

A MULTI DEPOT VEHICLE ROUTING PROBLEM WITH TIME WINDOW FOR DAILY PLANNED MAINTENANCE AND REPAIRMENT PLANNING



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A MULTI DEPOT VEHICLE ROUTING PROBLEM WITH TIME WINDOW FOR DAILY PLANNED MAINTENANCE AND REPAIRMENT PLANNING

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ABSTRACT

A compressor manufacturer producing in Kocaeli/Dilovasi region makes vehicle routing and employee planning daily to fulfill the maintenance and repair requests of the Marmara region and its surroundings the next day. The service types and times are agreed upon with the customer before service planning. The vehicles and their respective operators for a given planning day are known, with the service personnel's starting and ending points being the residences. All the planned services must be satisfied in the time windows customers give. We deal the issue as a multi-depot vehicle routing problem with time windows (MDVRPTW) and construct a mixed-integer linear programming framework. The mathematical model solution is sufficient to solve the company's 3.000-6.000 maintenance demand problems. A clustering heuristic that provides a good solution in a short time has been developed to solve large instances of malfunction and part replacement requests coming to the vehicle routing and after-sales service side.

Keywords: Multi Depot, Vehicle Routing Problem, Time Window

ÖZETÇE

Kocaeli/Dilovası bölgesinde üretim yapan bir kompresör üreticisi, Marmara bölgesi ve çevresinin ertesi günkü bakım ve onarım talebini karşılamak için günlük olarak araç rotalama ve personel planlaması yapmaktadır. Servis planlamasından önce servis türleri ve süreleri müşteri ile kararlaştırılır. Planlama günü mevcut araçlar ve operatörleri belirlidir, başlangıç ve bitiş noktaları çalışanların evleridir. Tüm talepler, müşteriler tarafından verilen zaman pencerelerinde karşılanır. Araç yönlendirmesi tüm taleplere cevap verecek şekilde planlanır. Problem, Zaman Pencereli Çok Depolu Araç Rotalama problemi (MDVRPTW) olarak ele alınmaktadır ve bir karma tamsayılı doğrusal programlama modeli geliştirilmiştir. Matematiksel model çözümü şirketin 3.000-6.000 bakım talep problemini çözmeye yeterlidir. Arıza ve parça değişimi taleplerinin araç rotalaması ve satış sonrası hizmet tarafına gelen büyük örnekleri çözmek için, kısa sürede iyi bir çözüm sağlayan bir kümeleme buluşsal yöntemi geliştirilmiştir.

Anahtar Kelimeler: Çoklu Depo, Araç Rotalama Problemi, Zaman Penceresi

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CHAPTER I

INTRODUCTION

The Vehicle Routing Problem (VRP) is a challenging optimization problem that involves determining the most efficient assignment of multiple customer locations to a fleet of vehicles. The objective is to create optimized routes for a set of vehicles that start and end their routes at a central depot. VRP is a well-known and extensively studied problem in the field of operations research. Large companies face complex vehicle routing problems in their distribution networks, where they aim to minimize distribution costs while providing high-quality services to their customers. Customer satisfaction is a crucial factor in this industry, and companies strive to provide fast and efficient delivery services. VRP the primary objective is to gain a thorough understanding of the vehicle routing methodology and apply it to a real-life distribution problem. Firstly, the problem is defined, and all the constraints are identified. Then, extensive research is conducted to gather relevant data such as vehicle types, their capacity, the number of vehicles required, the locations of the customers, distances between customers, the amount of product to be distributed, and the total cost of operations.

