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CLUSTER-FIRST ROUTE-SECOND APPROACH FOR EMPLOYEE SHUTTLE BUS ROUTING PROBLEM: A LARGE-SCALE COMPANY APPLICATION

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Supervisor

Prof. Dr. Eren ÖZCEYLAN

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Nur Sena ERTEM

ABSTRACT

CLUSTER-FIRST ROUTE-SECOND APPROACH FOR EMPLOYEE SHUTTLE BUS ROUTING PROBLEM: A LARGE-SCALE COMPANY APPLICATION

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M.Sc. in Industrial Engineering
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Developing logistics systems is one of the most important strategic steps companies can take toward differentiation in today's global market. In recent years, in addition to the transportation services of the products in the production system, the logistics services of the personnel working within the company have also gained importance. Personnel transportation services are examined within Vehicle Routing Problems (VRP) scope. In this thesis study, school bus routing problems (SBRP), which is a subtype of VRP, are examined and the personnel transportation problem is solved with the SBRP analogy. The personnel transportation problem discussed in the thesis has been solved with the SBRP analogy. Within the scope of the thesis problem, it is aimed to route the transportation between the house of 1361 personnel working in Kartal Carpet& Textile company and the factory. For the identification of personnel addresses and current situation analysis, markings and current situation routing was made with Google Earth Pro's help. Three different vehicle capacity scenarios were created to solve the problem. The problem was solved with the Capacity Vehicle Routing Problem (CVRP) without clustering in the first scenario. Then, P-median, K-means, and P-center clustering methods were applied and optimal results were sought with Cluster-first Route-second (CFRS). The models were run using Python 3.8-Gurobi 9.1.1. In the last part, all the data obtained were analyzed and compared and suggestions were made for future studies.

Key Words: Vehicle Routing Problems, School Bus Routing Problem, Personnel Transportation Service, Clustering Algorithms

ÖZET

ÇALIŞAN SERVİS ARACI ROTALAMA PROBLEMİ İÇİN ÖNCE KÜMELE-SONRA ROTALA YAKLAŞIMI: BÜYÜK ÖLÇEKLİ BİR ŞİRKET UYGULAMASI

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Günümüz küresel pazarında firmaların farklılaşma yolunda atabilecekleri en önemli stratejik adımlardan biri de lojistik sistemlerini geliştirmektir. Son yıllarda üretim sisteminde var olan ürünlerin taşımacılık hizmetlerinin yanı sıra, firmaların bünyelerinde istihdam ettikleri personele sundukları lojistik hizmetleri de önem kazanmıştır. Bu tez çalışmasında; Araç Rotalama Problemi (ARP)'nin bir alt versiyonu olarak incelenen Okul Servisi Rotalama Problemleri (OSRP) incelenmiş ve ele alınan personel taşıma sorunsalı OSRP benzerliği ile çözülmeye çalışılmıştır. Tez problemi kapsamında; örnekleme dahil edilen Kartal Halı Tekstil firmasında çalışan 1361 personelin evleri ile fabrika arasındaki ulaşımlarının rotalanması incelenmiştir. Personel adreslerinin tanımlanması ve mevcut durum analizi için Google Earth Pro yardımıyla işaretlemeler yapılmış ve problemi çözmeye yönelik üç farklı otobüs kapasiteli senaryolar oluşturulmuştur. Problem, ilk senaryoda kümeleme yapılmadan Kapasiteli Araç Rotalama Problemi (KARP) ile çözülmeye çalışılmıştır. Daha sonra P-medyan, K-ortalamalar ve P-merkez kümeleme yöntemleri uygulanarak önce kümele-sonra rotala yaklaşımıyla optimal sonuç aramış ve modeller Python 3.8-Gurobi 9.1.1 kullanılarak çözülmüştür. Son bölümde ise elde edilen tüm veriler analiz edilerek karşılaştırılmış ve gelecek çalışmalar için önerilerde bulunulmuştur.

Anahtar Kelimeler: Araç Rotalama Problemi, Okul Servisi Rotalama Problemi, Personel Ulaştırma Hizmeti, Kümeleme Algoritmaları

''Dedicated to my family''

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LIST OF SYMBOLS

VRP	Vehicle Routing Problem
CVRP	Capacitated Vehicle Routing Problem
DCVRP	Distance and Capacity Constrained VRP
TSP	Traveling Salesman Problem
SBRP	School Bus Routing Problem
HFSBRP	The Heterogeneous Fleet SBRP
SO-SR-SBRP	The Service-Oriented Single-Route SBRP
SBRP-SDDC	SBRP with Stochastic Demand and Duration Constraints
MVTPP	Multi-Vehicle Traveling Purchaser Problem
PSRP	Personnel Service Routing Problem
OVRP	The Open Vehicle Routing Problem
CFRS	Cluster-first Route-second
ARL	Allocation Routing Location
LAR	Location Allocation Routing
LRA	Location Routing Allocation
PALS	Partial Allocation–Routing
CA	Analytical Continuous Approximation
OR	Operation Research
MIP	Mixed Integer Programming
MILP	Mixed Integer Linear Programming
PDP	Pickup and Delivery
PDPTW	Time Windowed Pickup and Delivery
VRPTW	Time Window Vehicle Routing Problem
HVRP	The Heterogeneous Fleet Vehicle Routing Problem
DARP	Dial-A-Ride-Problem

DAFP	Dial-A-Flight-Problem
WPGP	Weighted Priority Goal Programming
PMP	P-Median Problem
VRP	Vehicle Routing Problem
TSP	Traveling Salesman Problem
SBRP	School Bus Routing Problem
PSRP	Personnel Service Routing Problem
OVRP	The Open Vehicle Routing Problem
ARL	Allocation Routing Location
LAR	Location Allocation Routing
MV-TPP	Multi-Vehicle Traveling Purchaser Problem
MTPVRP	Multi-Travel Periodic Vehicles Problem Route
LRA	The Location–Routing–Allocation
PALS	Partial Allocation–Routing
OR	Operation Research
OSDWVRP-IC	Open Split-Delivery Weighted Vehicle Routing Problem with Iterated Clustering

CHAPTER 1
INTRODUCTION

Nowadays, winning the market war between businesses has an important role in ensuring the continuity of the business and maintaining its profitability. In this case, the most important weapon businesses will use against their competitors is to increase customer satisfaction by meeting customer needs in the fastest way. Businesses use the logistics management approach to minimize deviations in the system as much as possible. Businesses use the existing resources effectively and reduce the cost to serve the customer about it. Factors such as cost savings and on-time delivery that affect customer satisfaction in logistics activities have made the concept of vehicle routing important.

In general terms, the transportation of a product or service from the point of supply to the point of demand is defined as logistics. To establish a complete logistics system, raw materials must first be transported from the supply or sales point. Logistics includes the distribution of the transported raw materials to the manufacturing factories for production, the shipment of the finished products to the distribution centers or warehouses, and then their distribution to the customers. Distribution and supply processes need an effective and accurate transportation method. An effective, accurate, and well-managed transportation and distribution management process can significantly reduce the logistics costs of enterprises.

The most important part and the problem of the logistics system is VRP [1]. VRP is the problem of designing optimum distribution/collection routes of vehicles assigned to serve geographically dispersed customers from one or more warehouses [2].

VRP are critical logistics problems for many industries and sectors. These problems often require many vehicles to travel in a given area to meet customer demands. Effective management of such problems is important for businesses to increase customer satisfaction, reduce operating costs and increase operational efficiency.

Successfully solving a VRP means optimizing the routes vehicles traveling, reducing delivery times, and optimally scheduling vehicles. Therefore, it is important for businesses to work on VRP and to manage these problems effectively to gain a competitive advantage.

In the most classical VRP known, the vehicles in the fleet start from a certain warehouse or warehouses and try to meet the demands of customers in different locations. The aim to be achieved during this service is to create an effective route in the shortest time, with the least cost, and by using the shortest route.

VRP was first expressed as the generalized Traveling Salesman Problem (TSP) by Dantzig and Ramser in 1959 [3]. TSP is the problem of visiting more than one customer once with a single vehicle and finding the vehicle to return to the starting point and travel the shortest distance.

CVRP occurs when vehicles have a certain capacity, in addition to VRP. In this problem, each customer has a specific demand and a specific quantity of material or product. Vehicles carry materials or products to customers within a certain capacity limitation.

In CVRP, all customers correspond to deliveries, demands are deterministic, known in advance, and cannot be divided, vehicles are identical and located in one central warehouse, and capacity constraints apply only to vehicles. The goal is to minimize the total cost (i.e., the number of routes, lengths, or travel time) required to serve all customers. In general, the travel cost between each pair of customer locations is the same in both directions, so the resulting cost matrix is also symmetrical. However, in some applications, the cost matrix may be considered asymmetric due to the distribution in urban areas with one-way directions applied to roads [4].

CVRP was created by extending the well-known TSP. It is required for the circuit to be determined at the minimum associated cost by visiting a given set of points exactly once. Therefore, many exact approaches for CVRP are inherited from large and successful studies for the definitive resolution of TSP [4].

VRP falls under the combinatorial optimization problem group. Most of the problems in this class are called NP-Hard [5]. One of the extensions of VRP problems that can be encountered in real-life scenarios is the routing problem of shuttle buses. In this context, there are SBRP in providing transportation activities for students, which are frequently encountered in the literature, and personnel service vehicles routing problems in providing transportation activities for personnel.

The SBRP is a variant of the VRP, where students must be picked up from the stop points by the school bus to get to their school at the school's ringing time [6].

In recent years, businesses have been working to increase the quality of business life and to increase the job satisfaction of the employees and, accordingly, their performance. One of these studies is personnel transportation planning [7]. The personnel shuttle routing problem or personnel service routing problem (PSRP) can be defined as an adaptation of the school bus routing problems.

VRP are similar to each other in terms of SBRP and PSRP objectives, constraints, and scenarios encountered within the scope of shuttle bus routing problems. In SBRP, a solution is sought for the transportation problem between the school and the student houses. In PSRP, on the other hand, a solution is sought for the transportation problem between the institution-staff houses.

VRP are logistical problems where many vehicles must receive material from certain points and deliver it to specified points. In such problems, it is aimed to increase the efficiency of vehicles on an optimized route. Clustering methods are an effective analytical tool that can be used in vehicle routing problems. Especially in problems with large data, more effective results are obtained by using clustering techniques. Clustering methods can provide efficiency, cost, and time savings in solving vehicle routing problems. Clustering algorithms are statistical and data mining methods used to group data points with similar characteristics in a dataset. These algorithms divide the dataset into homogeneous groups by measuring the similarities or differences between the data points. Each group is called a cluster and usually has a center or representative point. Clustering methods can be used in vehicle routing problems to cluster customers, cluster vehicles, or cluster routes while optimizing routes.

In the scope of the thesis, solutions are sought for the transportation problems of the personnel of Kartal Carpet and Textile company, which was established in Gaziantep in 1985. Kartal Carpet and Textile is a well-established company that makes part and wall-to-wall carpet weaving in the country and abroad. The company provides shuttle services to take its personnel from their homes to the company at the beginning of the shift and to take them to their homes at the end of the shift. The service is carried out with the help of a subcontractor company. This study, which has limited capacity since the service is provided by a subcontractor, is also an open-ended vehicle routing problem, which is a VRP type. The main difference between the Open Vehicle Routing Problem (OVRP) and traditional VRP is that vehicles do not return to the starting point after traveling through the entire network [6]. The problem will be solved with PSRP, defined as the VRP extension developed per the scenario to improve the existing transportation service. The number of personnel to be transported in the problem to be solved within the scope of the thesis contains large data. In this case, determined personnel addresses were clustered with clustering algorithms and then routing was done.

The main purpose of this study is to improve the transportation services between the houses and the factory. Improving the existing transportation service provides an increase in personnel satisfaction. It also reduces the cost of the institution on personnel transportation.

Transportation (Logistics) Services are an important part of personnel support activities. The transportation activities of the personnel and the transportation of transportation by the requests and needs of the company management and personnel can only be possible with a very well-functioning transportation service. For this reason, personnel transportation services, which are accepted as a very important function in terms of personnel support activities, should be carefully planned, controlled, and coordinated [7].

In light of this information, within the scope of the thesis, it is aimed to minimize the number of vehicles to be used in personnel transportation services and minimize the total distance while minimizing the cost function.

In the introduction, the definition of the problem, the purpose, and the scope of the study are explained. After this first part, which gives information about the general problem, the second chapter includes the source research. In this section, a general literature review of VRP and CVRP has been made. In the literature review section, a detailed literature review on OSRP and PSRP, which works on human logistics, was made and information was given about the studies on solution approaches. In addition, studies on cluster algorithms used to group data points with similar characteristics in a dataset are examined. In the third section, information about the methods used is given. In the fourth chapter, the scenario of the problem, current situation analysis and problem data, and assumptions about the problem are expressed. In the fifth chapter, the results are evaluated, discussed and suggestions are made for further studies. In the last part, the bibliographies and appendices used in the study were compiled.

CHAPTER 2
LITERATURE REVIEW

VRP was first described by Dantzig and Ramser in 1959. In their study, Dantzig and Ramser worked on a real-life application. They dealt with the problem of distributing gasoline to service stations. They used a mathematical programming model to solve the problem and introduced an algorithmic approach [8].

According to Pillac et al. (2013), the VRP branched out into several other methods that can be found in the literature, such as the Capacitated Vehicle Routing Problem (CVRP), where each point has a demand and vehicles have limited capacity; the VRP with Time Windows, which defines windows of time that each point must be visited; Pick-up and Delivery (PDP), in which each stop has a defined quantity that needs to be collected and delivered; the Heterogeneous Fleet VRP (HVRP), in which each vehicle has a different load capacity; the Open Vehicle Routing Problem (OVRP) whose main difference from the traditional VRP is that the vehicles do not return to the origin after traveling through the entire network; among other different variations [9-10]. Similarly, according to Rashidi et al. (2009), when VRP includes school buses and student transport and given a defined travel time, there is a problem called the School Bus Routing Problem (SBRP) in the literature [11].

2.1 Literature Review of SBRP /Employee Shuttle Bus Routing Problem

Bowerman et al. (1995) aimed to reduce the total route distance of buses. At the same time, they aimed to reduce the total walking distance of the students to the bus stops by considering student satisfaction. They proposed multi-objective optimization based on different criteria to achieve the purpose of the problem. They used the allocation-routing-location (ARL) approach [12]. The ARL approach was first introduced by Chapleau et al. (1985). With the ARL approach, students were first grouped with a cluster-covering algorithm. A traveling salesman algorithm was then used, to create a school bus route [13].

Park and Kim (2010) and Ellegood et al. (2020) conducted a general literature review on SBRP. The literature review is a study in which different sub-problems and criteria discussed in the school bus routing problem are explained in detail [14-15]. According to Park and Kim, the SBRP branches into a few subproblems: data preparation, bus stop selection, bus route generation, school bell time adjustment, and bus route schedule; it is possible to find studies that solve a single subproblem or even a set of them together in the same study [10]. Ellegood, Solomon, North, and Campbell continued the review by Park and Kim. Both studies were able to list numerous papers that fit within these categories, showing the range of varieties and the high number of possibilities in solving routing problems by this method. In addition, Ellegood et al. emphasized trends in the expansion of studies applied to scenarios with multiple schools, considering several subproblems simultaneously, and using heuristics to solve complex problems [15].

Martínez and Viegas (2011) solved the SBRP for students living in Lisbon. To solve this problem, a two-phase multi-objective integer programming (MILP) solution method was applied in the location-allocation-routing (LAR) approach [16].

Riera-Ledesma and Salazar-González (2012) proposed the multi-vehicle traveling purchaser problem (MV-TPP) to provide stop selection and route generation in SBRP. MV-TPP is a type of problem with multiple and homogeneous tools, which is formed by the generalization of an open-ended VRP. Using the LAR approach, the model tries to solve the problems of selecting stops, assigning students to stops, and creating routes at the same time. The model aims to minimize the total route distance and walking distance to designated stops for students [17].

Emrah and Tamer (2012) worked on a small-scale real-life application based on a school shuttle company. In the SBRP problem, the aim is to minimize the total cost by taking into account the capacity and distance. For this reason, the problem discussed in the article has been adapted to SBRP. In this model, the Distance and Capacity Constrained Vehicle Routing Problem (DCVRP) has been utilized. In the establishment of the problem, both the distance and the capacity were taken into account and the total cost was tried to be minimized in the established model [18].

There are different applications that integrate it with other methodologies and heuristics, beyond the use of known methods by SBRP [10]. The work of Park, Tae, and Kim (2012) developed a similarly formulated SBRP for Time Windowed Pickup and Delivery (PDPTW) [19].

Kim, Kim, & Park (2012) used VRPTW considering the time windows of each school. This article introduces a school bus scheduling problem where trips are given for each school. The problem tries to optimize the bus schedules to serve all the trips given considering the school time windows. First, the problem is treated as a virtual stop on a journey and modeled as a time window vehicle routing problem (VRPTW). Next, the branch-and-bound approach is proposed as the exact approximation method based on two assignment problems for special cases and a heuristic algorithm is proposed for more general cases. Comparison problems and computational experiments are presented. As a result of the study, it is suggested to use MIP models and assignment problem-based branch-and-bound algorithms for small homogeneous fleet problems, and heuristic algorithms for large problems and heterogeneous problems [20].

The more general method was to allow mixed load instead of separating students at stops. Park et al. (2012) proposed a mixed load algorithm for the SBRP [19]. Ellegood et al. (2015) formulated analytical continuous approximation (CA) models for the SBRP. The authors applied the mixed load method to minimize the total driving distance of school buses [21]. Two main strategies, the traditional strategy and the mixed load strategy, have been adopted by many researchers to solve SBRP. Studies adopting the traditional strategy include the single-school problem and the multiple-school problem. Lopez Santana and Romero Carvajal (2015) combined column generation and clustering methods to solve the single-school problem. In this study, the column creation method was used to create paths between different clusters [22].

Schittekat et al. (2013) worked on the real-life problem of students living in Belgium. The aim of the problem is to minimize the total route distance, but the proposed model has a limit of 750 meters for the maximum walking distance. The model was established with the location–routing–allocation (LRA) approach, which is solved in 3 steps. With the LRA approach, first, the stopping points are selected, then the routes visiting the selected stops are created and finally, the students are assigned to the stops. The model was set up for 800 students and 80 stops [23].

