 4 --> 1 --> 25	19	10	19
	20	4	0 --> 4 --> 22 --> 18 --> 25	19	6	19
	32	5	0 --> 10 --> 15 --> 1 --> 25	19	6	13
	27	6	0 --> 10 --> 14 --> 22 --> 25	19	6	18
GP Solution W1=10000 W2=1	24	1	0 --> 10 --> 7 --> 9 --> 25	19	6	18
	31	2	0 --> 6 --> 5 --> 16 --> 25	19	6	18
	30	3	0 --> 1 --> 8 --> 3 --> 4 --> 23 --> 25	19	10	19
	30	4	0 --> 22 --> 2 --> 17 --> 25	19	6	18
	29	5	0 --> 11 --> 15 --> 4 --> 25	19	6	13
	20	6	0 --> 9 --> 4 --> 25	19	4	14
GP Solution W1=1 W2=10000	15	1	0 --> 2 --> 25	19	2	17
	28	2	0 --> 6 --> 22 --> 25	19	4	17
	30	3	0 --> 23 --> 2 --> 3 --> 4 --> 8 --> 1 --> 25	19	12	17
	24	4	0 --> 22 --> 18 --> 25	19	4	16
	24	5	0 --> 7 --> 2 --> 9 --> 25	19	6	17
	28	6	0 --> 5 --> 2 --> 8 --> 25	19	6	16

Even just by looking at these solution values, it was seen that a much better travelling time is obtained with the GP Model compared to the current situation. In addition, it has been observed that the route can be completed by using fewer stops. Another issue that needs to be compared here is the optimum travelling time obtained from the MILP model and the results obtained from the GP model. Because of the strictly performed hard constraints in the MILP model the better results were obtained. The MILP model also works in the direction of company which has the limitation of maximum 20-minute walking distance. In other words, while minimizing the travel time and the number of vehicles in the objective function, the employees can be walk

more than current. Therefore, it was obtained the optimum solution from the MILP model.

The reason why we canalized from the MILP model to GP was to achieve a result that the employees' and the company’s interest. Although we obtained the best time which was spent by the employees on the buses with MILP model, it was necessary to consider the change in the walking distance of the employees to the stops. In this sense, according to the results we obtained from the MILP model and the GP model, the change in the walking time of the employees is given Table 4.5 as follows:

Table 4.5. Change in walking time of employees after GP model compared to MILP model

time in minutes	# of employee with worse walking time than MILP	# of employee with better walking time than MILP
1	0	4
2	1	3
3	3	7
4	2	6
5	6	6
7	5	1
8	0	2
9	1	0
10	2	2
11	1	1
12	0	2
13	0	3
14	0	1

Although the travelling time spent of the employees on the bus is shorter in the MILP model, it was seen that the walking time of the personnel to the stops in GP model. It was observed that 38 personnel had better walking time in solution of GP model. Despite that, 21 personnel had worse walking time, and there was no change in the walking time of 41 personnel in comparison to the MILP model result (see in Figure 4.4).

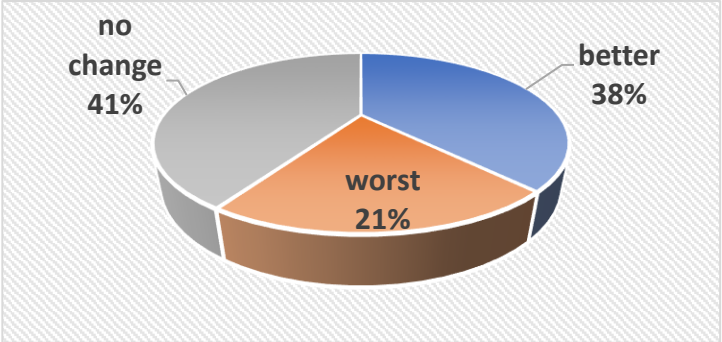


Figure 4.4. Comparison of employee walking time in GP model vs. MILP

It was summarized the solutions gathered from models as in the below Table 4.6.

Table 4.6. Comparison of all results as a summary

	Total travelling time (min)	Vehicle Population	Total Used Different Stops	Total processing time of buses (min)
Current Situation	193	6	25	48
MILP Solution	111	6	9	16
GP Solution W1=1 W2=1	164	6	15	38
GP Solution W1=10000 W2=1	164	6	17	38
GP Solution W1=1 W2=10000	149	6	13	34

According to table, it was observed that better results were obtained in both suggested cases (MILP or GP model), The MILP model gave the best results in total travelling time with using the same number of buses. However, it increased the number of employees who was walking to bus stop more than the current situation. With weighted prioritization, between the travelling time of employees on the bus and the number of used buses were balanced. In this way, company and employee satisfaction has been achieved together.