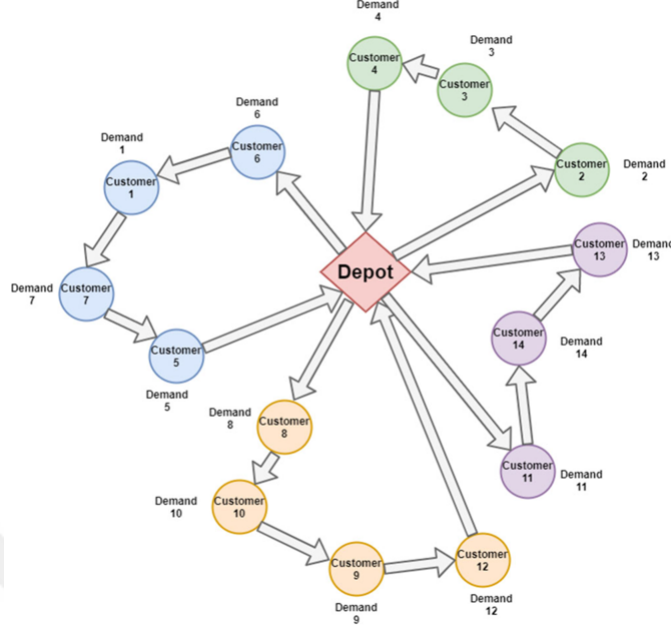


Figure 1: VRP

The Multi-Depot Vehicle Routing Problem (MDVRP) is a complex optimization problem that entails determining the most efficient allocation of customer locations to a fleet of vehicles originating and concluding their routes at multiple depots. The primary objective of this problem is to minimize the overall distance traveled by the vehicles, while simultaneously adhering to several constraints, including vehicle capacity, time windows, and delivery deadlines. MDVRP can be considered as an extension of the well-known Vehicle Routing Problem (VRP), which assumes a solitary depot. Due to its significant applications within the domains of logistics and transportation industries, MDVRP has garnered considerable attention within the field of operations research. It is worth noting that MDVRP falls into the category of NP-hard problems, which indicates that finding an optimal solution becomes computationally infeasible for instances involving large-scale scenarios. Consequently, researchers have focused on developing various heuristic and metaheuristic approaches to obtain high-quality solutions within reasonable computational timeframes[1]. Additionally, MDVRP exhibits numerous variants that incorporate diverse constraints and requirements. For

instance, the Capacitated Multi-Depot Vehicle Routing Problem (C-MDVRP) considers vehicle capacity, the Multi-Depot Vehicle Routing Problem with Time Windows (MDVRPTW) incorporates time windows for deliveries, and the Multi-Depot Vehicle Routing Problem with Backhauls (MDVRPB) allows for the retrieval of goods from customers in addition to their delivery. The practical applications of MDVRP span across multiple industries, including transportation, logistics, and supply chain management. By utilizing MDVRP, companies operating within these sectors can optimize their vehicle routing, reduce costs, and enhance customer service. However, it is important to acknowledge that the complexity of the problem, the multitude of constraints involved, and the necessity to balance different objectives continue to pose significant challenges. Nonetheless, MDVRP remains a formidable optimization problem with wide-ranging applications and ongoing research efforts dedicated to its resolution.