Kinable et al. (2014) proposed a branch-and-price algorithm based on a set covering formulation for the solution of SBRP. They stated that the formulations covered by the proposed algorithm gave better results than many previously proposed algorithms in cases where the number of students is more than the number of stops. In addition, they stated that in cases where the number of students increased, the results could be improved by adding appropriate inequalities to the formulations [24].

Toth and Vigo (2014) thought that the comfort, comfort, and safety of children are very important when routing school vehicles. One of the factors that can influence convenience and safety is the distance that students should walk from their homes to the pickup locations, and walking distance is generally considered a quality service measure. As such, high-quality solutions can be achieved if students are picked up from their home addresses rather than from bus stops. The authors noted that when formulating models for passenger transport, quality service factors, additional constraints, and targets should be considered [4].

Caceres et al. (2017) worked on SBRP focused on stochastic demand and indefinite travel time. An attempt was made to simplify the multi-school problem into multiple single-school sub-problems and a new algorithm was proposed [25].

Mohammed et al. (2017) used CVRP for university buses and applied a genetic algorithm to find the best route and cost-minimization solution [26].

Sales et al.(2018) solved problems involving a heterogeneous fleet of school buses solved by the application of a memetic algorithm. The article presents a memetic algorithm for the Heterogeneous Fleet School Bus Routing Problem (HFSBRP). An innovative integer programming formulation is described in the investigated problem. In comparison with the developed memetic algorithm, both a lower bound technique and a heuristic algorithm are presented. Computational evidence suggests that heuristics are needed to solve the problem within acceptable computational times. Three algorithms with distinctive features were evaluated: greedy, genetic, and memetic. Our proposed memetic algorithm achieves this goal while generating near-optimal solutions [27].

Ünsal and Yiğit (2018) used clustering and artificial intelligence methods to optimize the School Bus Routing Problem. A software was developed with GPS, GIS tools, and mobile application support, and the developed software was tested with an application. The results showed that the method developed by the authors can be successfully improved in terms of distance, time, and altitude change parameters on the routes [28].

Albayrak (2019) worked on a problem in which many schools with different entry-exit times are served and many service vehicles are used in her master's thesis. In the scope of the problem, students were grouped by using different clustering techniques depending on the constraints. It has produced solutions to the routing problem with linear programming and heuristic methods to determine the lowest number of services among the groups, to minimize the total distance traveled and to maximize the total profit. Depending on the results obtained, the problem was solved again with the saving algorithm, and the study of the author was completed with the comparison of the results [29].

Atan et al. (2019) have developed an alternative vehicle routing model proposal for personnel transportation of a private factory within the province. Within the scope of the study, the costs of transportation vehicles are fixed costs. Fuel and other periodic maintenance expenses are variable expenses. The goal is to minimize these variable costs. In the first stage, the geographical locations of a group of points corresponding to staff residences were determined on the existing road map, points corresponding to addresses were grouped and a stop was assigned to each group. For the created model, the definition area was created in the WinQSB package program. When the results are examined, the personnel can be transported in a shorter time with less fuel consumption. In the current practice, the distance traveled has decreased from 1075 km per day to 1013 km [30].

Calvete et al. (2020) proposed an SBRP model that aims to minimize the total route distance, but students are restricted walking distance to stops in the model. They proposed partial allocation–routing (PALS), which is a metaheuristic approach for solving the model. First, a feasible solution is created using mixed integer linear programming to generate subsets of bus stops with this algorithm. Then the students are partially allocated to the stops and the first route is created to collect the allocated students. Students who were not assigned in the previous routing are assigned to the existing routes, and this process is continued until all students are allocated to the routes [31].

Farnaz Farzadnia and Jens Lysgaard (2021) considered the service-oriented single-route school bus routing problem (SO-SR-SBRP). This article considers a single vehicle, starting and ending its route at the school and available to pick up all students from stop points. There is a limitation in walking distance for each student, which defines the area where the student must be picked up and the problem aims to minimize the total walking distance of students from their homes to their meeting places. In addition, the total driving distance limit for the school bus in the problem should not exceed the maximum. The proposed model focuses more on providing good quality service for students who are sensitive and need more care and safety. This is also the background for including the term ‘Service-Oriented’ in the name of the introduced problem. A new model was formulated in the paper by the authors. This model developed a heuristic in two variations with a precise method to solve the problem. Through computational experiments, the effectiveness of the proposed approach was validated on both real-world and randomly generated samples [32].

Durak (2021) examined the routing problem of personnel services of an enterprise operating in the Eskişehir Organized Industrial Zone in her master's thesis. The problem dealt with in the study includes all three types of open-ended vehicle routing problems, capacity-constrained vehicle routing problems, and heterogeneous fleet vehicle routing problems, which are sub-branches of vehicle routing problems. The problem addressed in this study has been examined for multiple purposes, taking into account user preferences, both to minimize the cost in terms of operation and to minimize the maximum time spent by the personnel in the services in a way that balances the tour. The multi-objective mixed integer mathematical model proposed for the solution of the problem was solved using GAMS software for a small data set of the problem, and then the cluster-then route method was applied to solve the entire problem. The proposed multi-objective mixed integer mathematical model was solved for the first 3 existing routes of the problem. Then, to solve the whole problem, the stops were clustered with the K-means (K-means) algorithm by applying the cluster-then route method [33].

Şahin (2021) worked on real-time optimization of the dynamic school bus routing problem (DSBRP) using metaheuristic methods in his master's thesis. Different students were grouped using global positioning system (GPS) locations, and it was aimed to reduce the number of shuttles and the total distance through groups. In the study, the distances between the points were taken instantly by using the Google Maps Distance Matrix API application. The Google Maps Directions API application was used to draw the route. The data obtained by this method is evaluated in the genetic algorithm and a route is created, and the routes are drawn as real routes with the Google Maps Directions API application [34].

Muzulon et al.(2022) have worked in a small city where there is more than one school in a small city. This article is examined the real problem of routing school buses. A network is designed with multiple schools from different schools on the same bus. This school fleet of buses is homogenous. The aim of the study is to minimize the distance traveled and, as a result, to minimize the costs. In the solution phase of the problem, the CVRP method was initially applied to determine the assembly points for each bus. After each vehicle was assigned to the stops, TSP was applied to find the minimum route for each route defined at this stage. Finally, a correction heuristic was implemented to ensure the correct sequence between the routes' points of origin and destination. With the resulting solution, it was found that a total reduction of 1096 km per year is possible, considering that this route is implemented every school day (minimum 200 days) throughout the year [10].

Liu et al. (2022) applied the transfer strategy to solve the SBRP in small cities, in which the accessibility of schools and the equity of schemes are considered. First, the mixed integer programming model was formulated to solve the SBRP with the transfer strategy by combining the accessibility of schools and the equity of programs. Secondly, the equality of the plans was ensured by reducing the deviation times of the students. Finally, the quality of the solutions based on the transfer strategy was compared with the other two strategies, namely the traditional strategy and the mixed load strategy. In addition, sensitivity analyzes are also presented in this study [35].

Gaye Peker and Deniz Türsel Eliiyi (2022) studied a detailed literature review on shuttle bus routing. They determined 7 different research questions to conduct the literature research. These questions were classified in a way that will guide the research methodology and create a roadmap for the researchers. This study by Gaye Peker and Deniz Türsel Eliiyi presents a systematic literature map in the field of the shuttle bus route to understand research trends between 2000 and 2020. Within the scope of this study, research questions were determined and a search strategy was designed and implemented. All relevant studies within the specified period were systematically reviewed based on the search strategy. Within the scope of the research, a total of 75 research articles were examined. When the results were examined, it was seen that most of the studies in the field of study reached solutions with heuristic and metaheuristic methods. Although this rate has a share of close to 80%, they stated that the rate of those who reached a solution using only the exact method is 9% [36].

Gaye Peker and Deniz Türsel Eliiyi (2023) described the real-life application of a personnel service routing problem. To solve the problem, a mathematical model was developed that aims to minimize the total travel time of the employees, including the walking times to the service stops and the time spent in the shuttles. The study was resolved by using dual-purpose Weighted Priority Goal Programming (WPGP) that takes into account both company interests and staff satisfaction. As in many publications, in this study, a solution to the employee service routing problem of a real-life company has been found by using a single mathematical model with using multi-purpose. The goal programming model was coded and solved using the commercial solver IBM ILOG CPLEX Optimization Studio. When the numerical results obtained from the model are compared with the company's current practice, it is observed that the savings in total travel time are quite striking [37].

Wang et al. (2023) focused on customized shuttle bus services in their studies. In established studies, bus route planning of private shuttle buses and other similar systems has rarely considered service quality while minimizing operating costs. This study proposes an open split delivery weighted vehicle routing problem with iterative clustering (OSDWVRP-IC) to simultaneously optimize bus routing and passenger walking distance. A maximum-min ant system algorithm was developed to solve the problem. The simulation results show that the algorithm proposed in this study sacrifices a very limited in-vehicle distance in exchange for a significant reduction in passenger walking distance [38].

2.2 Literature Review of Clustering Algorithm in VRP

Newton and Thomas proposed a computer-based approach to routing school buses in their 1969 article "School Bus Routing by Computer" [39]. This article is the first study to address SBPP. They created a series of mathematical models to determine the bus routes based on each student's home address, school address, and the details of the possible paths that each student could take from home to school. This data was processed using a routing algorithm to ensure students traveled to school the shortest distance and with the least number of bus transfers. Newton and Thomas noted that this approach not only optimized the routing process but also reduced fuel consumption and total travel time. Today, this study still forms the basis of mathematical models used to solve the school bus routing problem.

Garside et al. (2019) wrote an article discussing periodic vehicle routing problems that allow vehicles to make multiple trips in a single day. In this study, the CFRS heuristic was proposed to solve the problem known as Multi-Travel Periodic Vehicles Problem Route (MTPVRP). In stage 1, customers were clustered using integer programming formulation. In phase 2, were determined the route of the cluster and confirmed that the total travel time to visit the excursions was not exceeded the operating hours of the vehicle [40].

Kassem et al. (2019) proposed a hybrid bat algorithm in their research to solve VRP. The Bat algorithm also uses a modified k-means algorithm and a hybridized Bat algorithm. The proposed solution technique adopts the cluster first route second methodology to decouple the original VRP from the reduced complexity TSPs [41].

Putri et al. (2021) first carried out research aiming to design a distribution route that produces a minimum distribution distance by clustering the demand points. A clustering method was created to cluster the demand points by considering the proximity between the demand points and the total vehicle capacity. In solving this problem, a genetic algorithm is used to determine the distribution route with the properties of the p-median and CVRPTW problem to determine the cluster. The research concluded that clustering of demand points provides up to 16.26% better results than the current delivery plan in terms of total distribution costs. The performance of the genetic algorithm shows an average of 1.73% difference compared to the exact or optimal method. The genetic algorithm is 89.68% faster than the exact method in computation time [42].

Dutta et al. (2022) focused on cluster primary route secondary approach to solve the multi-purpose light green vehicle routing problem under a sustainable environment.

The proposed model considers two conflicting realistic goals: minimizing operating costs and minimizing carbon emissions from fuel consumption of service vehicles. Unlike the existing multi-objective problems, in this multi-objective model, the decision maker chooses the most appropriate path based on his selection from a set of alternative solutions. Initially, it clusters all customers by applying a modified k-means algorithm. Only one vehicle serves each cluster. Then, a multi-objective evolutionary algorithm, the VIKOR method, is used to search for the best sub path to cover all customers belonging to a cluster. The VIKOR method is used to determine the decision maker's choice-based solution for each cluster. In the next step, all the compromise solutions are combined to produce the final result of the proposed problem [43].

A summary of the applications of VPR and especially SBRP in the literature is given in Table 2.1 chronologically.

Table 2.1 Summary of Previous Research

Author	Problem Type	Solution Method	Method
Newton & Thomas(1969)	SBRP	Cluster-first, Route-Second	Exact
Chapleau et al. (1985)	SBRP	ARL - The cluster-covering algorithm	Heuristic
Bowerman et al. (1995)	SBRP	ARL-Multi objective	Heuristic
Rashidi et al. (2009)	SBRP	The Mixed Algorithm (Tabu Search and Ejection Chain Method)	Metaheuristic
Park and Kim (2010)	SBRP	*General Literature review*	-
Martínez and Viegas (2011)	SBRP-LAR	LAR- MILP (a two-phase multi-objective integer programming)	Heuristic
Park, Tae, and Kim (2012)	SBRP-PDPTW	A Mixed Load Algorithm (Nearest Neighborhood Search, 2-opt Algorithm, Insertion Algorithm, and Sweep Algorithm)	Metaheuristic
Riera-Ledesma and Salazar-González (2012)	SBRP - MVTPP	LAR	Heuristic

Table 2.1 Summary of Previous Research (Cont.)

Author	Problem Type	Solution Method	Method
Kim, Kim, & Park (2012)	SBRP-VRPTW	MIP (The Branch-And-Bound Approach) & A Heuristic Algorithm	Exact and Heuristic
Emrah and Tamer (2012)	SBRP- DCVRP	Mathematical Modeling -GAMS	Exact
Schittekat et al. (2013)	SBRP	LRA	Heuristic
Pillac et al. (2013)	CVRP, VRPTW, PDP, HVRP and DARP, DAFP	*The general description of dynamic routing and solution methods*	-
Kinable et al. (2014)	SBRP	Branch-And-Price Algorithm	Metaheuristic
Toth and Vigo (2014)	Vehicle Routing Problems, Methods and Applications	*The general description of Vehicle Routing Problems, Methods and Applications*	-
Lopez Santana and Romero Carvajal (2015)	SBRP	Column Generation and Clustering Methods	Metaheuristic
Ellegood et al. (2015)	SBRP-Mixed Load	CA	Exact
Mohammed et al. (2017)	CVRP	Genetic Algorithm	Metaheuristic
Caceres et al. (2017)	SBRP-SDDC	Column Generation	Exact
Sales et al.(2018)	HFSBRP	Memetic Algorithm	Metaheuristic
Ünsal and Yiğit (2018)	SBRP	K-Means and Genetic Algorithm	Metaheuristic
Atan et al. (2019)	SBRP-PSRP	Mathematical Modeling- WinQSB	Exact
Albayrak (2019)	SBRP	Hierarchical Clustering and The Saving Algorithm	Metaheuristic
Garside et al. (2019)	MTPVRP	CFRS	Heuristic

Table 2.1 Summary of Previous Research (Cont.)

Author	Problem Type	Solution Method	Method
Kassem et al. (2019)	VRP	Bat algorithm and K-Means Algorithm	Metaheuristic
Ellegood et al. (2020)	SBRP	*General Literature review*	-
Calvete et al. (2020)	SBRP	PALS	Metaheuristic
Farnaz Farzadnia and Jens Lysgaard (2021)	SO-SR-SBRP	A New Model (A Heuristic, in Two Variations, Together with An Exact Method)	Heuristic
Durak (2021)	SBRP-PSRP	MIP and K-means algorithm (Cluster-first, Route-Second)	Exact and Heuristic
Şahin (2021)	DSBRP	Genetic Algorithm	Metaheuristic
Putri et al. (2021)	CVRPTW	CFRS -p-median	Heuristic
Muzulon et al.(2022)	SBRP- Multiple schools	Mathematical Modeling (CVRP & TSP) and Correction heuristic	Exact and Heuristic
Liu et al. (2022)	SBRP-The Transfer Strategy	MIP	Exact
Dutta et al. (2022)	VRP	CFRS- VIKOR method	Metaheuristic
Gaye Peker and Deniz Türsel Eliiyi (2022)	SBRP-Shuttle service routing	*General Literature Review on Shuttle Bus Routing*	-
Gaye Peker and Deniz Türsel Eliiyi (2023)	SBRP-PSRP	WPGP	Exact
Wang et al. (2023)	OSDWVRP-IC	Ant System Algorithm	Metaheuristic
This thesis	SBRP-PSRP	CVRP -CFSR (P-median-means and P-center)	Exact and Heuristic

CHAPTER 3
METHODOLOGY

3.1 Vehicle Routing Problem

VRP is one of the main areas that has received a lot of attention over the years related to operations research and routing in logistics systems. Significant achievements have been made since the introduction of OR in solving transportation problems. In particular, efficient results have been obtained by using optimization techniques. Some techniques on exact methods and heuristics with strong formulations have been proposed and these techniques developed in solving the VRP [44].

VRP is the problem of designing optimal routes of vehicles assigned to serve geographically dispersed customers from one or more warehouses [45]. Figure 3.1 shows the routing of vehicles with a classical vehicle routing problem [46].

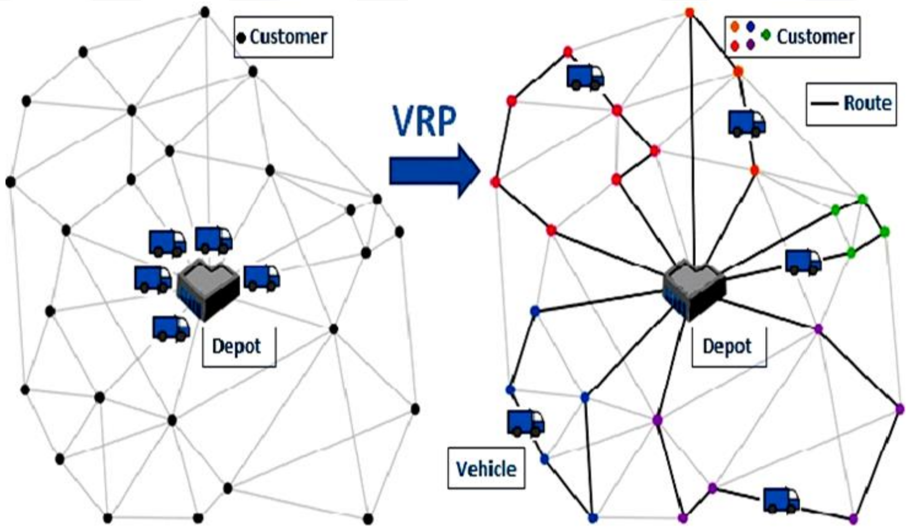

Figure 3.1 Classical vehicle routing problem [46]

VRP is generally defined as the problem of designing the most appropriate delivery or collection routes for customers located geographically dispersed from one or more warehouses under different constraints [45].