To conduct the computational experiments, it was generated benchmark data sets for the MILP and GP models. Since it was important to validate the model, random numbers which are so close to reality were generated. First, keeping the number of

locations the same, data sets were created for 25, 50, 100, 200 and 300 employees and the model solved with those data sets. Afterwards, the model was solved by changing the target value R to verify whether the targets set reflect the truth and whether the GP model works logically. Finally, the number of locations was changed to 15 and 8 different data sets were prepared for 25 different employees and the models were run with these data.

First of all, the demographic information of İzmir was obtained from the internet. There were 29 different districts in İzmir. Since the aim was only to check whether the models work correctly or not, 5 sections in Table 4.7 were selected between the 29 districts. In general, companies try to choose their employees from those who live close to the company due to the additional bus rental cost. Especially the reason for choosing these 5 sections was to assume that the company is located in Çiğli Organized Industrial Zone. Because of it is desired to create a scenario close to the real-life random data was generated according to the light of this assumption. Within these sections, the percentages of the relevant district to the total population were determined.

Table 4.7. Selected districts and percentage of population

District	Total population	Percentage of population
BORNOVA	452867	30,19%
KARŞIYAKA	347023	23,14%
BAYRAKLI	296839	19,79%
ÇİĞLİ	209951	14,00%
MENEMEN	193229	12,88%
	1499909	100,00%

Then, the relevant district was proportioned to the total population of these five districts. According to these percentages, different number of employee sets were created. For example, 30% of 25 employees live in Bornova, while 23% live in Karşıyaka. Distribution of population according to percentage is shown at Table 4.8.

Table 4.8. Percentage distribution of population

Employee sets	*Bornova*	*Karşıyaka*	*Bayraklı*	*Çiğli*	*Menemen*
25	5	4	3	2	2
50	10	7	6	4	4
100	19	15	13	9	8
200	38	29	25	18	16
300	96	74	63	45	41

Since the deviations from the target will be minimized in the GP model, R and F values were determined for each employee set. R values were the same as the real data. F value was determined by dividing the vehicle capacity by the number of employees, and the number of vehicles was determined to be two times the F value in K. The values determined according to the employee sets were included in the Table 4.9.

Table 4.9. Employee sets with R, F and K values

Employee sets	*R*	*F*	*K*
25	60	2	4
50	60	3	6
100	60	6	12
200	60	11	22
300	60	16	32

After all this data was determined, areas were selected by throwing random points on Google Map (see in Figure 4.5) and the corner coordinates of these areas were recorded as reference points.

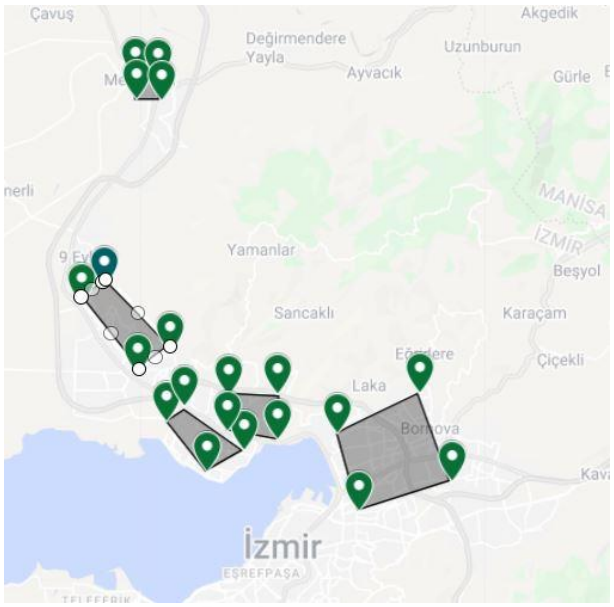


Figure 4.5. Random corner points for the five districts

These corner coordinates were accepted as the border. The bus stops and the employees' addressees in each district were randomly generated. As described in Section 3.3, time matrices were created by measuring the travelling times between all coordinates. Models have been tested for each different employee data set created, and it has been observed that the model gives logical results or not. The model was run with 25 locations and 25, 50, 100, 200, 300 employees, and it gives optimal solutions till 300 employees. In other words, the MILP and GP models we have established can be used in real life up to 200 employees and 25 locations. Obtained results were shown in the Table 4.10.

Table 4.10. Solutions of random employee data sets with different numbers

		Employee data sets				
	Weights	**25**	**50**	**100**	**200**	**300**
MILP	-	104	140	268	420	OPL Run-time error
W1	1	120	160	297	441	OPL Run-time error
W2	1					
W1	10000	114	160	297	441	OPL Run-time error
W2	1					
W1	1	120	173	333	594	OPL Run-time error
W2	10000					
# of bus	-	2	3	6	11	OPL Run-time error

In addition to these data, the model was also tested by creating personnel data

residing in Güzelbahçe, which is far from Çiğli Organized Industry, to observe how the model gave results. In this condition, the model reached a solution by increasing the number of buses by one more. This proves why companies do not want to work with employees in remote locations.