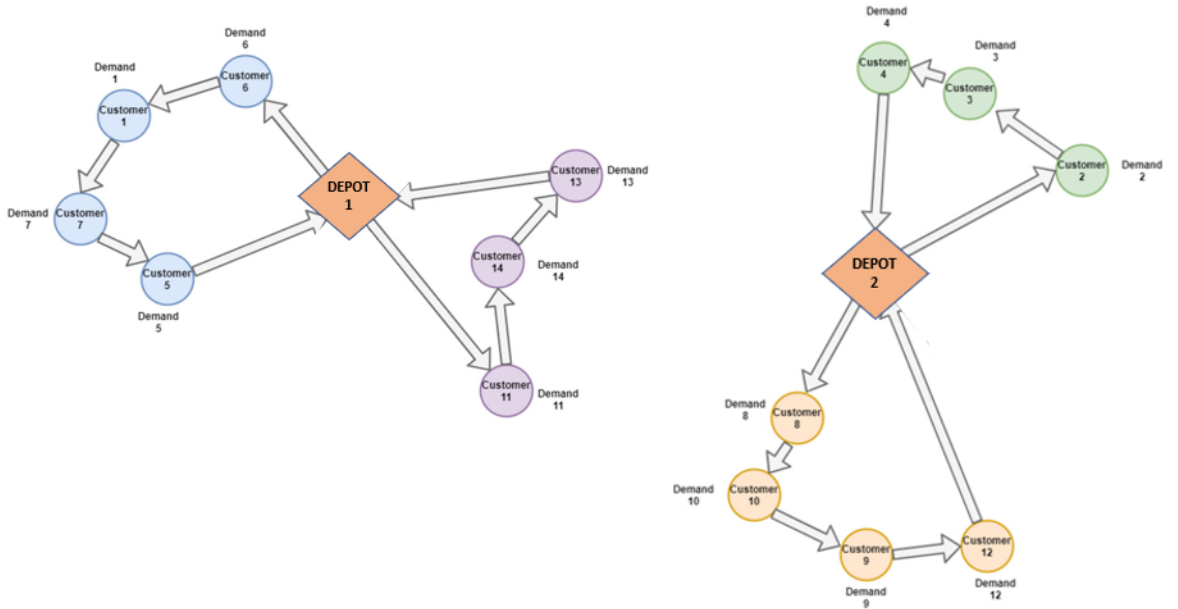


Figure 2: Multi Depot VRP

This thesis focuses on Dalgakiran Compressor, which was established in 1965 and

has become a renowned manufacturer of industrial compressors in Turkey. The company operates in Sancaktepe, Istanbul and exports seventy percent of its products to over 130 countries worldwide through its international branches in Russia, the USA, Ukraine, and Germany. Dalgakıran Compressor places a strong emphasis on after-sales service, which is a critical aspect of the company's marketing strategy. The company aims to promptly address customer maintenance and repair requests through competent service personnel, recognizing that after-sales service can significantly impact customer loyalty and satisfaction. In today's highly competitive market, where products are becoming increasingly similar, companies must focus on providing high-quality pre-sales, customer experience, and after-sales services. After-sales service includes a range of free services such as a return policy, technical support, installation, software support, shipping, and basic warranty coverage for maintenance and repair. These services can be crucial differentiators for a company and heavily influence consumer purchasing decisions.

In today's competitive marketplace, the importance of services and service businesses has significantly grown. Among these services, after-sales service activities hold great significance in maintaining customer satisfaction and fostering long-term relationships. Businesses that provide prompt and effective support, addressing any issues that arise after a sale, demonstrate their commitment to customer satisfaction and gain a competitive advantage in the market. After-sales services are instrumental in ensuring customer satisfaction and fostering customer loyalty. By offering activities that address potential problems during product use and enhance the value of consumption post-sale, businesses can establish and maintain customer trust. Customers are often influenced by the quality of after-sales services provided when making purchasing decisions[2]. Consumers place importance on the after-sales services associated with a product, recognizing the added value it brings. The provision of comprehensive after-sales services can help to differentiate products in the market

and influence consumer choices. When businesses prioritize after-sales service activities, they cater to the needs and concerns of their customers, ultimately enhancing their satisfaction and loyalty. In summary, after-sales services are integral in meeting customer expectations and building enduring relationships. Customers consider the after-sales services offered when making purchasing decisions, particularly for durable consumer goods. By prioritizing after-sales services, businesses can enhance customer satisfaction and loyalty, differentiate themselves in the market, and ultimately drive increased sales and revenue. Hence, after-sales service should be viewed as a critical investment in long-term success.

Dalgakıran Compressor is well aware of the crucial role that after-sales services play in influencing customer preference for their products over those of other brands. The company has made it a key priority to provide reliable and efficient after-sales services to its customers. To achieve this goal, the company has implemented a range of after-sales service plans that have been developed with the assistance of experienced planners and intuitive vehicle routing. However, it is important to note that these approaches can often be time-consuming and prone to errors. The primitive processes of after-sales service planning can result in excessive traveling and unmet customer service demands, which can lead to additional costs for the company. To optimize the guidance of vehicles and ensure efficient delivery of after-sales services, it is essential to rely on scientific methods and expert opinions. Advanced scientific approaches can help overcome the challenges faced by companies in providing effective after-sales services. Effective after-sales service can bring numerous benefits to companies. It can help to enhance customer loyalty and satisfaction, which are critical aspects of a company's marketing strategy. It can also be a significant differentiator for a company in a highly competitive market where products are becoming increasingly similar. Companies must prioritize providing high-quality pre-sales, customer experience, and after-sales services to gain a competitive edge in the market.