The factors to be considered while creating a route in VRP are as follows [47];

- Each route created starts and ends in the warehouse,
- Each customer is visited only once,
- Each customer is visited by only one vehicle,
- Customer demand on routes should not exceed vehicle capacity,
- The duration of any route must not exceed the specified time
- It should be aimed to minimize the total route cost.

VRP is included in the set of NP-hard problems. A problem being NP-hard means that the effort required to solve the problem increases exponentially with the size of the problem [48].

Different perspectives have been adopted while classifying VRP types in the literature. VRP types are basically examined in 4 sections and are given in Figure 3.2. While explaining the types of VRP, this thesis problem was also defined.

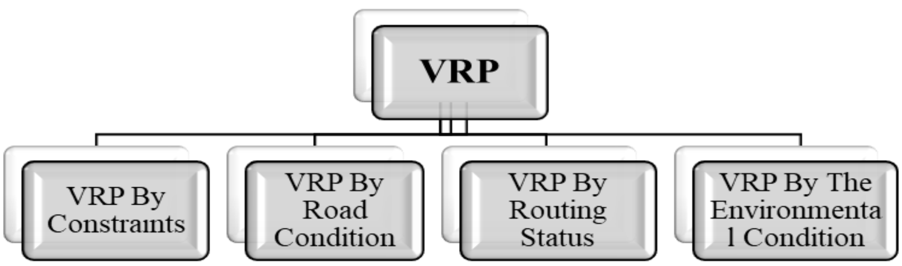

Figure 3.2 Types of VRP

<u>VRP By Constraints</u>

Capacitated Vehicle Routing Problem

Each vehicle has a certain capacity and vehicle capacities are equal. All of the personnel vehicles in examined problems belong to the same transportation company, so the capacities and other technical features of a total of 32 service services, 19 blue collar services, 7 technical personnel services, and 6 personnel, are exactly the same.

Customer requests are known in advance and are delivered in one go, no shredding is possible. In the problem, customer demands were considered as reaching their homes.

Vehicles start moving from the warehouse and return to the warehouse. In the investigated problem, the warehouse was considered a factory. The personnel collected from their homes come to the factory and are then distributed back to their homes from the factory. In this case, vehicles do not start from the factory and return to the factory.

The distance between the warehouse and the customers is symmetrical and the travel time of the vehicles can be taken in direct proportion to this distance.

In the problem, the distance between the homes of the personnel and the distances from their homes to the factory are equal to each other. In this case, the problem is defined as both symmetrical VRP.

Taking into account the capacity in the problem makes the name of the problem the Capacity Vehicle Routing Problem (CVRP). Considering the real-life applications of the problem, the vehicles' physical capacities must be considered. However, in CVRP, vehicles have an obligation to return to where they started. The vehicle must return to the point from where it started when it completes its lap. However, in SVRP, the vehicle does not have to return to where it started and can go to a different point at the end of its lap. Therefore, the points where the vehicles start to move and finish their movements are different. In that case, routes are called tours in CVRP, and routes are called roads in school vehicles routing problem [49].

Distance-Constrained Vehicle Routing Problem

A distance restriction is set when creating routes so that each assigned vehicle can travel. This can be a real problem depending on the type of product being transported, vehicle, or driver restrictions. This restriction should be added if the transported product deteriorates due to long-term transportation or the vehicle driver cannot travel continuously for more than a certain period [50].

Personnel transportation will be made in the analyzed problem. Distance will not be used as a constraint. Distance will be the goal to be reached in problem-solving, and it is aimed to create a route with a minimum distance.

<u>VRP By Road Condition</u>

Asymmetric Vehicle Routing Problem

In some cases, for the y and z points in the VRP, the distance required to go from point y to point z may not be equal to the distance from point z to point y. ($d_{yz} \neq d_{zy}$)

In this type of VRP, it is important to which customer the vehicles will go first, which determines the route direction and the route distance calculation [51].

<u>VRP By Routing Status</u>

Opened Vehicle Routing Problem

Routes start with the central warehouse and end with the demand point. ON account of achieving this, an additional constraint does not need to be added to the model. The result will already spawn open-ended routes [51].

In the examined problem, the service vehicles start from the personnel addresses (demand points) and end at the factory, and on the way back, they start from the factory and end at the personnel addresses (demand points).

3.1.1 Capacitated Vehicle Routing Problem

The capacity vehicle routing problem is an optimization problem that seeks a solution to determine the most effective and efficient routes to serve a set of customers with a given fleet of vehicles. This problem can be applied to practical problems in areas such as distribution, logistics, and transportation.

The capacity vehicle routing problem arises when a certain number of customers must be served, with several vehicles and the capacity limitations of each vehicle. Each customer requests a quantity of goods or services and vehicles are assumed to be limited to a certain capacity. Also, distances and travel times between customers are taken into account. Its purpose is to create a route planning that best meets a criterion such as the least possible total distance, total cost, or total time. This planning must meet the demands and capacity constraints of all customers and ensure that each vehicle follows the optimal route.

Capacitated Vehicle Routing Problem (CVRP) is defined as the most general version of the VRP. In this type of problem, mutual round-trip is assumed to be symmetrical when calculating the distances between customers. If the demands of all vehicles are met, there are k routes. If the existing roads are open or closed, the edges showing the closed roads can be made passive and routes can be determined according to the current situation [52].

CVRP is intended to calculate a set of routes for a fleet of vehicles in a warehouse for a set of geographically dispersed customers. Also, CVRP refers to a class of problems where vehicles in the warehouse must have a maximum loading capacity. CVRP aims to reduce total costs while serving a group of customers with known needs [53].

Let $G = (V, E)$ be a directed graph with vertices $V = \{ 0, 1, \ldots n \}$ and edges $H = \{(i, j)$: $i, j \in V, i \neq j$. The depot is represented by vertex 0, and each remaining vertex i represents a customer with a positive demand d_i. There is a fleet of p vehicles with the same capacity Q. The non-negative cost/distance c_{ij} is associated with each arc $(i, j) \in H$. The minimum number of vehicles needed to serve all customers is $\sum_{i=1}^{n} di / pQ$. x_{ij} takes the value 1 if the edge belongs to the optimal solution, and value 0 otherwise, $\forall i, j \in V : i \neq j$. u_i is an additional continuous variable representing the load of the vehicle after visiting customer *i.* The mathematical formulation which is used in this study is described below [53].

Objective function:

$$Min\sum_{i=0}^{n}\sum_{j=0}^{n} x_{ij}c_{ij} \qquad (1)$$

Subject to

$$\sum_{i\in V} x_{ij} = 1 \qquad \forall j \in V \qquad (2)$$

$$\sum_{j\in V} x_{ij} = 1 \qquad \forall i \in V \qquad (3)$$

$$\sum_{i\in V} x_{i0} = p \qquad (4)$$

$$\sum_{j\in V} x_{0j} = p \qquad (5)$$

$$u_i - u_j + Qx_{ij} \leq Q - d_i \qquad (6)$$

$$d_i \leq u_i \leq Q \qquad \forall i \in V \qquad (7)$$

$$x_{ij} \in \{0,1\} \qquad \forall i, j \in V \qquad (8)$$

The CVRP consists of finding a collection of simple circuits (corresponding to vehicle routes) with minimum cost, defined as the sum of the costs of the arcs belonging to the circuits (Eq. 1). Constraints (2) and (3) (indegree and outdegree of nodes) impose that exactly one edge enters and leaves each vertex associated with a customer, respectively. Analogously, Constraints (4) and (5) ensure the degree requirements for the vertex of the depot. Constraints (6) and (7) impose the capacity requirements of CVRP while eliminating the sub-tours. Finally, Constraint (8) is the integrality conditions [53].

3.1.2 School Bus Routing Problem / Shuttle Bus Routing Problem

Combinatorial optimization-type problems are usually NP-Hard. The solution time of the problem increases exponentially depending on the size of the problem. Therefore, it becomes difficult to solve medium and large problems reasonably. Among the combinatorial optimization type problems, the Traveling Salesman Problem (TSP) is perhaps the most studied [54].

When TSP is examined in detail, a large family of problems consisting of extensions of different problems is reached. Among them, the known and most common problem is the VRP. Considering the capacity in a vehicle routing problem examined turns the problem into a CVRP. However, one of the primary criteria sought by CVRP is that vehicles must return to their starting point.

The vehicle must return to the point from where it started when it completes its lap. However, in SBRP, the vehicle does not have to return to where it started and may go to a different point at the end of its lap [54].

In SBRP, the points where vehicles start and end their movement are different. Thanks to this feature, the problem is also defined as an open-ended vehicle routing problem. Thus, in CVRP, routes are called tours, and in school vehicle routing problems, routes are called roads [49].

The most general definition of SBRP; It is the problem of minimizing the total cost and leaving the students to school by picking them up from certain collection stops or picking them up from school and leaving them at certain distribution points. The first researches were projects made to solve real-life problems. The first article brought to the literature was published in 1969 by Newton, R. M., and Thomas, W.H. Published by Socio Planning Science [55].

According to Park and Kim, the SBRP branches into a few subproblems;

- Data preparation,
- Bus stop selection,
- Bus route generation,

- School bell time adjustment,
- Bus route schedule.

It is possible to find studies that solve a single subproblem or even a set of them together in the same study [14].

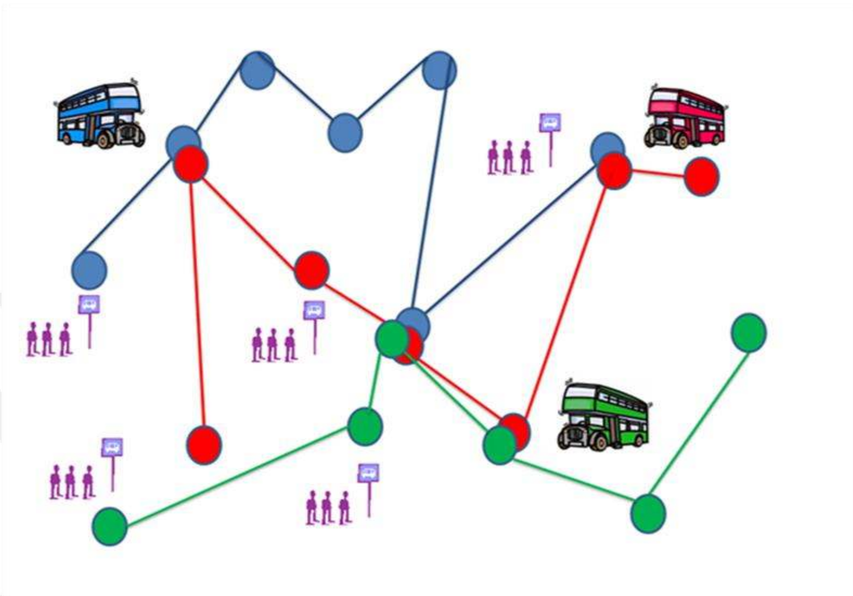

Figure 3.3 Bus Routing for School [56]

Logistics services are an important issue in terms of personnel support activities. Only a well-functioning transportation service can ensure that the transportation activities of the personnel are provided and that transportation is carried out in accordance with the wishes and needs of the company management and personnel. For these reasons, businesses should ensure that personnel transportation services, which are considered a very important function in terms of personnel support activities, are carefully planned, controlled, and coordinated. is necessary [57].

Although there is more than one factor affecting success in businesses, the most important role here is the performance of the personnel performing the business functions. Especially recently, businesses have been working to increase the quality of life of their personnel and to increase the job satisfaction of their employees. At the beginning of these studies is the transportation planning of the personnel. It is desired to save on the cost of transportation by using various models and techniques. Solving route problems will reduce transportation costs in the future. The purpose of solving these problems is to minimize the travel time people spend in vehicles [57].

In today's conditions, a rapidly increasing economic crisis has continued in the world, especially with the effect of the pandemic and the Russia-Ukraine war. This situation is also felt throughout Turkey, and 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 and companies that provide transportation services to bring their personnel to work. From this point of view, companies with a large number of employees need to perform service routing effectively. The extra distances covered turn into extra paid service rents or gas money. Considering all these, the importance of personnel routing problems, which is a sub-branch of VRP, has increased considerably in recent years. To resist rising gasoline prices, personnel services must complete the most appropriate route with the least number of vehicles. However, the human factor should not be forgotten while doing this. Concepts such as the time the personnel will spend in the service and the delivery points affect the transportation systems [37].

The field of shuttle bus routing can be considered under the type of VRP or location-routing problems (LRP). Generally, the researchers dealing with this kind of problem employ a mathematical model like mixed integer linear programming (MILP) or nonlinear mixed integer programming (NLMIP) [37].

When VRPs in the literature, which are about human transportation, are evaluated according to their application areas, it has been seen that 5 main headings are more intense. These are Employee/Personnel, Patient/Hospital, Students, Elderly/Disabled, and Airport Shuttle. The larger number of publications mainly involved students, patient/hospital, and employee/personnel, whereas elderly/disabled and airport shuttles attracted less attention analytically during the last 20 years [37].

The personnel service route problem/Employee Shuttle Bus Routing Problem could be defined as a sub-branch of VRP that deal with human transportation. It is accepted as an adaptation of the school vehicle routing problem, which is widely encountered in the literature. PSRP, which is the subject of transportation of personnel by vehicles, is considered a CVRP due to its constraints. It is abbreviated as PSRP within the scope of this study.

The personnel service route problem/Employee Shuttle Bus Routing Problem is an optimization problem that aims to determine the most suitable routes to take the employees of an enterprise from different locations and reach the target points within a certain period of time. This type of problem is often encountered by institutions such as large companies, schools, or hospitals.

PSRP requires planning suitable routes to take a certain number of personnel from different locations at a certain time and reach the destination points. Some restrictions are usually taken into account when determining these routes, for example:

- Personnel capacity: The number of personnel that the vehicles can carry is limited and these capacity limitations should be taken into account.
- Time constraints: Personnel service may need to be completed within a certain time frame. Each staff member may have to start or leave work at a certain time.
- Travel times: The distance of each point to other points and the travel time should be taken into account. Traffic, road conditions, and other factors can also affect these times.

The personnel service route problem is usually solved using optimization techniques such as mathematical programming models, heuristic methods, or meta-heuristic algorithms. Its purpose is to minimize the total distance or time or to achieve other set goals. In this way, an efficient and optimized personnel service route can be planned and the enterprise's resources can be optimally utilized.

3.2 Clustering Algorithm

Clustering algorithms are machine learning techniques used to group data sets based on similar characteristics. These algorithms categorize data points into groups based on a particular criterion or measure of distance. It is used in clustering, data discovery, pattern recognition, image processing, and many other fields.

Clustering is an automatic process in which samples are divided into categories whose members are similar to each other, and these categories are called clusters. A cluster is a collection of samples in which the samples are similar to each other. But this collection of samples is not similar to the samples in other clusters. Different criteria could be considered for similarity within the cluster. For example, the distance criterion could be used for clustering, which is considered distance-based clustering, and samples close to each other can be considered as a cluster. In simple terms, the goal is to separate groups with similar characteristics and form clusters [58].

The differences between the clustering methods are the distance/similarity criteria, the first cluster values and how the final clusters will be created. These differences have led to the development of different clustering methods over time. There are five main clustering methods in the literature. These are Density-Based Clustering (DC), Grid Based Clustering (GC), Model-Based Clustering (MC), Hierarchical Clustering (HC), and Partial Clustering (PC).

Clustering methods are an effective analytical tool used in VRP. VRPs are logistical problems where many vehicles must receive material from certain points and deliver it to specified points. Clustering algorithms are a powerful tool to increase efficiency, reduce costs and use resources effectively in VRPs.

Clustering methods can be used in the VRP in the following ways:

1. **Customer Clustering:** This grouping allows vehicles to focus on specific areas and create more efficient routes.

2. **Vehicle Clustering:** In VRP, when many vehicles are used, it is important that these vehicles work with optimized routes. Clustering methods can help you sort tools into groups with similar characteristics or capabilities. This ensures load balance between vehicles and allows routing problems to be solved more efficiently.

3. **Route Optimization:** Clustering algorithms help create optimized routes based on customer groups. By grouping customers with similar characteristics on the same route, the total distance can be reduced and delivery times can be improved. Thus, more efficient routes can be planned and time and fuel savings of vehicles can be achieved.

4. **Resource Management:** Clustering algorithms help to effectively manage resources in VRPs. It prevents vehicles from operating at optimum capacity and wasting resources such as an empty vehicle or an overloaded vehicle.

5. **Flexibility**: Clustering algorithms provide flexibility in adapting to varying customer demands or routing constraints. Customer demands or service requirements may change over time. Clustering algorithms facilitate the integration of new customers or changing demands into the routing plan.

Capacity clustering algorithms are designed to obtain more balanced and consistent groupings by complying with the capacity limits of the groups. Capacity clustering algorithms could also be applied to VRPs. Capacity clustering algorithms group customers by dividing them into certain groups. The capacity limits of the groups represent the carrying capacities of the vehicles. In this way, similar customers are brought together and more effective vehicle routes can be created. The total demands or carrying capacities of the customers in the groups should be compatible with the group capacities. Capacity clustering algorithms make route planning by assigning grouped customers to different routes. Each route must meet a specific capacity limitation of a vehicle. The algorithm can use various optimization objectives to optimize customer queues and visit orders on routes, for example minimizing total travel distance or total delivery time. Capacity clustering algorithms provide capacity control by controlling group capacities and carrying capacities of vehicles while planning routes. A balance is achieved between customer demands, group capacities, and vehicle capacities. When group or route capacities are exceeded, new routes can be created or customers can be redirected to different routes.

3.2.1 P-Median (Capacitated)

The capacity p-median approach is a method used to solve an optimization problem that aims to select an optimally located facility to meet service demands among many settlements. This method tries to determine the locations of the best-established facilities, taking into account the location of the residential units, the service demands, and the capacities of the facilities.

The p-median problem (PMP) is an important topic within the field of logistics and supply chain management [59]. In general, the PMP is focused on finding the best location of p facilities to minimize the distance between n demand nodes (customers) and the nearest of the selected facilities [60]. For the capacitated p-median problem (CPMP) the total demand of the set of customers assigned to a facility must not exceed its capacity [61].

Similar to CPMP, CVRP also consists of finding the best p routes of minimum distance to meet n customer demands [62].