The second created dataset was about the targets. Here, a target was specified, and the deviation amounts from this target were kept in a decision variable. The positive ones were put into the objective function. In this data set, only the target value R was changed without touching the time matrix and location information of 25 randomly generated employees. Accordingly, it has been observed that when the R value was reduced from 40 to 36, that was, when the target set narrows, the amount of deviation decreased and approached the optimum solution obtained from the MILP model (see in Table 4.11). The results obtained were shown in the Table 4.12 below, clearly proving the validity of the GP model.

Table 4.11. Solution of MILP model with random data set

	Total used different stops	**# of bus**	**total travelling time (min)**
MILP	6	3	81

Table 4.12. 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	1	90	109	89	88
W2	1				
# of bus	-	3	3	3	3
	Weights	**R=40 F=2**	**R=37 F=2**	**R=36 F=2**	**R=35 F=2**
W1	10000	101	90	87	83
W2	1				
# of bus	-	3	3	3	3
W1	1	90	90	88	88
W2	10000				
# 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 4.13.

Table 4.13. Result for 8 different random employee sets

		Employee data sets							
	Weights	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
MILP	-	83	47	29	48	26	40	34	40
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

It was seen that the results obtained from the MILP model and the GP model with these randomly generated data sets were quite similar except for the 1st set. Since the number of stops used in the 1st data set was higher than the other data sets, process time was added to the objective function value for each stop visited by the buses, depending on the number of stops. This showed that the model gave correct logical and stable results with different data sets.

5. CONCLUSION

In direct proportion to the effect of the rapidly increasing population, there is also a growing need to the transportation systems in many areas. At the beginning of these needs are the service vehicles provided by the companies to transport their employees home to company and from company.

Within the scope of this thesis, a vehicle routing that minimizes the total traveling time and the number of buses used by the personnel on the way to work is aimed. Since these two goals created a conflict with each other, first a solution was sought by establishing a MILP model, and then the limit targets were determined for these two conflicting goals. And then a GP model was established.

For the application of the study, home addresses of the employees from an electromechanical company in Ankara, route and vehicle information were collected from the 3PL service company where this company works with. According to the data collected, 3PL 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. Firstly, the MILP model was coded into IBM ILOG CPLEX Optimization Studio 20.1.0, and then solved, taking into account the constraints which were determined by the company, accompanied by these data. As a result, a much better result than the company's current contracted 3PL company was obtained by using the same number of buses. Secondly, soft constraints were added to the MILP model and a WPGP model was constructed by determining target values for these constraints. Here, deficiency variables were used and the objective function was gathered under a single objective. The positive amount of deviation from the target were tried to be minimized.

The results obtained from both models were run with real-life data and the obtained results were compared with each other. In the MILP model, an optimal solution has been obtained that minimizes both the number of used buses and the total spent travelling time. However, in order to achieve this result, the model used the maximum walking time to the stops that the company has set for its employees, and it caused to increase the walking time of the employee to home to bus stop. Although it prolongs the walking time of the employees to the bus stops, this situation shortened the time spent by the employee on the bus. For this reason, it was desired to use GP and established a balance between these two goals. 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 both models 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, both models can be used up to 200 employee and 25 locations with real life data. However, when these numbers are increased, the model run time also increase. Since the model run time limit has been specified as 12-hour, the data boundary of the models can be accepted as 200 employees and 25 locations. Therefore, as the data size increases, 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.

Another issue is that, since the time between stops in the model will vary according to the traffic situation in the morning and evening, the durations of both situations are calculated and the average time is taken as a basis. If the average time hadn't been for calculated, a solution could be sought by using two different models since the traffic conditions would be different. In other words, the problem could be solved by running a model on the way to work in the morning and a different model on the way home from work in the evening.

In multi-capacity VRP, drawing routes and obtaining the optimal solution with large data sets require large processing time. It is also very difficult to reach the result with exact solutions methods due to the amount of data. For this reason, it may be possible to reach the solution of the problem in a shorter time by grouping the data with the clustering algorithm. With this algorithm, all small groups can be solved within themselves and more appropriate solutions can be obtained. In future studies, data can be grouped using the clustering algorithm and a mixed solution method can be obtained with the WPGP model.

In addition, because 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. Due to road conditions and one-way streets being, the distance from X to Y location may be different in the Y to X. In future studies, the best route can be drawn by calculating asymmetrical distances instead of symmetrical.

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