After-sales services typically include a range of free services such as technical support, installation, software support, shipping, and basic warranty coverage for maintenance and repair[3]. These services can play a critical role in influencing consumer purchasing decisions. Customers are more likely to choose products from companies that offer reliable after-sales services, as it assures them that they can count on the company to support them even after the sale.

Dalgakıran Compressor's emphasis on providing high-quality after-sales services is a crucial aspect of their business strategy. Through the implementation of advanced scientific methods and expert opinions, the company can ensure optimal guidance of vehicles and efficient delivery of after-sales services. By prioritizing after-sales service, companies can enhance customer loyalty and satisfaction, gain a competitive edge in the market, and ultimately achieve long-term success.

The main purpose of this thesis is to investigate the after-sales service planning problem for Dalgakıran Company and devise a solution to minimize transportation costs by optimizing vehicle routes. The service planning department determines the routes of each vehicle based on customer locations, service time windows, and service types provided by the service personnel. The primary objective is to minimize the distance traveled by each vehicle while servicing the customers, thereby reducing transportation costs. To achieve this, each vehicle is assigned to a specific service personnel, and the service tour begins and ends at the service personnel's residence. The problem is known as the Multiple Depot Vehicle Routing Problem with Time Windows (MDVRPTW). In this problem, vehicles originate from designated depots, adhere to predetermined time windows during service, and ultimately complete their tours by returning to their point of origin. The MDVRPTW is a challenging problem that requires sophisticated algorithms and optimization techniques because it includes multiple depots, time windows, and dynamic nature. The MDVRPTW has been addressed using various heuristic methods, such as local search, tabu search, genetic

algorithm, and hierarchical hybrid meta-heuristic. These methods can provide an optimized solution to the problem by minimizing transportation costs, thereby improving after-sales service quality and customer satisfaction. However, each method has its advantages and disadvantages, and the choice of a particular method depends on the specific problem requirements. After-sales service planning is a complex problem that requires careful consideration to provide an optimal solution. The MDVRPTW is a more intricate and demanding challenge compared to other forms of the VRP [4]. Hence, selecting the most appropriate heuristic method and developing an efficient algorithm are crucial to resolving this problem. Ultimately, an optimized solution to the MDVRPTW can improve after-sales service quality, reduce transportation costs, and enhance customer satisfaction.

In this thesis, a mathematical model has been developed to address the MDVRPTW problem. The model provides a powerful tool for enhancing the efficiency and effectiveness of the after-sales service operations of the company. With the aim of solving the problem of serving the demands of 10-15 customers daily, the proposed mathematical model is deemed sufficient. However, the model may not be sufficient to produce optimal solutions in cases where there are many customers and when malfunction and maintenance demands are added. To address this issue, a clustering heuristic has been developed. The heuristic is designed to cluster the customers based on the service capacity of the vehicles, thereby providing a fast and efficient solution. Clustering is a technique that groups similar objects or data points together. By clustering the customers based on the service capacity of vehicles, the heuristic aims to minimize the distance traveled by the service vehicles while meeting the demands of all customers. The developed heuristic is particularly useful when there are high numbers of customers to be served. In such cases, the mathematical model may take a long time to solve the problem optimally, making it impractical for practical purposes. The clustering heuristic, on the other hand, provides an effective solution

quickly. It helps to optimize the service operations of the company, thereby reducing transportation costs and improving customer satisfaction. Overall, the combination of the mathematical model and the clustering heuristic provides an effective solution to the MDVRPTW problem[5]. The model serves as a powerful tool to optimize service operations, while the heuristic offers a quick solution for large instances of the problem. By utilizing these techniques, the company can improve its after-sales service operations, reducing transportation costs and improving customer satisfaction.