Transportation Planning is involved in the assessment, design, and scheduling of transportation facilities and it is based on specific planning models for each context. Within the context of transportation planning the CVRP is an important element. CVRP is described in detail in section 3.1.1. Another problem of interest in transportation planning is the Capacitated p-Median Problem (CPMP). As shown in Figure 3.4 the CPMP consists of finding the most suitable locations of distribution centers to provide maximum coverage for a set or cluster of points. Each distribution center has a finite capacity and must meet the demands of the associated points [62].

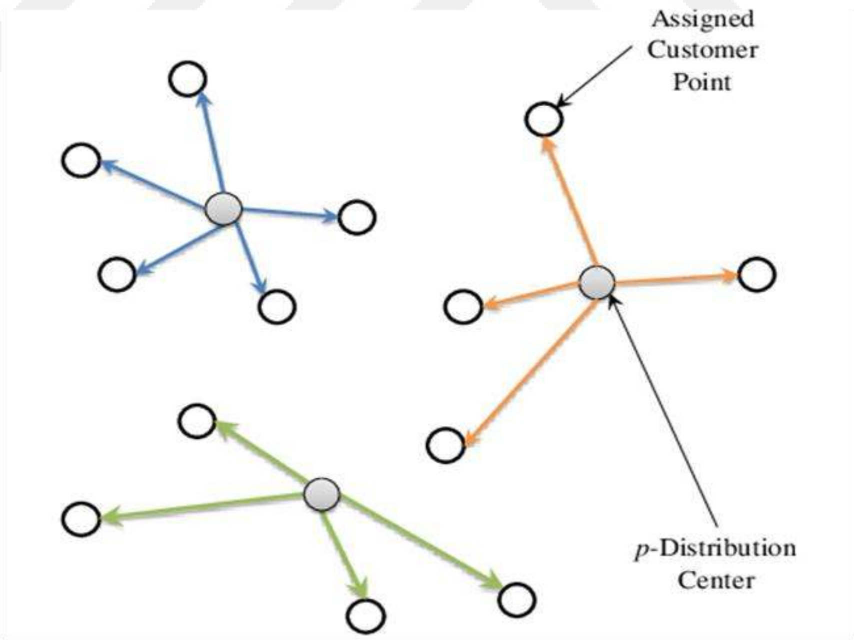

Figure 3.4 Example of a distribution network under the CPMP [61]

In the VRP, it is determined how to most effectively use a fleet of vehicles to serve many customers. This is an optimization problem that determines which customers will be served by vehicles and in what order.

The capacity p-median approach allows customers to be considered as settlements and facilities as tools to solve this problem. In this method, each customer's service request determines the amount of load to be assigned to a vehicle. In addition, the capacities of the vehicles are taken into account. The aim of the optimization problem is to minimize the number of vehicles required to meet the service demands of all customers. This is aimed at determining the vehicles to be assigned to customers and not exceeding the capacity of each vehicle.

The capacity p-median approach could help to optimally position the vehicles according to the locations of the customers to be served and to use the capacities of the vehicles effectively. This ensures that vehicles are used less and more customers are served at less cost.

The P-median model is applied to minimize the employees' total walking distance to the meeting point by clustering the employees. Due to a limited capacity of clusters, capacitated P-median on a discrete space is considered in this study. The capacitated P-median problem seeks to define the number of P-candidate facilities (clusters) to be opened, and which customers (employees) will be assigned to each facility (cluster). In the model, every cluster has a limited employee capacity and each employee has one demand. The problem should consider that each cluster can serve only a limited number of demands so that the sum of distances between each demand point (employee home) and the facility (cluster center) assigned to that demand point is minimized [53].

In the model, i and $j = 1, 2,\ldots, n$ is the set of employees and also of possible medians where P clusters j will be located, di is the demand of employee i, Qj is the capacity of the median (cluster) j, $dij > 0$ ($i \neq j$) is the distance between employee i and cluster median j. xij is a binary decision variable that takes 1 if an employee i is assigned to a cluster j, otherwise it is 0. yj is also a binary decision variable that takes 1 if an employee is selected as a cluster median j, otherwise it is 0. The problem formulation is given as follows [63]:

Objective function:

$$Min\sum_{i}^{n}\sum_{j}^{n} x_{ij} d_{ij} d_i \qquad \textbf{(9)}$$

Subject to:

$$\sum_{j} x_{ij} = 1, \forall i, \qquad \textbf{(10)}$$

$$\sum_{j} y_j = p, \qquad \textbf{(11)}$$

$$x_{ij} d_i \le Q_j y_j, \forall i, j, \qquad \textbf{(12)}$$

$$x_{ij}, y_j \in \{0,1\}. \qquad \textbf{(13)}$$

The objective function (Eq. 9) aims to minimize the total walking distance of all employees. Constraint (10) imposes that each employee is assigned to one and only one cluster median, Constraint (11) guarantees that P cluster medians are selected, Constraint (12) forces that a total median capacity to be respected, and Constraint (13) prepares the binary integer conditions [53].

3.2.2 K-Means (Capacitated)

The capacity k-median approach is a method used to solve an optimization problem that determines the locations of facilities to minimize distances between many points. This method tries to determine the locations of the best-established facilities, taking into account the capacities of the facilities.

In the capacity k-median problem, k facilities need to be selected. Each facility has a capacity and this capacity represents its ability to meet service demands. At the same time, each point (customer, facility, or other point) receives service at a cost that is determined by the distance from the facilities.

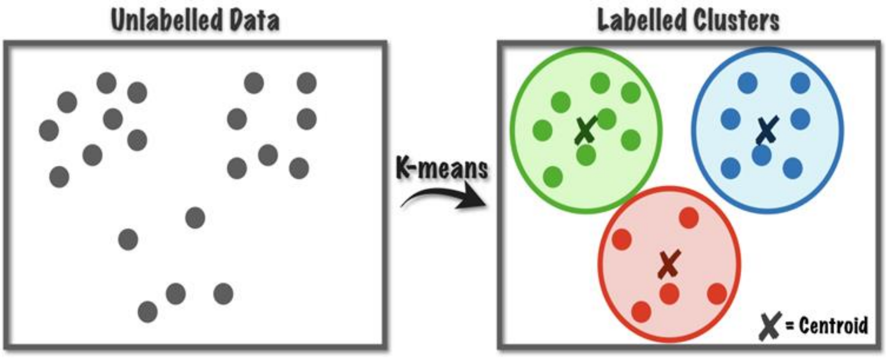

Figure 3.5 K-means clustering algorithm

Capacitated K-means is also applied to cluster the employees. The capacitated K-means approach seeks to define the K amount of candidate cluster centers to be decided and which employees will be assigned to each cluster center while employees attended to nearest the cluster center [53].

In VRPs, it is aimed to determine vehicle routes to visit many customers by using capacity k-median problems. In this scenario, customers are represented as data points and vehicles are center points. Each customer has a certain demand (capacity) value and the capacity of the vehicles to meet these demands is limited.

The capacitated K-means problem formulation is given as follows [64].

Objective function:

$$Min\sum_{i=1}^{n}\sum_{h=1}^{k}T_{i,h}*\left(\frac{1}{2}\left(x_i-\mu_{h,t}\right)^2\right) \qquad \textbf{(14)}$$

Subject to:

$$\sum_{i=1}^{n}T_{i,h}\geq\tau_h, h=1,2,...,k \qquad \textbf{(15)}$$

$$\sum_{h=1}^{k}T_{i,h}=1, i=1,2,..,n \qquad \textbf{(16)}$$

$$T_{i,h}\geq 1, i=1,2,..,nh=1,2,..,k \qquad \textbf{(17)}$$

where, Given a database X of n points, minimum cluster membership values $\tau_h \geq 0$, $h = 1,\ldots,$ k and cluster centers $\mu_{1,t}, \mu_{2,t}, \ldots \mu_{k,t}$ at iteration t. $T_{i,h}$ is a binary variable that demonstrates attendance of data point x_i is to the nearest center μ_h or not [64].

The objective function (14) aims to attend nodes to their nearest cluster center. Constraint (15) ensures the attendance of a minimum number of nodes in one cluster. Constraint (16) ensures that one node is allowed to attend just one cluster center and constraint (17) forces all nodes to attend cluster [53].

3.2.3 P-Center (Capacitated)

The capacity p-center clustering method selects a certain number of centers among many points or customers, ensuring that each center does not exceed a certain capacity. This clustering method, it is aimed to minimize the sum of the distances to the centers. In this method, the location information of the points or customers in the data set, their associated distances, and capacity demands should be found. The capacity demands of the points represent customer demands or resource usage. For example, in a logistics routing scenario, points can represent vehicle demands or product quantities to be transported.

The capacity p-center clustering method assigns the points in the data set to p-centers and ensures that each center does not exceed a certain capacity. While making the assignment, the demands of the points and the capacities of the centers are taken into consideration. Each point is assigned to the nearest center and the demand of the point to be assigned should not exceed the remaining capacity of the center to be assigned. The capacity p-center clustering method is used in various application areas such as facility layout planning, logistics routing, and emergency response planning. This method ensures efficient use of resources, reduces costs, and increases operational efficiency.

The method updates the locations of the centers to obtain the most optimal clustering result and aims to minimize the sum of the distances to the centers. This is usually accomplished using mathematical optimization techniques. The clustering results of points associated with optimized centers can include the centers to which each point is assigned and the distances to the centers. The problem formulation is given as follows [63]:

Objective function:

$$Min \sum_{i}^{n} \sum_{j}^{n} x_{ij} d_{ij} d_i \qquad \textbf{(14)}$$

Subject to:

$$\sum_{j} x_{ij} = 1, \forall i, \qquad \textbf{(15)}$$

$$x_{ij} d_i \le Q_j y_j, \forall i, j, \qquad \textbf{(16)}$$

$$x_{ij}, y_j \in \{0,1\}. \qquad \textbf{(17)}$$

The objective function (Eq. 14) aims to minimize the total distance between data points and cluster centers. Constraint (10) imposes that each employee is assigned to one and only one cluster median, Constraint (11) guarantees that P cluster medians are selected, Constraint (12) forces that a total median capacity to be respected, and Constraint (13) prepares the binary integer conditions [53].

In this method, there is no constraint to control the capacity of cluster centers. Without any capacity limitations, data points are assigned to clusters and cluster centers are determined.

As mentioned before, in a p-center problem, the objective is to locate facilities (service points) among demand points in such a way that the maximum distance between the demand points and their nearest facility becomes minimum. Figure 1 shows a set of demand points and service points. Red points indicate service points and blue ones are the demand points. In this figure, the maximum distance between a demand point and a service point is specified with a highlighted circle. The aim of the p-center problem is to find the location of the service points, in order to minimize the maximum distance between demand points and their nearest facility [65].

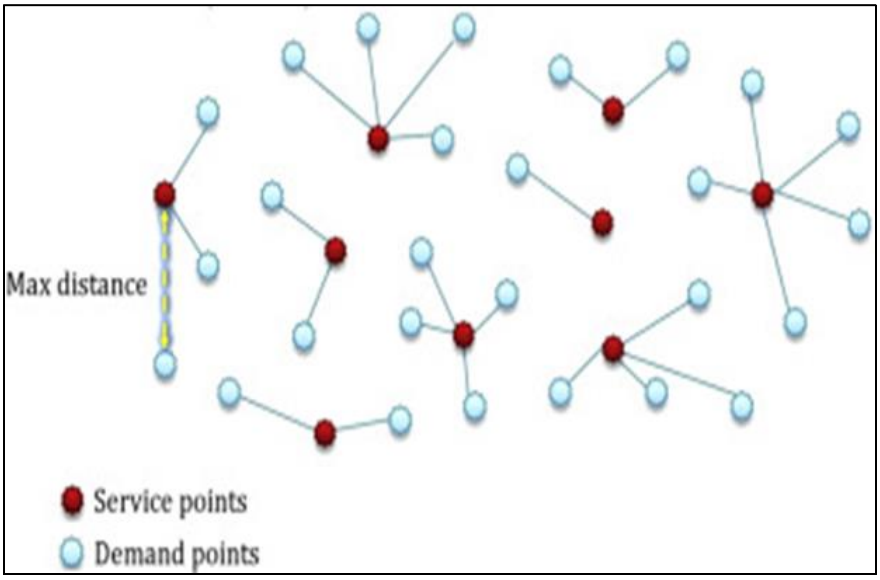

Figure 3.6 A set of demand points and service points and the maximum distance between them [65]

CHAPTER 4
IMPLEMENTATION AND RESULTS

4.1 Problem Definition

4.1.1 Case Study

In this thesis, the transportation problems of the personnel working in "The Kartal Carpet and Textile" factory are discussed. Kartal Carpet and Textile is a carpet production factory located in Gaziantep. Factory employees are taken from their homes every morning and left to the factory, and the personnel taken from the factory are left to their homes at the time of departure. The factory employs approximately 1500 personnel. However, the number of personnel using the active shuttle is 1361.

Personnel is divided into two administrative personnel and operating personnel. Figure 4.1 is also shown.

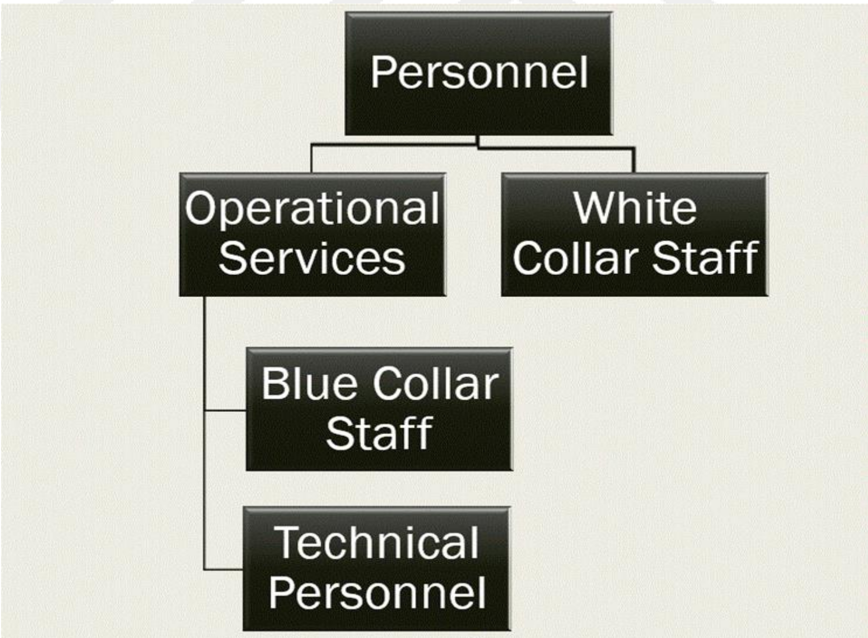

Figure 4.1 Personnel Information

The problem aimed to be solved within the scope of the thesis;

- *Capacity is limited,*
- *Equal capacity (homogeneous),*

In the investigated problem, both in the current situation and in the solution scenarios, the vehicles have equal capacity and all vehicles can carry passengers with equal capacity. So, the problem is a capacity-limited problem.

- *Symmetrical;* The symmetric VRP is the round-trip distance from one point to another is equal. ($d_{ij} = d_{ji}$) In the examined problem, the round-trip distances between the points defined as the personnel addresses are equal. So, if it takes x km to get from point a11 to point a12, it takes x km to go from point a12 to point a11. The distance between the factory and the personnel is symmetrical and the travel time of the vehicles can be taken in direct proportion to this distance.

- *Open Ended;* The routing starts with the address of the personnel and ends at the factory. Vehicles do not have to go back to where they started. This turns the problem into an open-ended routing problem.

- *Static – Deterministic;* In static VRPs, all necessary information (constraints, demands, capacities, cost information, etc.) is known before the problem is solved, and this information does not change during the solution phase of the problem. In the investigated problem, information such as constraints, demands, and vehicle capacities are known before the routing process is started. During the resolution phase, this information will not change and will be considered the same.

- *Single store (Factory),*
- *Ignoring the time window and time zone,*
- *It will be defined as problems without distance and time constraints.*

In addition, constraint analysis was carried out for the speciation of the factory sample examined in the thesis. It is summarized in detail and shown in Table 4.1. The problem constraint types given in the table are explained below.

Table 4.1 Summary of The Problem Speciation Examined

Components	Types
Vehicle Types	Equality capacity (homogeneous)
Number Of Warehouses	Single (One)
Objectives	Single (One)
Station	Staff home addresses
Station Selection	No
Distance Between Points	Asymmetric
Warehouse	Driver's home / last staff address
Time Zone and Time Window	No
Determining Capacity by Class Type	No
Each Stop is Assigned to Only One Vehicle	Yes
Mixed Load	No
Time Constraint	No
Capacity Constraint	Yes
Distance Constraint	No

Vehicle Types: Equal capacity (homogeneous)

In the examined problem, vehicles are vehicles of equal capacity and it is based on the assumption that all vehicles will be of equal capacity. All vehicles have the same number of seats.

Number Of Warehouses: Single (One)

There is only one warehouse in the examined problem under consideration. The vehicles depart from a single factory, leave the personnel at certain points, and leave the personnel collected from certain points in a single warehouse.

Objectives: Single (One)

As the number of decision-makers increases, the number of targets to be optimized also increases. There is more than one purpose in the examined problem, but these goals will be evaluated on a single purpose. Vehicles leaving the factory within the scope of the problem will distribute the personnel to the determined points. It is aimed to make this distribution in the shortest way.

Station (Points of Getting on And Off the Vehicle): Staff home addresses

It can be taken from the homes of the personnel or from the stops. If it is taken from the stops, the problem of determining the stops will also arise. For this, one of the potential stopping points in a region should be selected as a stop. While doing this, the walking distance of the personnel to the stops should be taken into account. The station selection can be made before the routing problem or simultaneously with the routing problem.

Warehouse (Road Start/End Points): Driver's home / last staff address

In the examined problem, the start of the route is accepted as the first personnel address and the end of the route is accepted as the factory. In the scope of the problem, since the route to the factory is considered the same as the route to be made on the return, a solution has been sought only for the route to the factory.