The remaining sections of this paper are organized as follows. Section 2 comprises the literature review and our original contributions. Section 3 provides a comprehensive definition of the problem at hand. The developed mathematical model and heuristic are given in Section 4. In Section 5, the computational experiments are presented. The subsequent sections will provide the conclusion and potential avenues for future research, which are outlined in Section 6.

CHAPTER II

LITERATURE REVIEW

The Vehicle Routing Problem (VRP) is a complex issue within integer programming, and finding the most optimal solutions can be a significant challenge. The Vehicle Routing Problem (VRP) is commonly acknowledged as one of the most intricate challenges in the field of integer programming [6]. The VRP has been the subject of extensive research in the context of heterogeneous fleets, where multiple types of vehicles are employed. A variant of the VRP that merits attention is the Fleet Size and Mix Vehicle Routing Problem (FSMVRP), which introduces additional complexity by not fixing the number of available vehicles for each type [7]. Another variation of the VRP is the VRP with Backhauls (VRPB), which simultaneously considers delivery and pickup services for customers [8]. The combination of FSMVRP and VRPB presents a realistic and practical challenge in the field of routing and logistics distribution [9]. Contemporary research on the VRP has expanded to encompass practical scenarios involving overtime and capacity overload. To address VRPTWVOV in Literatur a mixed-integer programming model and a genetic algorithm to address the VRPTWVOV, which incorporates driver overtime and vehicle outsourcing into the problem [10]. Some studies have proposed a decentralized deployment approach that addresses large-scale operations with additional service level constraints[11]. They also proposed an ant colony algorithm to optimize delivery schedules. Furthermore, they introduced an expert system that utilizes the aforementioned algorithm to improve the overall quality of customer service.

The Vehicle Routing Problem with Time Windows (VRPTW) is a widely recognized combinatorial optimization problem that involves serving customers in different

geographical locations while adhering to specific time constraints[12]. The MDVRP can be viewed as an extension of the traditional Capacitated Vehicle Routing Problem (CVRP), which is known to be a difficult combinatorial problem. Typically, heuristics are used to solve the CVRP [13]. However, the availability of integer programming software systems has greatly improved the ability to solve larger CVRP instances [14]. The MDVRP is a generalized form of the Capacitated Vehicle Routing Problem (CVRP), which is a challenging combinatorial problem typically [13]. However, with the progress in integer programming software systems, the ability to solve larger problem. [14].

However, for the MDVRP, there are limited exact algorithms available in the literature, while several heuristic procedures have been proposed.[15] , a literature review on the MDVRP showed that only 25 percent of the works employed exact solution techniques, while the remaining 75 percent used heuristics or meta-heuristics techniques.

In contrast to heuristics, exact algorithms provide guarantees of optimality, and their solution quality is independent of user expertise or problem characteristics. However, developing exact algorithms for the MDVRP is challenging due to the problem's combinatorial complexity. Despite this difficulty, several researchers have attempted to develop exact algorithms for the MDVRP. [16] For instance, developed branch and bound algorithms for solving the symmetric and asymmetric versions of the MDVRP [17]. More recently, Baldacci proposed an exact method for solving the Heterogeneous Vehicle Routing Problem (HVRP), which is capable of solving the MDVRP[18]. Their algorithm is based on the set partitioning formulation, where routes are generated using a procedure followed by three bounding procedures to reduce the number of variables. In the set partitioning formulation, variables represent the previously generated routes. The authors presented computational results for MDVRP instances

with up to 200 customers and 2–5 depots. Additionally, Bettinelli, Ceselli, and Righini proposed a branch-and-cut-and-price algorithm for the multi-depot heterogeneous vehicle routing problem with time windows, considering different combinations of cutting and pricing strategies[19]. The results of three different sets of experiments over three datasets of instances were explored [20] . Furthermore, Contardo and Martinelli presented a new exact method for the MDVRP based on variable fixing, column-and-cut generation, and column enumeration [21]. The proposed method was able to prove optimality for the first time for some benchmarking instances. While exact algorithms provide optimality guarantees, their application to large-scale problem instances remains a challenge due to the computational complexity of these problems.

MDVRPTW is an extension of the VRP that adds an additional layer of intricacy by integrating time windows and multiple depots, thereby establishing its NP-hardness in the strong sense. The primary objective of the MDVRPTW is to identify the most efficient routes for the vehicles to serve customers while complying with time window constraints and minimizing the total cost of transportation.[22] The complexity of MDVRPTW further increases with the inclusion of heterogeneous service vehicles and supplementary service level constraints. MDVRPTW is intrinsically interconnected with other combinatorial optimization problems, notably the Location Routing Problem (LRP)[23] . The LRP revolves around pinpointing the most favorable locations for depots, as well as their optimal operational timetables, taking into account the specific routes taken by the vehicles. The Fleet Size and Mix Vehicle Routing Problem (FSMVRP) is another variant that considers the presence of vehicles with varying fixed costs within a given fleet[24]. The Vehicle Routing Problem with Release Dates (VRPRD) is a recent extension to the Vehicle Routing Problem literature. In this variant, the arrival time of products at the depot, known as the release date, is incorporated into the problem formulation as a crucial constraint.

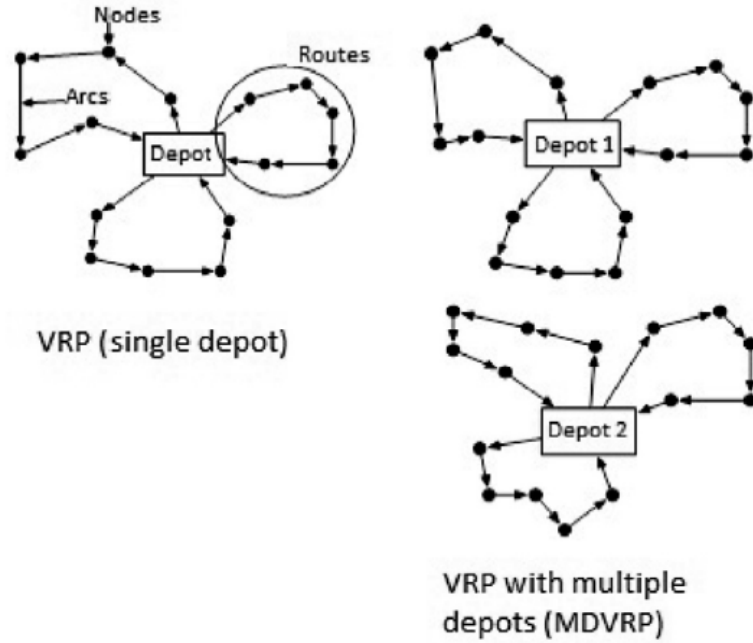


Figure 3: Comparison Between VRP Versus MDVRP.

The MDVRPTW (Multi-Depot Vehicle Routing Problem with Time Windows) is distinct from other variants of the VRP (Vehicle Routing Problem) in several ways.

- **Multiple Depots:** In the MDVRPTW, multiple depots are involved, which makes the problem more complicated as each vehicle must be assigned to a specific depot, and routes must be optimized accordingly. This adds a new layer of complexity to the problem, as the depots must be taken into account in addition to the customers. Furthermore, the problem is further complicated by the constraint that the vehicles must initiate and terminate their routes at distinct locations. This means the vehicles cannot simply travel in a loop but must return to their original starting point after completing their routes. This adds a level of intricacy to the problem, as the optimization algorithm must account for the fact that the vehicles will not be able to take the same route in reverse.