4.1.2 Data Collection

For the transportation problems of the personnel working in Kartal Carpet company, which was examined within the scope of the thesis, firstly, the information of the personnel addresses was obtained. Personnel addresses were taken from the Kartal Carpet Human Resources department. The address information registered in the Human Resources department is the information received on the employment dates of the personnel and has not been updated over time. Since the accuracy of the address data directly affects problem-solving, it is necessary to reach up-to-date data. Therefore, a form was prepared and given to the service drivers. The prepared form was filled out by the personnel in each service. The prepared form is given in the appendices section.

In the current situation, while personnel are being transported, the personnel are taken from their homes and brought to the company. The service route is made at the discretion of the service driver. A second form was prepared in order to analyze the current situation. In this form, the total distance and total time information were asked for and filled in by the service drivers. The prepared form is given in the appendices section.

All forms were collected and evaluated in detail after they were filled. The data obtained formed the current situation. All forms were collected and evaluated in detail after they were filled. The data obtained formed the current situation.

The factory employs approximately 1500 personnel. However, the number of personnel using the active shuttle is 1361. In reality, blue-collar personnel work in a shift system. However, in the problem solved within the scope of the thesis, the assumption was made as a single shift. Since the routes are separate for each service and the transportation is done independently of each other in the real-life example, it has been considered as a single problem while solving is being made. In this case, 85 shuttles provide service to a total of 1361 personnel.

The personnel transportation of the company is carried out by a subcontractor company. Currently, 85 services, including 6 personnel services, 7 permanent day services, and 72 (24*3) operational services, serve the personnel. Personnel/Shuttle distribution is given in Table 4.2.

Table 4.2 Summary of The Problem Speciation Examined

	Number of Personnel	**Number of Services**
White-Collar	106	6
Technical Personnel	128	7
Blue-Collar	1127	(24*3) 72

Google Maps roadmaps provide basic functions such as a route planner for vehicles and public transport. In addition to these basic functions, it includes hydrography, settlement data, satellite images, and terrain relief in Google Earth content to support the roadmap. Map and satellite images can be combined. Although it varies by country, traffic information is also provided for some countries [66].

The application has the same content as satellite images and Google Earth information and offers high-resolution images of many important settlements on Earth. Similar to Google's other web applications, Google Maps also uses the JavaScript programming language [66].

Google Earth, originally called Earth Viewer 3D, is a map and geographic information software developed by a company called Keyhole, which was acquired by Google in 2004 and founded by the US Central Intelligence Agency (CIA). It was launched in 2005. While the Google Earth program can be installed on any computer system (PC, Mac, and Linux) free of charge, it also aims to provide users with a more realistic view of the world through satellite images, maps, earth models, 3D buildings, and other data [67].

The 1361 personnel address data obtained were marked and visualized via Google Earth. While marking on the map, white-collar, blue-collar, and technical personals are shown in different colors and codes. Google Earth markings are shown in Figure 4.2.

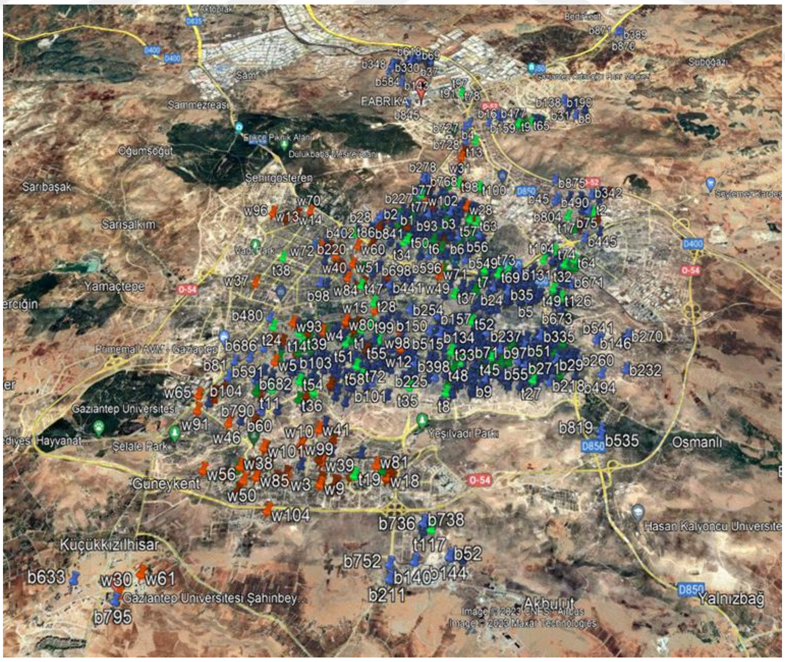

Figure 4.2 Google Earth Markings

In order to analyze the current situation, the forms filled by the shuttle drivers were analyzed and it was determined which service each employee group was transported. In addition, the services were numbered and it was determined which service carried how many passengers. The current service capacity information used for white-collar personnel, technical personnel, and blue-collar personnel within the scope of the thesis problem is shown in Table 4.3.

Table 4.3 Current status service capacity information

Service Name	Service Number	Capacity (person)
White Collar	1	20
	2	19
	3	19
	4	17
	5	16
	6	15
Technical Personal	1	19
	2	17
	3	20
	4	17
	5	18
	6	21
	7	16
Blue Collar	1	44 (19,18,7)
	2	38 (15,17,6)
	3	61 (20,17,24)
	4	40 (17,13,10)
	5	40 (12,15,13)
	6	43 (15,13,15)
	7	50 (16,19,15)
	8	67 (25,24,18)
	9	56 (16,24,16)
	10	56 (20,18,18)
	11	37 (14,9,14)
	12 *** 3**	47 (17,15,15)
	13	50 (13,19,18)
	14	44 (17,18,9)
	15	45 (15,10,20)
	16	36 (10,14,12)
	17	47 (17,11,19)
	18	34 (12,10,12)
	19	40 (15,16,9)
	20	43 (15,16,12)
	21	41 (11,13,17)
	22	48 (20,22,6)
	23	52 (18,15,19)
	24	68 (26,18,24)

The company does not plan for the road route of the services in the present situation. The subcontractor company providing the shuttle services uses a system that tracks the movements of the shuttles during the day but does not use a scientific method to route the road routes. The routing is done at the discretion of the service driver. The forms required to be filled by the service drivers were examined and the distances covered by each service while transporting the personnel were determined. The kilometer information on the current route used for the white-collar and technical personnel within the scope of the problem is shown in Table 4.4.

Table 4.4 Current status service distance information

Service Name	Service Number	Distance (km)
White Collar	1	45
	2	22
	3	30
	4	33,5
	5	52
	6	27
Technical Personal	1	28
	2	20
	3	22
	4	27
	5	20
	6	17
	7	27
Blue Collar	1	45
	2	60
	3	90
	4	49,5
	5	78
	6	70
	7	39
	8	39
	9	84
	10	135
	11	84
	12 * **3**	56
	13	66
	14	42
	15	54
	16	57
	17	72
	18	63
	19	54
	20	70
	21	64
	22	66
	23	70
	24	45

In light of this information, the total distance covered one-way during the transportation of 1361 personnel in the current situation is 1786.5 km/178.650,00 meters.

The routes drawn for a total of 13 services that currently serve white-collar and technical personnel are drawn using Google Earth’s tools and are shown in the figures. In addition, there are a total of 72 service routes for blue-collar employees.

- 6 vehicles serve white-collar personnel, so a total of 6 routes have been created.

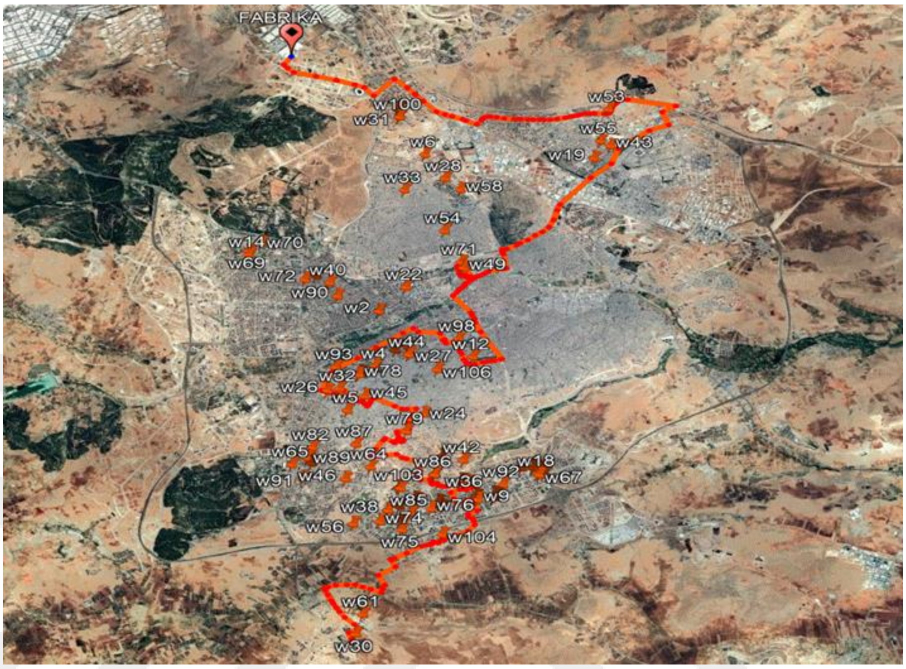

Figure 4.3 1st route for white collar personnel service

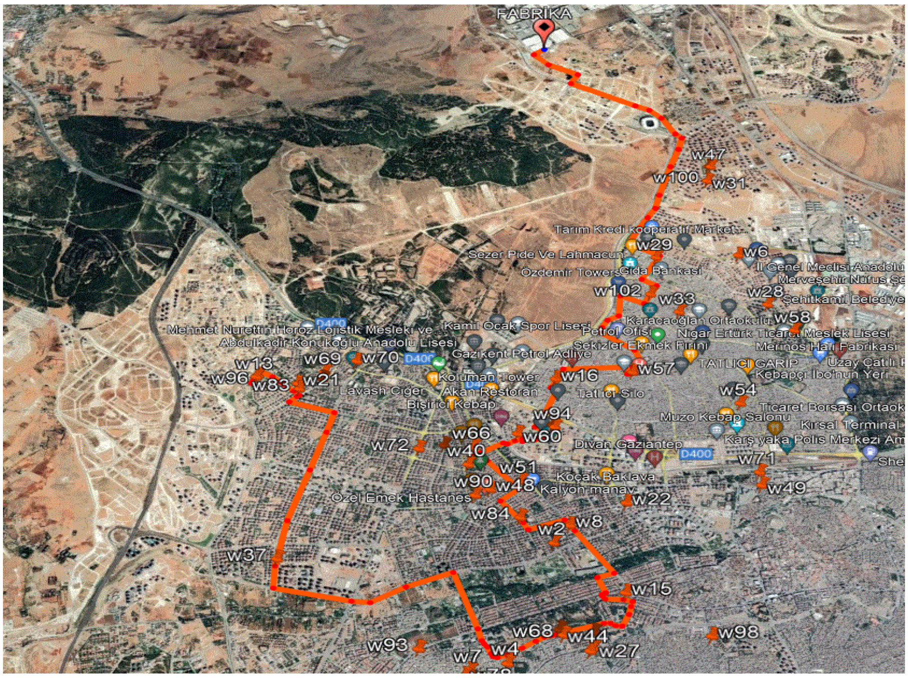

Figure 4.4 2nd route for white collar personnel service

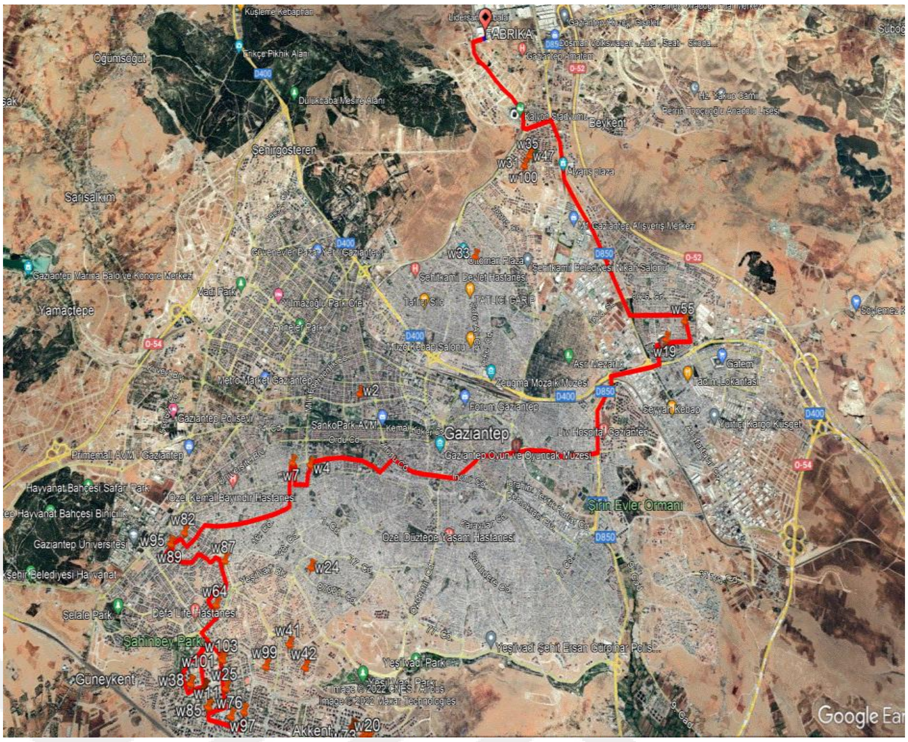

Figure 4.5 3rd route for white collar personnel service

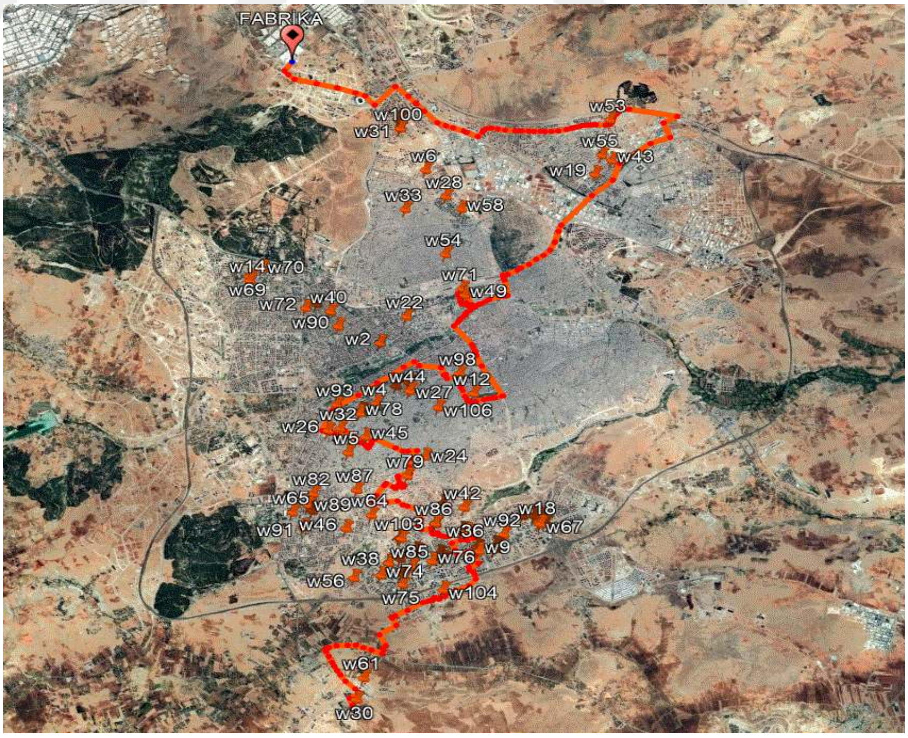

Figure 4.6 4th route for white collar personnel service

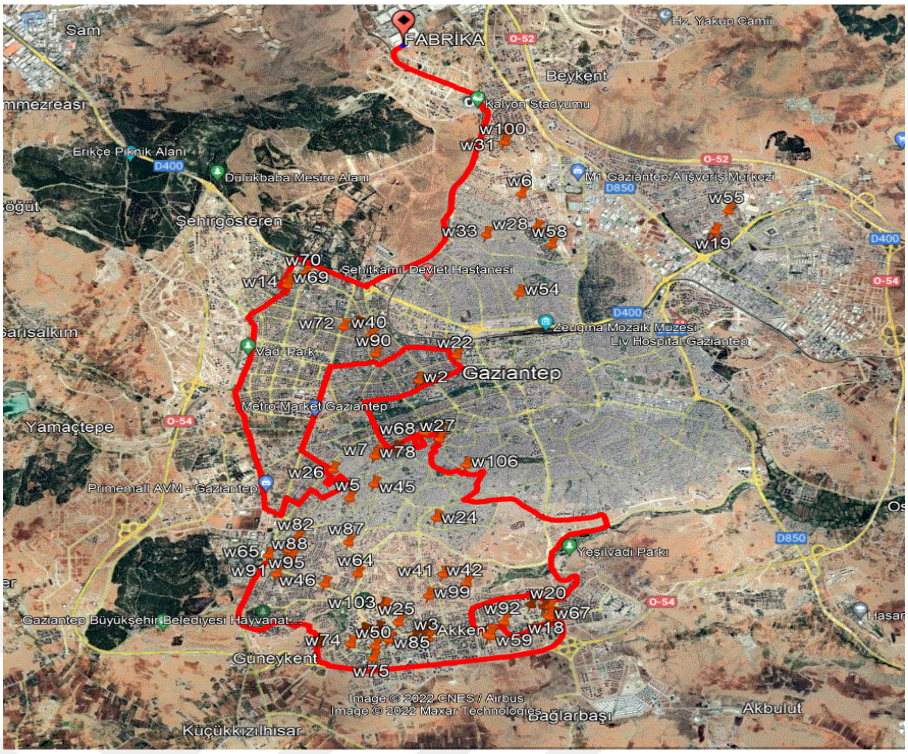

Figure 4.7 5th route for white collar personnel service

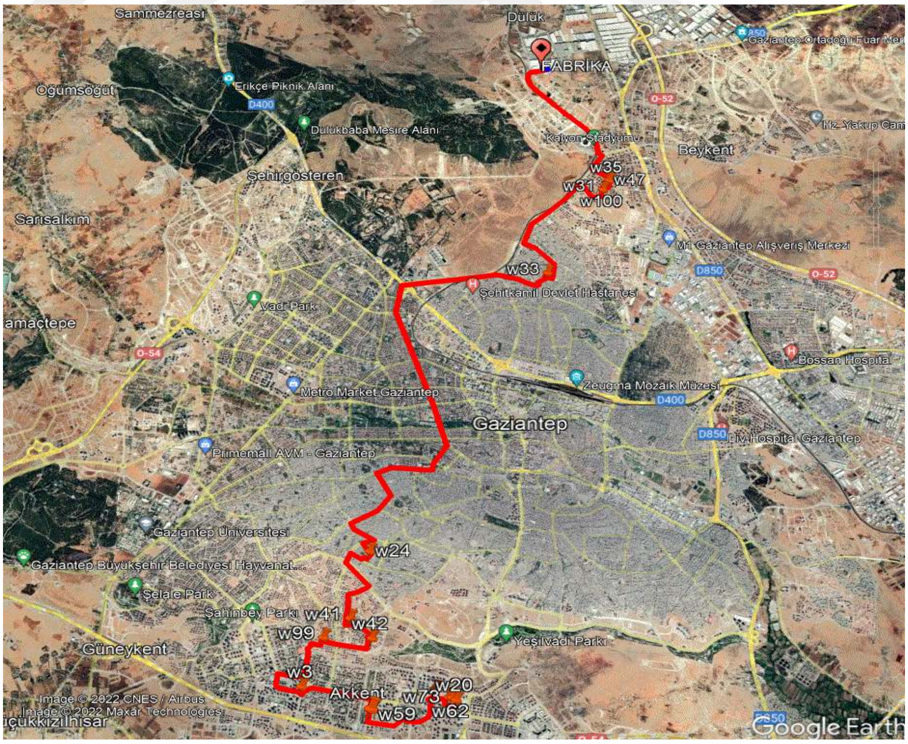

Figure 4.8 6th route for white collar personnel service

- 7 vehicles serve for technical personnel, so a total of 6 routes have been created.