- Time windows: The Multiple Depot Vehicle Routing Problem (MDVRP) is a complex problem that involves several constraints. In addition to the standard limitations such as vehicle capacity and travel distance, time windows are also a crucial factor in the MDVRP. Specifically, the MDVRP requires that customers be visited during specific time intervals, which further adds to the complexity of the problem. Time windows, therefore, represent an additional constraint that must be taken into consideration in optimizing the MDVRP solution. Managing time windows effectively is a critical aspect of the MDVRP, as failure to meet these constraints can result in significant consequences such as missed delivery deadlines, increased transportation costs, and decreased customer satisfaction.
- Dynamic nature: In addition to the inherent complexity of the MDVRP, the problem can also be dynamic, giving rise to further challenges. Specifically, the Multiple Depot Vehicle Routing Problem with Time Windows (MDVRPTW) can involve changes in customer demands and locations over time. This dynamic nature of the problem requires a more adaptable and flexible approach to route optimization, as the routes must be adjusted in real-time to account for the changes. In this context, an effective solution requires the use of sophisticated algorithms that can re-optimize routes and schedules based on new data in a timely manner. Such algorithms must also be able to consider various factors, such as the travel time, the capacity of the vehicles, and the delivery deadlines while ensuring that the cost of transportation is minimized[1]. Thus, the dynamic nature of the MDVRPTW poses additional challenges and requires innovative solutions to ensure efficient and effective delivery operations.
- Optimization goals: When it comes to the Multiple Depot Vehicle Routing Problem with Time Windows (MDVRPTW), the optimization goals can differ from those of other variants of the Vehicle Routing Problem (VRP). Unlike other

VRP variants, the MDVRPTW considers specific time constraints that limit the window of opportunity for servicing each customer. As a result, the optimization goals in the MDVRPTW must account for these constraints, as well as the usual constraints of the VRP, such as vehicle capacity and travel distance[25]. The optimization objectives can take on various forms, depending on the needs of the business or organization. For example, the optimization goal in the VRP can be to minimize the overall travel time, maximize the number of serviced customers, or minimize the number of vehicles utilized. In the context of the MDVRPTW, however, the primary objective is typically to optimize the delivery schedules to ensure that all customers are serviced within their respective time windows while minimizing the total transportation cost[4]. Achieving this objective requires the use of sophisticated optimization algorithms that can account for multiple constraints and objectives simultaneously.

The literature has extensively studied various aspects of Heterogeneous Vehicle Routing Problems (HVRP), including backhauls, multi-depots, split delivery, pickup and delivery, carbon emissions, site dependency, open routes, and time windows. However, one area that has received limited attention in the literature is the skill level of technicians on board, particularly in the context of technician routing and home care schedules[26]. The current problem being considered addresses this challenge by focusing on optimizing the dispatch of technicians through skill matching, which presents a unique challenge not previously explored in the literature [27]. As such, this research aims to contribute to the existing body of knowledge by providing novel insights into the optimization of HVRPs with a specific emphasis on skill matching.

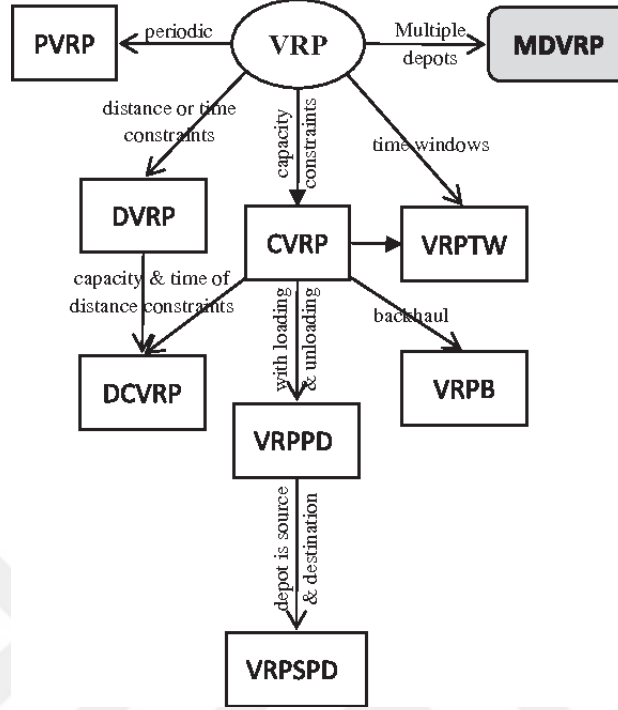


Figure 4: Different Variants Of The VRP (Dongxu Chen1and Zhongzhen Yang , 2017)