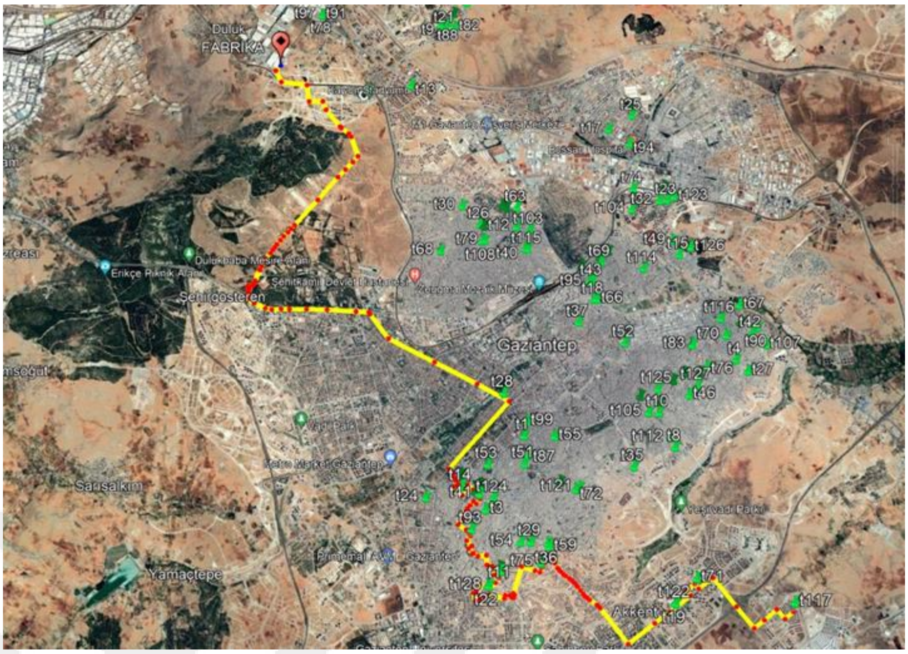

Figure 4.9 1st route for technical personnel service

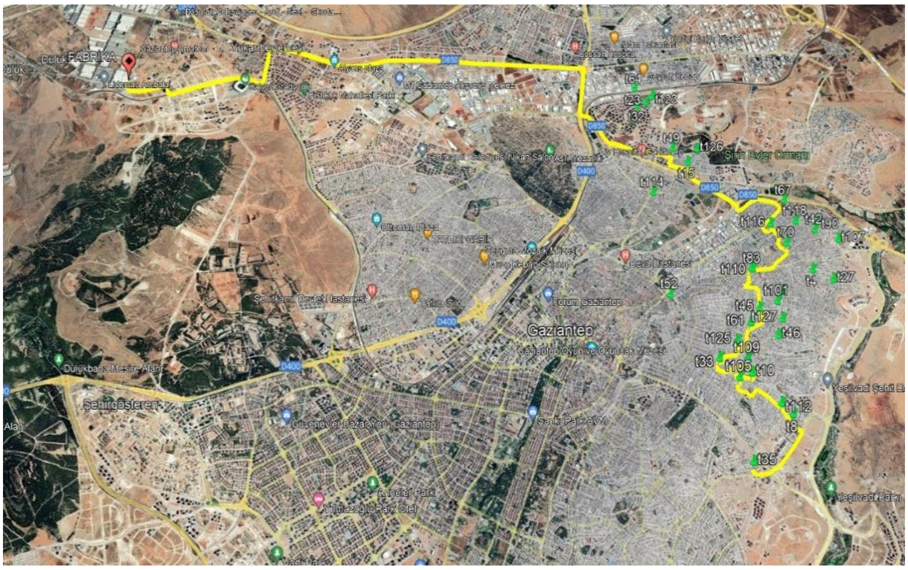

Figure 4.10 2nd route for technical personnel service

Figure 4.11 3rd route for technical personnel service

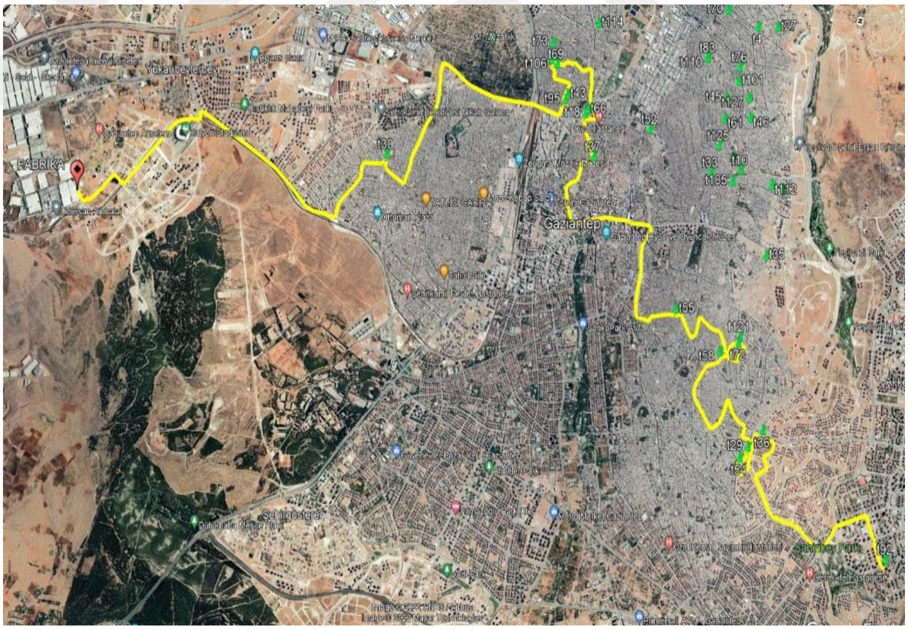

Figure 4.12 4th route for technical personnel service

Figure 4.13 5th route for technical personnel service

Figure 4.14 6th route for technical personnel service

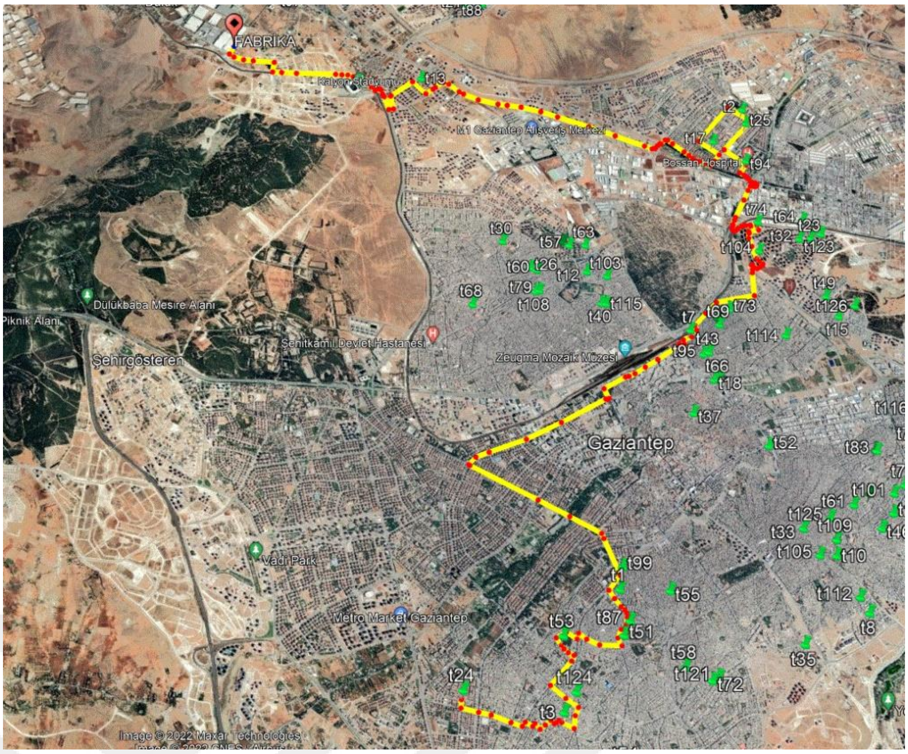

Figure 4.15 7th route for technical personnel service

Coordinate information was accessed from the points marked on Google Earth by using application tools. Coordinate information was saved in *.kmz or *.kml format by right-clicking on the directory name and choosing “save location as” after completing the data collection phase. Geographical coordinates found through Google Earth tools are latitude-longitude (X/Y axis) data. First, these coordinates were converted to decimal expressions. The mathematical formula used to convert a geographic latitude-longitude coordinate to decimal format;

- Decimal Latitude = Degree + (Minute / 60) + (Second / 3600)
- Decimal Longitude = Degree + (Minute / 60) + (Second / 3600)

The distance between latitude and longitude calculated as a decimal was calculated with the Euclidean distance formula. Euclidean distance formula;

$$d = \sqrt{(x_2 - x_1)^2} + \sqrt{(y_2 - y_1)^2}$$

(x_1, y_1) represents the coordinates of the first point.

(x_2, y_2) represents the coordinates of the second point.

The distances of the points to each other were found with the code written over Excel Visual Basic for Applications (Macro). The macro written is given in Figure 4.16.

ondalık_Koordinatlar.xlsm - Module1 (Code)

(General) DONGU

```
Sub DONGU()

SATIR = 3
For I = 2 To 306
For X = 2 To 306

If Cells(X, 5).Value = "FACTORY" Then Exit For
If Cells(I, 5).Value = "FACTORY" Then Exit For
If Cells(I, 5).Value = "" Then Exit For

Dim DEGER

If Cells(I, 5).Value <> Cells(X, 5).Value Then

DEGER = Mesafe(Cells(I, 9).Value, Cells(I, 13).Value, Cells(X, 9).Value, Cells(X, 13).Value, "Km")

Cells(SATIR, 17).Value = Cells(I, 5).Value
Cells(SATIR, 18).Value = Cells(X, 5).Value
Cells(SATIR, 19).Value = DEGER

SATIR = SATIR + 1
End If

Next
Next


End Sub
```

Figure 4.16 Distance Macro (Visual Basic for Applications)

4.1.3 Assumptions

While working on the problem discussed in the thesis, some assumptions were made and these are listed below:

- Vehicles are vehicles of equal capacity and it is based on the assumption that all vehicles will be of equal capacity.

- In the examined problem, it is assumed that the round-trip distances between the points defined as personnel addresses are equal. While creating the distance matrix, real-life traffic rules and road conditions were not considered.

- The factory was chosen as the starting point. It is assumed that all services are at the factory during the specified hours. The ending point will be the address of the last personnel left at the end of the route.

- Currently, blue-collar personnel work three shifts a day. However, this study only focused on recruiting workers for one shift.

- In the current situation, it is assumed that the number of vehicles used for blue-collar personnel is unlimited and the company will accept the number of vehicles to be given in the solution.

- While evaluating the calculated results, only the profit from the distance was evaluated.

4.2 Implementation and Computational Results

In this study, the problem of moving the personnel of a carpet company operating in Gaziantep was studied. The company employs approximately 1500 workers. However,1361 personnel benefit from the transportation service offered by the company. In this study, the problem of collecting 1361 personnel from their homes and bringing them to the company was examined. Currently, 85 shuttle services are provided for the transportation of 1361 personnel, and each personnel is picked up in front of their homes. All services have homogeneous capacities of 20 people. All data currently examined are given in section 4.1.2. Currently, the total distance covered one-way during the transportation of 1361 personnel in the current situation is 1786.5 km/178.650,00 meters.

In order to solve the problem examined within the scope of the thesis, 4 different scenarios were designed. Four different scenarios were solved with three different tool capacities, 20, 30, and 50. The first scenario is CVRP. The other 3 scenarios cover clustering methods. The clustering methods studied are P-median, P-Center, and K-means. In this case, the 2nd scenario was determined as P-Median, the 3rd scenario as K-means, and the 4th scenario as P-Center.

In 4 scenarios, it was first run on the Gams 23.5 program. The program was run without a time limit, and was stopped after about 14 hours because it did not yield any results.

The first scenario, CVRP, is solved without clustering. Since the problem is in the NP-hard problem class, it did not yield results with mathematical modeling methods. The problem code was solved using Python programming language via Google Or-Tools for 3 different capacities. The installed model worked for 400 seconds (1.5 hours) over the PyCharm Python development environment with the Intel Core i5 8265U CPU with 8 GB RAM features and gave feasible results. It is shown in Figure 4.17.

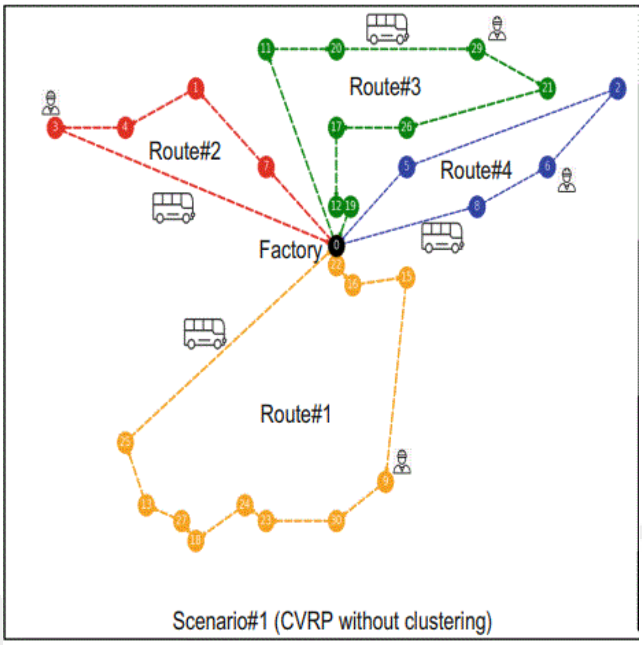

Figure 4.17 Scenario#1

In the second scenario, P-median clustering method was used. Since the problem is in the NP-hard problem class, it did not yield results with mathematical modeling methods. The problem code was solved using the Python programming language Gurobi library for 3 different capacities. Scenario is applied with the time limit set to three hours with a computer that has an Intel Core i5 8265U CPU with 8 GB RAM features. It is shown in Figure 4.18.

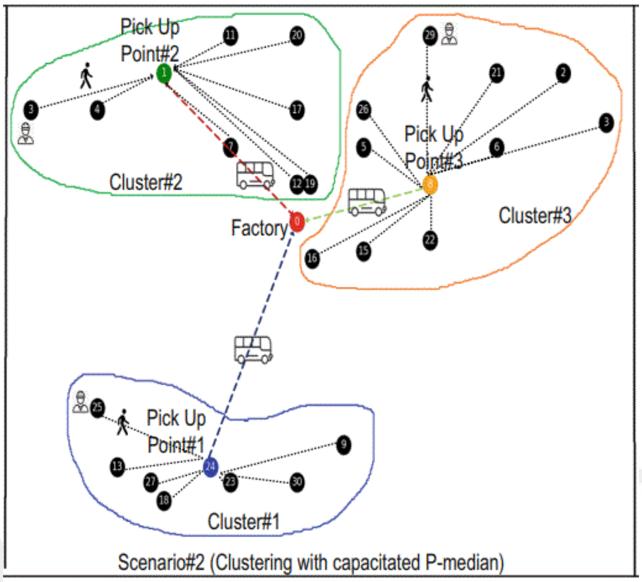

Figure 4.18 Scenario#2

In the third scenario, K-means clustering method was used. Since the problem is in the NP-hard problem class, it did not yield results with mathematical modeling methods. The problem code was solved using the Python programming language Scikit-learn library for 3 different capacities. Scikit-learn is an open-source machine learning library for the Python programming language. Scenario is applied with the time limit set to three hours with a computer that has an Intel Core i5 8265U CPU with 8 GB RAM features. It is shown in Figure 4.19.

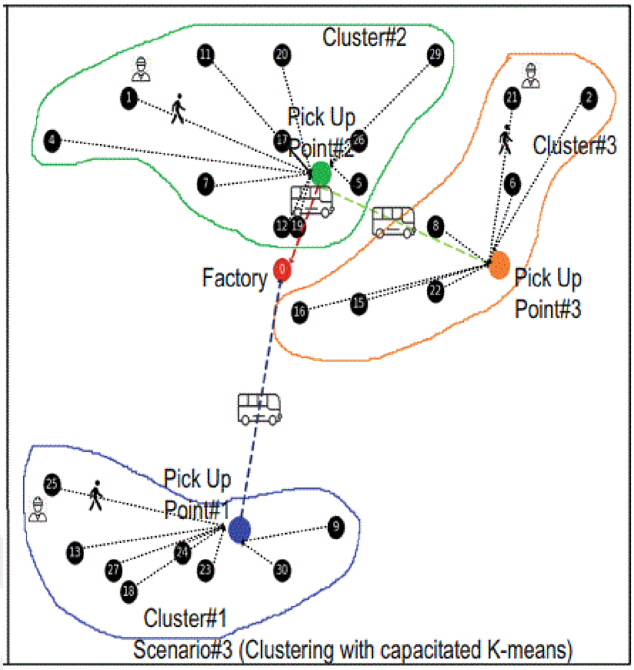

Figure 4.19 Scenario#3

In the fourth scenario, P-center clustering method was used. Since the problem is in the NP-hard problem class, it did not yield results with mathematical modeling methods. The problem code was solved using the Python programming language Gurobi library for 3 different capacities. Scenario is applied with the time limit set to three hours with a computer that has an Intel Core i5 8265U CPU with 8 GB RAM features. It is shown in Figure 4.20.

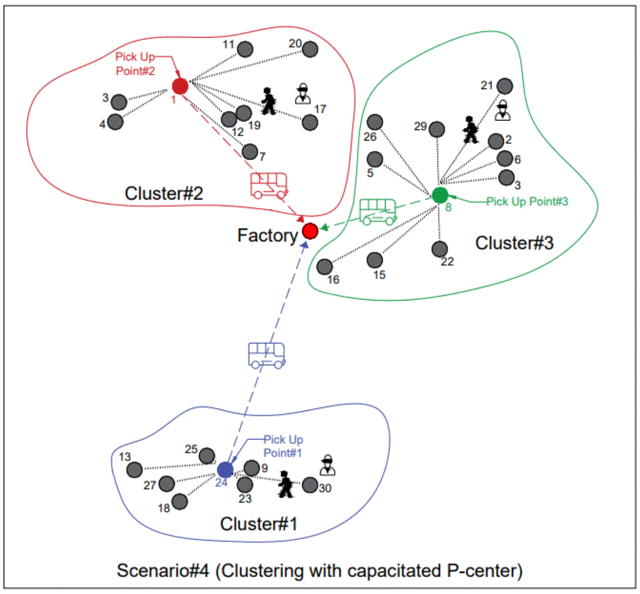

Figure 4.20 Scenario#4

4.2.1 Application of CVRP

Within the scope of the thesis, the CVRP described in section 3.1.1 has been applied in this part of the thesis. In the current situation, the method used by the company for transportation is CVRP. However, the results were different because the capacities of the service vehicles could not be used efficiently. Among the solution methods, CVRP was accepted as the 1st scenario. In the 1st scenario, 1361 personnel were taken from their home addresses and the personnel were not walked. The first scenario was solved with 3 different vehicle capacities.

The number of routes is found by dividing the total number of people by the vehicle capacities determined and decimals are rounded up.

- There are 69 routes for a vehicle with a capacity of 20 people (1361/20). If a bus with 20 people capacity is chosen, then scenario#1 has to visit 1,361 workers with 69 routes/buses.
- There are 46 routes for a vehicle with a capacity of 30 people (1361/30). If a bus with 30 people capacity is chosen, then scenario#1 has to visit 1,361 workers with 46 routes/buses.

- There are 28 routes for a vehicle with a capacity of 50 people (1361/50). If a bus with 50 people capacity is chosen, then scenario#1 has to visit 1,361 workers with 28 routes/buses.

The CVRP Gurobi Library, which is accepted as the 1st scenario, has been solved in the Python programming language. The data set created for the distances was added to the library as a file and added to the solution. The solution was evaluated in 3 different vehicle capacities, 20, 30, and 50 and it was solved again by changing the capacity data in the code. The data sets studied in the literature were tested in the code and the solution data were checked.

The results of the problem solved without clustering in the first scenario to collect 1361 personnel from their home addresses and bring them to the factory are given below.

- Vehicles with a capacity of 20 covered an average of 118,900.00 meters on each route and covered a total of 8,204,100.00 meters on 69 routes. Since customers are taken in front of their houses, the walking distance is 0.

- Vehicles with a capacity of 30 covered an average of 82,700,00 meters on each route and covered a total of 3,804,200.00 meters on 46 routes. Since customers are taken in front of their houses, the walking distance is 0.

- Vehicles with a capacity of 50 covered an average of 55,700.00 meters on each route and covered a total of 1.559.600.00 meters on 28 routes. Since customers are taken in front of their houses, the walking distance is 0.

In the method used by the company when transporting personnel in the current situation, each personnel is taken from their home and brought to the firm. In the first scenario implemented, transportation was carried out in the same way. However, in the current situation, vehicle capacities are not used efficiently as explained in section 4.1.2. As a result, when the current situation and the 1st scenario were compared, the 1st scenario gave better results. The results are shown in Table 4.5.

Table 4.5 Comparison of First Scenario and Current Situation

Capacity	Scenario	Total Walking Distance	Average Distance Per Worker	Total Bus Distance	Average Distance Per Bus	Total Distance
20	#1	0.00	0.00	8,204,100.00	118,900.00	118,900.000
	Current Situation	0.00	0.00	12,326,850.00	178,650.00	178,650.00
30	#1	0.00	0.00	3,804,200.00	82,700.00	82,700.00
	Current Situation	0.00	0.00	8,217,900.00	178,650.00	178,650.00
50	#1	0.00	0.00	1.559.600.00	55,700.00	55,700.000
	Current Situation	0.00	0.00	5,002,200.00	178,650.00	178,650.00

According to the results obtained, each vehicle traveled 59,750.00 meters less in the first scenario compared to the current situation and covered a total of 4,032,750.00 meters less. In this case, the distance is approximately 33.4% less than the current situation in scenario 1. In the current situation, the total distance is assumed to be the same and the assumption that the vehicle capacities are 30 or 50 is also considered. In this assumption, the first scenario gave better results.

4.2.2 Application of Clustering Method

The clustering algorithms problem explained in Section 3.2 within the scope of the thesis has been applied in this part of the thesis. The clustering algorithms applied were chosen to be suitable for grouping large-scale personnel numbers. Thus, within the scope of the thesis problem solution, the capacity p-median algorithm as the 2nd scenario, the capacity K-means algorithm as the 3rd scenario, and the capacity p-center algorithm as the 4th scenario were solved. In all scenarios where clustering algorithms were applied, 1361 personnel were taken from the centers assigned as a result of the solutions and taken away to the company. As in the first scenario, these three scenarios were solved with 3 different vehicle capacities.

The number of clusters is found by dividing the total number of people by the vehicle capacities determined and decimals are rounded up.

- There are 69 clusters for a vehicle with a capacity of 20 people (1361/20). If a bus with 20 people capacity is chosen, then scenarios #2, #3, and #4 then the buses have to pick up 20 workers from each 69 cluster and then back to the factory.

- There are 46 clusters for a vehicle with a capacity of 30 people (1361/30). If a bus with 30 people capacity is chosen, then scenarios #2, #3, and #4 then the buses have to pick up 30 workers from each 46 cluster and then back to the factory.

- There are 28 clusters for a vehicle with a capacity of 50 people (1361/50). If a bus with 50 people capacity is chosen, then scenarios #2, #3, and #4 then the buses have to pick up 50 workers from each 28 cluster and then back to the factory.

P-median, k-means, and p-center considered as the 2nd, 3rd, and 4th scenarios are solved in the Python programming language. The data set created for the distances was added to the library as a file and added to the solution. The solution was evaluated in 3 different vehicle capacities, 20, 30 and 50, and the capacity information in the code was changed and resolved again. The data sets examined in the literature were tested in the code and the solution data were checked.

The results of the problem solved by grouping the personnel in the 2nd, 3rd, and 4th scenarios for the collection of 1361 personnel from the designated centers and bringing them to the factory are given below.

Scenario#2: P-Median

- Vehicles with a capacity of 20 covered an average of each bus 56,900.00 meters and covered a total of 3,926.100.00 meters on 69 clusters (69 cluster center points). Since the personnel are taken from the determined cluster centers, the average of each worker's walking distance to the center is 38.9 meters and the total walking distance is 52,943.00 meters. The total distance (vehicle distance + walking distance) is 3,979.043.00 meters.

- Vehicles with a capacity of 30 covered an average of each bus 38,600.00 meters and covered a total of 1.775.600.00 meters on 46 clusters (46 cluster center points). Since the personnel are taken from the determined cluster centers, the average of each worker's walking distance to the center is 42.3 meters and the total walking distance is 57,570.00 meters. The total distance (vehicle distance + walking distance) is 1.833.170.00 meters.

- Vehicles with a capacity of 50 covered an average of each bus 25,540.00 meters and covered a total of 715.120.00 meters on 28 clusters (28 cluster center points). Since the personnel are taken from the determined cluster centers, the average of each worker's walking distance to the center is 30.3 meters and the total walking distance is 41,238.00 meters. The total distance (vehicle distance + walking distance) is 756.358.00 meters.

Scenario#3: K-Means

- Vehicles with a capacity of 20 covered an average of each bus 58,700.00 meters and covered a total of 4,050.300.00 meters on 69 clusters (69 cluster center points). Since the personnel are taken from the determined cluster centers, the average of each worker's walking distance to the center is 36.6 and the total walking distance is 49,812.60 meters. The total distance (vehicle distance + walking distance) is 4,100.112.60 meters.

- Vehicles with a capacity of 30 covered an average of each bus 38,555.10 meters and covered a total of 1.773.534.60 meters on 46 clusters (46 cluster center points). Since the personnel are taken from the determined cluster centers, the average of each worker's walking distance to the center is 26.7 and the total walking distance is 36,338.70 meters. The total distance (vehicle distance + walking distance) is 1.809.873.30 meters.

- Vehicles with a capacity of 50 covered an average of each bus 24,258.40 meters and covered a total of 679.235.20 meters on 28 clusters (28 cluster center points). Since the personnel are taken from the determined cluster centers, the average of each worker's walking distance to the center is 70.1 and the total walking distance is 95,406.10 meters. The total distance (vehicle distance + walking distance) is 774.641.30 meters.

Scenario#4: P-Center

- Vehicles with a capacity of 20 covered an average of each bus 56,937.00 meters and covered a total of 3,928.653.00 meters on 69 clusters (69 cluster center points). Since the personnel are taken from the determined cluster centers, the average of each worker's walking distance to the center is 56.2 meters and the total walking distance is 76,550.00 meters. The total distance (vehicle distance + walking distance) is 3,936.308.00 meters.

- Vehicles with a capacity of 30 covered an average of each bus 38,600.00 meters and covered a total of 1.179.308.00 meters on 46 clusters (46 cluster center points). Since the personnel are taken from the determined cluster centers, the average of each worker's walking distance to the center is 39.9 meters and the total walking distance is 54,430.00 meters. The total distance (vehicle distance + walking distance) is 1.179.308.00 meters.

- Vehicles with a capacity of 50 covered an average of each bus 27,360.00 meters and covered a total of 766.080.00 meters on 28 clusters (28 cluster center points). Since the personnel are taken from the determined cluster centers, the average of each worker's walking distance to the center is 18.6 meters and the total walking distance is 25,320.00 meters. The total distance (vehicle distance + walking distance) is 768.612.00 meters.

Comparative results solved with three different vehicle capacities in 4 different scenarios are given in Table 4.6.

Table 4.6 Results of the three methods (in meters)

Capacity	Scenario	Total Walking Distance	Average Distance Per Worker	Total Bus Distance	Average Distance Per Bus	Total Distance
20	#1	0.00	0.00	8,204.100.00	118,900.00	8,204.100.00
	#2	52,943.00	38.9	3,926.100.00	56,900.00	3,979.043.00
	#3	49,812.60	36.6	4,050.300.00	58,700.00	4,100.112.60
	#4	76,550.00	56.2	3,928.653.00	56,937.00	3,936.308.00
30	#1	0.00	0.00	3,804.200.00	82,700.00	3,804.200.00
	#2	57,570.00	42.3	1.775.600.00	38,600.00	1.833.170.00
	#3	36,338.70	26.7	1.773.534.60	38,555.10	1.809.873.30
	#4	54,430.00	39.9	1.179.308.00	38,980.00	1.179.308.00
50	#1	0.00	0.00	1.559.600.00	55,700.00	1.559.600.00
	#2	41,238.00	30.3	715.120.00	25,540.00	756.358.00
	#3	95,406.10	70.1	679.235.20	24,258.40	774.641.30
	#4	25,320.00	18.6	766.080.00	27,360.00	768.612.00

In Table 4.6, the feasible results of three scenarios are given. When the results are evaluated, it is clear that the results obtained by clustering methods in all vehicle capacities reduce the total distance compared to the scenario applied with CVRP. If the decision maker accepts all the results and only wants to shorten the total distance, then it should be applied scenario#2 route with a vehicle with a capacity of 50 people. Because scenario#2 with a capacity of 50 vehicles gives the smallest total distance among all alternatives.

The centers determined in the P-median and P-center methods are close to each other. Therefore, the distance from the centers to the factory is approximately equal and the total bus distances are very close to each other. In this case, when vehicles with a capacity of 20 are used, the total walking distance increases, and the total distance gives the worst result. However, when 30 and 50-capacity vehicles are used, scenario#4 will be the least walking distance. When walking distances are compared for all scenarios, the best result for vehicles with 20 capacity is obtained in scenario#3. However, when 30 and 50-capacity vehicles are used, the best results are obtained in scenario#4.

Capacitated K-means (scenario#3), demonstrates better performance with a capacity of 30 people compared to the other third scenarios. On the other hand, the capacitated P-median gives a better result than the application of capacitated K-means and capacitated P-center for the capacity of 20 and 50 people. The general view shows a significant difference between capacitated P-median/P-center and K-means approaches. Capacitated P-median outperforms the capacitated K-means by 1.48 km and 4.13 km with capacities 20 and 50, respectively. However, capacitated K-means with a capacity of 30 shorten the distance compared to the capacitated P-median with a capacity of 30. As a result, the minimum total distance is obtained by scenario 2 with a capacity of 50. When the average walking distance per worker is considered, the minimum distance is gathered by applying scenario 3 with capacity 30. When the average walking distance per worker is considered, the minimum distance is gathered by applying scenario 3 with capacity 30. Lastly, if the average distance per bus is aimed, the best result is obtained by applying scenario 2 with a capacity of 20.

For the solution of the thesis problem, 4 different solution scenarios are presented for 3 different vehicle capacities. These alternatives need to be examined by the decision maker and a scenario is able to be selected according to the primary objectives.

According to the results of the scenarios, which routing will be applied depends on the preference of the decision maker. However, in Table 4, carbon emissions are given based on the total distance reduction for each scenario. This ratio can be considered an important criterion for the decision maker. The carbon emission has been calculated according to the international criteria determined on The Defra Site. According to the information obtained from the site, the carbon footprint per kilometer of each passenger for a local bus is 0.096 [68].

Table 4.7 Carbon Emission Calculation for Scenarios

Capacity	Scenario	Total Distance (in meters)	Activity data (passenger. km)	Carbon Emission (passenger. km)
20	Current Situation	8,204.100.00	3573	344,7945
	#1	3,979.043.00	2378	229,477
	#2	4,100.112.60	1244	120,046
	#3	3,936.308.00	1273,6	122,9024
	#4	3,804.200.00	1291,8	124,6587
30	#1	1.833.170.00	2481	239,4165
	#2	1.809.873.30	1330,8	128,4222
	#3	1.179.308.00	1265,7	122,14005
	#4	1.559.600.00	1332,6	128,5959
50	#1	756.358.00	2785	268,7525
	#2	774.641.30	1483,5	143,15775
	#3	768.612.00	1690	163,085
	#4	8,204.100.00	1494,5	144,21925

In the light of this information, it is seen that carbon emissions have decreased significantly for each scenario implemented. For the lowest carbon emission, routing should be done with the p-median scenario with vehicles with a capacity of 20. In this case, if routing is done with scenario 2, there will be a 65% reduction in carbon emissions compared to the current situation.

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

In this study, a real-life problem was discussed. The problem of moving the personnel of a carpet company operating in Gaziantep was studied. Kartal Carpet and Textile Company is a large-scale carpet and yarn production company operating in Gaziantep, with a domestic and international sales portfolio. The company employs approximately 1500 workers. Employees come to the company in the morning and leave the company in the evening every day. The company provides a shuttle service to its employees. This service includes picking up each personnel from their homes in the morning and leaving them to the company, and distributing each personnel taken from the firm to their homes in the evening. 1361 personnel benefit from the transportation service offered by the company. The problem of collecting 1361 personnel from their homes and bringing them to the company covers SBRP problems, which is a type of VRP.

The problem studied within the scope of the thesis; it was aimed to minimize the total distance required to transport the employees to the factory. In the current situation analysis, it was determined that the company did not apply a scientific method during the transportation process and the capacity of the vehicles was not used efficiently. Currently, 85 shuttle services are provided for the transportation of 1361 personnel, and each personnel is picked up in front of their homes. All services have homogeneous capacities of 20 people.

Firstly, staff addresses were collected to reach distance information. The 1361 personnel address data collected was marked on the map using Google Earth. Google Earth markings were made by coding according to the departments of the staff. Geographical location data of 1361 points marked using Google Earth tools were obtained and the distances between the coordinates were calculated. For the solution of the examined problem, different scenarios were considered and implemented both in the solution method and in the capacity. Capacity constraints of vehicles were taken into account in all scenarios. All scenarios were run with three different vehicle capacities, 20, 30, and 50. Each scenario was solved using Python 3.8- Gurobi 9.1.1

programming language. Due to the size of the problem, feasible solutions were obtained by considering the three-hour time limit.

The first scenario is CVRP, which is the most common type of ARP in the literature. The method also currently used by the company is CVRP. However, the results were different as the capacities of the service vehicles were not used efficiently. In the first scenario implemented, each personnel were taken from their home and brought to the company without clustering. 1361 employees were transported in front of their homes in vehicles with three different capacities and the results were recorded. The other 3 scenarios applied include clustering methods. A central station was selected by clustering personnel addresses and working according to the logic of personnel walking to the centers selected for them. Among the clustering methods, the three most suitable methods for the problem were selected and studied according to three different capacities. The clustering methods studied are P-median, P-Center, and K-means. In this case, the 2nd scenario was determined as P-Median, the 3rd scenario as K-means, and the 4th scenario as P-Center.

It was concluded that the total distance for all 4 scenarios decreased with the increase in capacity. The total distance was calculated as the distance traveled by vehicles only for CVRP. However, in the clustering methods (P-median, P-Center, and K-means), the walking distance of the personnel was added to the path traveled by vehicles while calculating the total distance. The results achieved with vehicles with 20, 30, and 50 capacities were compared. When the total distance covered in the current situation is compared, it is concluded that all 4 scenarios give better results. When the 4 scenarios were compared within themselves, it was determined that the first scenario, CVRP, gave the longest total distance. The minimum overall distance is obtained when workers are clustered with the P-median and a 50-seat bus is used. On the other hand, clustering with a bus with a capacity of 30 people with the K-means approach gives the minimum total walking distance.

In the 4 different scenarios solved for the problem examined within the scope of the thesis problem, different results were obtained to be evaluated both for the personnel requests and the profit of the company. In this respect, the solution to the problem has been made flexible according to demand and need. In addition, different scenarios offered decision-makers the opportunity to change transportation services according to their preferences. The problem examined within the scope of the thesis has been added to the literature by bringing a multi-faceted solution with different needs and requests. In companies working with the shift system, the same vehicle brings the blue-collar workers in the first shift to the company and distributes the blue-collar workers in the second shift to their homes. For this reason, personnel transportation can be examined as a time-limited problem suitable for the shift system. In addition, the personnel transportation problem can be examined in the dynamic vehicle routing class suitable for real-life scenarios. In this case, road and traffic conditions can be taken into account.

REFERENCES

[1] Braca, J., Bramel J., Posner B., SimchiLevi D. (1997). A computerized approach to the New York City school bus routing problem, *IIE Transactions*. **29(8)**, 693-702.

[2] Laporte, G., Nobert, Y., Taillefer, S. (1988). Solving a Family of Multi-Depot Vehicle Routing and Location-Routing Problems. *Transportation Science*. **22(3),** 161–172.

[3] Pala, O., Aksaraylı, M. (2018). Çok amaçlı kapasite kısıtlı araç rotalama problemi çözümünde bir karınca kolonisi optimizasyon algoritması yaklaşımı. *The Journal of Operations Research, Statistics, Econometrics and Management Information Systems*, **6**, 37-48.

[4] Toth, P., Vigo, D. (2014). *Vehicle Routing: Problems Methods Applications*. MOS-SIAM series on optimization Philadelphia, PA, USA.

[5] Uzumer, E., Eren, T. (2012). Okul Servisi Rotalama Problemi: Bir Uygulama. *International Journal of Engineering Research and Development*, **4(2)**, 26-29.

[6] Farzadnia, F., Lysgaard, J. (2021). Solving the service-oriented single-route school bus routing problem: Exact and heuristic solutions, *EURO Journal on Transportation and Logistics*, **10,** 100054.

[7] Atan, M., Yaşar, Z.R., Öksüzkaya, M. (2019). Vehicle Rotation Problem in Personnel Transport Services, *II. International Congress of Business, Economics, and Marketing*. 39-50.

[8] Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem, *Management Science*. **6(1)**, 80-91.

[9] Pillac, V., Gendreau, M., Guéret, C., & Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European Journal of Operational Research*, **225(1),** 1-11.

[10] Muzulon, N. Z., Ferrari, G. N., Turra, A. E., Leal, G. C. L., & Lima, R. H. P. (2022). Proposal of a method for routing school buses in a small-sized county. *Acta Scientiarum. Technology,* **44(1),** e58638.

[11] Rashidi, T. H., Zokaei-Aashtiani, H., & Mohammadian, A. (2009). School bus routing problem in large-scale networks: new approach utilizing tabu search on a case study in developing countries. *Transportation Research Record*, **2137(1),** 140-147.

[12] Bowerman, R., Hall, B., Calamai, P., (1995). A multi-objective optimization approach to urban school bus routing: Formulation and solution method. Transportation Research Part A: Policy and Practice. **29 (2)**, 107–123.

[13] Chapleau, L., Ferland, J.A., Rousseau, J.M., (1985). Clustering for routing in densely populated areas. *European Journal of Operational Research*. **20 (1)**, 48–57.

[14] Park, J., Kim, B., (2010). The school bus routing problem: A review, *European Journal of Operational Research*. **202 (2)**, 311–319.

[15] Ellegood, W.A., Solomon, S., North, J., Campbell, J.F., (2019). School bus routing problem: Contemporary trends and research directions. *Omega,* 102056.

[16] Martínez, L.M., Viegas, J.M., (2011). Design and deployment of an innovative school bus service in Lisbon. *Procedia Social Behavioral Sciences.* **20,** 120–130.

[17] Riera-Ledesma, J., Salazar-González, J.-J., (2012). Solving school bus routing using the multiple vehicles traveling purchaser problem: A branch-and-cut approach. *Computers & Operations Research.* **39 (2),** 391–404.

[18] Uzuner, E., Eren, T. (2012). Okul Servisi Rotalama Problemi: Bir Uygulama. *International Journal of Engineering Research and Development.* **4(2),** 26-29.

[19] Park, J., Tae, H., & Kim, B.-I. (2012). A post-improvement procedure for the mixed load school bus routing problem. *European Journal of Operational Research*, **217(1),** 204-213.

[20] Kim, B. I., Kim, S., & Park, J. (2012). A school bus scheduling problem. *European Journal of Operational Research,* **218(2),** 577-585.

[21] Ellegood, W.A., Campbell, J.F., North, J. (2015). Continuous approximation models for mixed load school bus routing. *Transportation Research Part B: Methodological*. **77,** 182–198.

[22] López Santana, E. R., & Romero Carvajal, J. D. J. (2015). A hybrid column generation and clustering approach to the school bus routing problem with time windows. *Ingeniería*, **20(1),** 101-117.

[23] Schittekat, P., Kinable, J., Sörensen, K., Sevaux, M., Spieksma, F., Springael, J., (2013). A metaheuristic for the school bus routing problem with bus stop selection. *European Journal of Operational Research.* **229 (2),** 518–528.

[24] Kinable, J., Spieksma, F.C.R., Berghe, G.V., (2014). School bus routing—A column generation approach. *International Transactions in Operational Research.* **21 (3)**, 453–478.

[25] Caceres, H., Batta, R., He, Q. (2017). School bus routing with stochastic demand and duration constraints. *Transportation Science.* **51,** 1349–1364.

[26] Mohammed, M. A., Ghani, M. K. A., Hamed, R. I., Mostafa, S. A., Ahmad, M. S., & Ibrahim, D. A. (2017). Solving vehicle routing problem by using improved genetic algorithm for optimal solution. *Journal of Computational Science*, **21**, 255-262.

[27] Sales, L. P. A., Melo, C. S., Bonates, T. O., & Prata, B. A. (2018). Memetic algorithm for the heterogeneous fleet school bus routing problem. *Journal of Urban Planning and Development*,**144(2).**

[28] Ünsal, Ö. ve Yiğit, T. (2018). Yapay zekâ ve kümeleme teknikleri kullanılarak geliştirilen yöntem ile okul servisi rotalama probleminin optimizasyonu. *Mühendislik Bilimleri ve Tasarım Dergisi,* **6(1),** 7-20

[29] Albayrak, S. (2019). Okul servisi araçlarını rotalama problemi için yenilikçi bir yaklaşım. *Master's Thesis*. Ankara: Hacettepe Üniversitesi.

[30] Atan, M., Yaşar, Z., R., Öksüzkaya, M. (2019). Vehicle Rotation Problem in Personnel Transport Services. *II. International Congress of Business, Economics and Marketing*. 39-50.

[31] Calvete, H.I., Galé, C., Iranzo, J.A., Toth, P., (2020). A partial allocation local search matheuristic for solving the school bus routing problem with bus stop selection. *Mathematics*. **8 (8),** 1214.

[32] Farzadnia, F., Lysgaard J, (2021). Solving the service-oriented single-route school bus routing problem: Exact and heuristic solutions. *EURO Journal on Transportation and Logistics.* **10,** 100054.

[33] Durak, P. (2021). *Personel Servisi Rotalama Probleminin Optimizasyonu.* Master's Thesis. Eskişehir: Eskişehir Teknik Üniversitesi.

[34] Şahin, H. (2021). *Çoklu Öğrenci Servislerinin Rota Optimizasyonu.* Master's Thesis. İstanbul: İstanbul Kültür Üniversitesi.

[35] Liu, Z., Gang, L., Yu, B., Zhang, H. (2022). The Routing Problem for School Buses Considering Accessibility and Equity. *Transportation Research Part D: Transport and Environment.* **107,**103299.

[36] Peker, G., & ELİİYİ, D. T. (2022). Shuttle bus service routing: A systematic literature review. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*. **28(1),** 160-172.

[37] Peker, G., & ELİİYİ, D. T. (2023). Employee Shuttle Bus Routing Problem: A Case Study. *European Journal of Science and Technology*. **46,** 151-160.

[38] Wang, J., Lian, Z., Liu, C., Liu, K. (2023). Iterated clustering optimization of the split-delivery vehicle routing problem considering passenger walking distance, *Transportation Research Interdisciplinary Perspectives*. 17, 100751.

[39] Newton, R. M., & Thomas, W. H. (1969). Design of school bus routes by computer. *Socio-Economic Planning Sciences*, **3(1),** 75-85.

[40] Garside, A. K., & Laili, N. R. (2019). A Cluster-First Route-Second Heuristic Approach to Solve the Multi-Trip Periodic Vehicle Routing Problem. *Jurnal Teknik Industri*. **20(2),** 172–181.

[41] Kassem, S., Korayem, L., Khorshid, M., Tharwat, A. (2019). A hybrid bat algorithm to solve the capacitated vehicle routing problem. *Novel Intelligent and Leading Emerging Sciences Conference (NILES).* **1,** 222-225.

[42] Putri, K. A., Rachmawati, N. L.., Lusiani, M., Redi, A. A. N. P. (2021). Genetic Algorithm with Cluster-first Route-second to Solve the Capacitated Vehicle Routing Problem with Time Windows: A Case Study. *Jurnal Teknik Industri.* **23(1),** 75-82.

[43] Dutta, J., Barma, P. S., Mukherjee A., Kar, S., De, T. (2019). A hybrid multi-objective evolutionary algorithm for open vehicle routing problem through cluster primary-route secondary approach. *International Journal of Management Science and Engineering Management.* **17(2),** 132–146

[44] Ibrahim A.A, Lo N., Abdulaziz R.O, and Ishaya J.A (2019). Capacitated Vehicle Routing Problem. *International Journal of Research – Granthaalayah.* **7(3),** 310-327.

[45] Laporte, G., Nobert, Y., Taillefer, S., (1988). Solving a family of multi-depot vehicle routing and location routing problems. *Transportation Science.* **22 (3),** 161-172.

[46] Gupta, A., Saini, S., (2017). An Enhanced Ant Colony Optimization Algorithm for Vehicle Routing Problem with Time Windows, *Ninth International Conference on Advanced Computing (ICoAC)*. 10, 267-274.

[47] Cordeau, J-F., Gendreau, M., Laporte, G., Potvin, J-Y., Semet, F. (2002). A guide to vehicle routing heuristics. *Journal of the Operational Research Society.* **53,** 512- 522.

[48] Karagül, K. (2013). Turistlerin otellere dağıtım problemine bir çözüm önerisi ve Alanya'da bir uygulama. *PhD Thesis*. Isparta: University of Süleyman Demirel Üniversitesi.

[49] Bektaş, T., Elmastaş, S. (2007). Solving school bus routing problems through integer programming*, Journal of the Operational Research Society.* **58,** 1599-1604.

[50] Dursun, P. (2009). Zaman pencereli araç rotalama problemi 'nin genetik algoritma ile modellenmesi. *Master's Thesis.* İstanbul Teknik University. İstanbul.

[51] Erol, V. (2006). Araç rotalama problemleri için popülasyon ve komşuluk tabanlı metasezgisel algoritmanın tasarımı ve uygulaması. *Master's Thesis.* Yıldız Teknik University. İstanbul.

[52] Ünsal, M.Ç. (2010). Açık Uçlu Araç Rotalama Problemi: M.T.A. Servis Güzergâhlarının Belirlenmesi. *Master's Thesis.* The University of Gazi. Ankara.

[53] Eligüzel, İ.M., Yağbasan, N.S., Özceylan, E. (2021). Investigating Alternative Routes for Employee Shuttle Services Arising in a Textile Company: A Comparative Study, *Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems*. **634,** 68-76.

[54] Demir, E. (2008). Okul Taşıtları Rotalama Problemi İçin Tamsayılı Karar Modelleri. *Master's Thesis.* Baskent University. Ankara.

[55] Newton, Rita M., Thomas, Warren H., (1969). Design of school bus routes by computer. *Socio-Economic Planning Science,* **3**, 75-85.

[56] Mumford, C. (2017). Research on the urban transit routing problem (bus routing). structure, 2, y2.

[57] Atan, M., Yaşar, Z. R., Öksüzkaya, M (2019). Vehicle Rotation Problem in Personnel Transport Services. *Economics And Marketing 18-20,* Istanbul, 39-50.

[58] Zhou, B., Lu, B., Saeidlou, S. (2022). A Hybrid Clustering Method Based on the Several Diverse Basic Clustering and Meta-Clustering Aggregation Technique. *Cybernetics and Systems,* DOI: 10.1080/01969722.2022.2110682.

[59] Yaghini, M., Momeni, M., Sarmadi, M., and Ahadi, H. (2013). An efficient heuristic algorithm for the capacitated p-median problem. *4OR: Quarterly Journal of the Belgian, French and Italian Operations Research Societies,* **(11),** 229–248.

[60] Daskin, M.S. and Maass, K.L. (2015). The p-Median Problem. In Laporte, G., Nickel, S., and Saldanha da Gama, F. (Eds.), *Location Science, Springer International Publishing,*21-45.

[61] Herda, M. (2015). Combined Genetic Algorithm for Capacitated p-Median Problem. *Proceedings of the 16th IEEE International Symposium on Computational Intelligence and Informatics, CINTI 2015,* 151–154.

[62] Morales, S.O., Rahim, A. (2017). Heuristic for the Capacitated p-Median Problem under a CVRP Approach. *7th Annual International Conference on Industrial Engineering and Operations Management.*

[63] Shamsipoor, H., Sandidzadeh, M.A., Yaghini, M. (2012). Solving capacitated P-median problem by a new structure of neural network. *The International Journal of Industrial Engineering: Theory, Applications and Practice.* **19(8),** 305–319.

[64] Demiriz, A., Bennett, K.P., Bradley, P.S. (2008). Using assignment constraints to avoid empty clusters in k-means clustering. *In: Constrained Clustering: Advances in Algorithms, Theory, and Applications,* **201.**

[65] A. Kaveh, H. Nasr. (2011). Solving the conditional and unconditional p-center problem with modified harmony search: A real case study. *Scientia Iranica.* **18(4),** 867-877.

[66] Bildirici, İ. Ö., Böge, S. (2010). Google Map API Teknolojisi ile Web Harita Uygulamaları. *Akademik Bilişim Konferansı Bildirileri.* 133-140.

[67] Mohammed, N.Z., Ghazi, A. ve Mustafa, H.E. (2013). Positional Accuracy Testing of Google Earth. *International Journal of Multidisciplinary Sciences and Engineering,* **4(6),** 2045-7057.

[68] Greenhouse gas reporting: conversion factors (2022), Greenhouse gas reporting: conversion factors 2022 - GOV.UK (www.gov.uk) .

APPENDIX

	Kartal Halı Servis Güzergahları Çizelgelemesi
Taşınan Personellerin Vardiyaları (Birinizi seçiniz)	08:00-16:00 Vardiya veya Daimi Gündüz Servisi ☐
	16:00-00:00 Vardiya Servisi ☐
	00:00-08:00 Vardiya Servisi ☐
	08:00-18:00 Personel Servisi ☐
	08:00-18:00 Daimi Gündüz Servisi ☐
Servis Numarası:	
Servis Plakası:	
Servis Şöför Adı:	
Servis Şoför Adresi:	
Servis süresinde yapılan Kilometre(Fabrikaya Geliş):	
Servis süresinde yapılan Kilometre(Fabrikadan Dönüş):	
Mevcut Taşınan Personel Sayısı(Ortalama) :	

Figure A.1 Form 1 Used for Current Situation Analysis

PERSONEL LİSTESİ

	AD SOYAD	AÇIK ADRES	SERVİSE BİNDİĞİ DURAK
1			
2			
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BİLGİLERİ 15 MART-21 MART VARDİYA DÜZENİNE GÖRE DOLDURUNUZ.

ADRES DOĞRULUĞU ÇOK ÖNEMLİDİR.LÜTFEN DOĞRU VE GÜNCEL ADRES BİLGİLERİNİ YAZALIM.

Figure A.2 Form 2 Used for Current Situation Analysis

CURRICULUM VITAE (CV)

Name Surname: Nur Sena ERTEM

Education Information

- Gaziantep University, Faculty of Engineering, Industrial Engineering GPA:3.25/4.00, Continuing – Master's Degree
- Gaziantep University, Faculty of Engineering, Industrial Engineering GPA:2.63/4.00 – Bachelor's Degree

Work Experience

- Planning Engineer- Lotus İplik (June 2019-September 2019)
- Planning Engineer and Order Preparation Specialist – Kartal Halı & Tekstil (September 2019-December 2021)

Publications and Conferences

- Eligüzel, İ.M., Yağbasan, N.S., Özceylan, E. (2021). Investigating Alternative Routes for Employee Shuttle Services Arising in a Textile Company: A Comparative Study, *Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems*. **634,** 68-76.

- Ertem, N.S., Günaydın G., Özceylan, E. (2023). 3D-Printing Impacts on Türkiye's Defense Industry: An Implementation of SWOT and DEMATEL Methods. *6th European Conference on Industrial Engineering and Operations Management. Lisbon, Portugal, July 18-20, 2023*

- Ertem, N.S., Günaydın G., Özceylan, E. (2023). The Role of Stakeholders and Their Participation in Additive Manufacturing Technology Roadmapping: A Case of a Defense Industry. 4th South American Conference on Industrial Engineering and Operations Management. Lima, Peru, May 9-11, 2023