To sum up, the MDVRPTW is a challenging combinatorial optimization problem, which requires the identification of the most efficient fleet routes that meet the delivery requirements of a given customer set while accounting for time window constraints across multiple depots situated at distinct locations. Owing to the formidable computational complexity of achieving an optimal solution for the MDVRPTW, numerous heuristic methodologies have been devised to tackle this problem[6]. Heuristic technique and a genetic algorithm to tackle the MDVRPTW, which takes into account the installation of vehicles and dual time constraints for customers. [28] , have delved into the MDVRPTW and have proposed distinct heuristic algorithms to address this problem, such as the endosymbiotic evolutionary algorithm, ant colony algorithm, and genetic algorithm. These algorithms have been applied in the practical settings of logistics companies to find optimal solutions.

CHAPTER III

MULTI DEPOT VEHICLE ROUTING PROBLEM

The MDVRPTW problem is defined in terms of various constraints and objectives that must be considered to achieve optimal solutions for a company's service routing operations. One of the unique characteristics of this problem is that each vehicle originates from the location where the corresponding maintenance technician resides and terminates at the technician's residence after completing their service routes. This feature justifies the use of the term "multiple depots" in the problem's name, MDVRP. Additionally, given the time window constraints, the problem is classified as MDVRPTW [29]. To address the maintenance and repair needs of customers, the company offers planned maintenance agreements based on usage hours specific to the machine. In addition to these agreements, customers can request repairs, including part replacements and breakdowns. The company and customer clarify their terms of service, including preferred parts and prices. Negotiates to manage the maintenance and repair order process on an appropriate date and time frame for maintenance and repair. To streamline the after-sales service planning process, the planning department combines the maintenance and repair demands into a single-vehicle routing plan. This plan aims to optimize the use of resources while ensuring that each customer's needs are met within their specified time window.

The planning department to achieve the goal, must consider multiple factors, such as vehicle capacity, travel distance, and the technicians' availability, while also minimizing the transportation cost. The successful execution of the routing plan requires the use of efficient algorithms and processes to manage the various constraints and objectives involved in the MDVRPTW problem.

The planning department plays a crucial role in coordinating and executing the scheduled maintenance and customer repair requests. To optimize the maintenance schedule, the department takes into account the usage of the machines, which determines the maintenance intervals. These intervals are typically set at 3000 hours and 6000 hours, depending on the specific machine type. Furthermore, the department standardizes the maintenance times for different machine groups, considering factors such as the machine's size and KW information. This standardization allows for more efficient planning and execution of maintenance schedules. To calculate the standard work times, the department takes into account the size and workload of the compressors, which are essential factors in determining the time required for maintenance and repair tasks. By standardizing the maintenance times, the planning department can optimize the use of resources and minimize the time required to complete the maintenance and repair tasks. This approach helps to ensure that the machines are serviced in a timely and efficient manner and that customer requests are fulfilled within the specified time frame.

Each planning day in the MDVRPTW, every vehicle and technician are allocated a fixed time of 10 hours (0-600 minutes) to complete their assigned delivery tasks. The vehicles are dispatched from the employee's residence addresses and aim to provide service to customers in the most efficient manner possible. The routing plan considers the proximity of the service points to the customer locations to minimize travel time and maximize efficiency. After completing their assigned delivery tasks, the vehicles return to their designated depots or starting points. To calculate the travel distance and time between the depots and customers, the planning department uses the Google API integrated into the model. The distance and travel time matrices consider highway information to ensure accurate and efficient calculations. By leveraging technology to optimize the routing plan, the planning department can minimize transportation costs and improve the overall efficiency of the service delivery process.

The following assumptions are made.

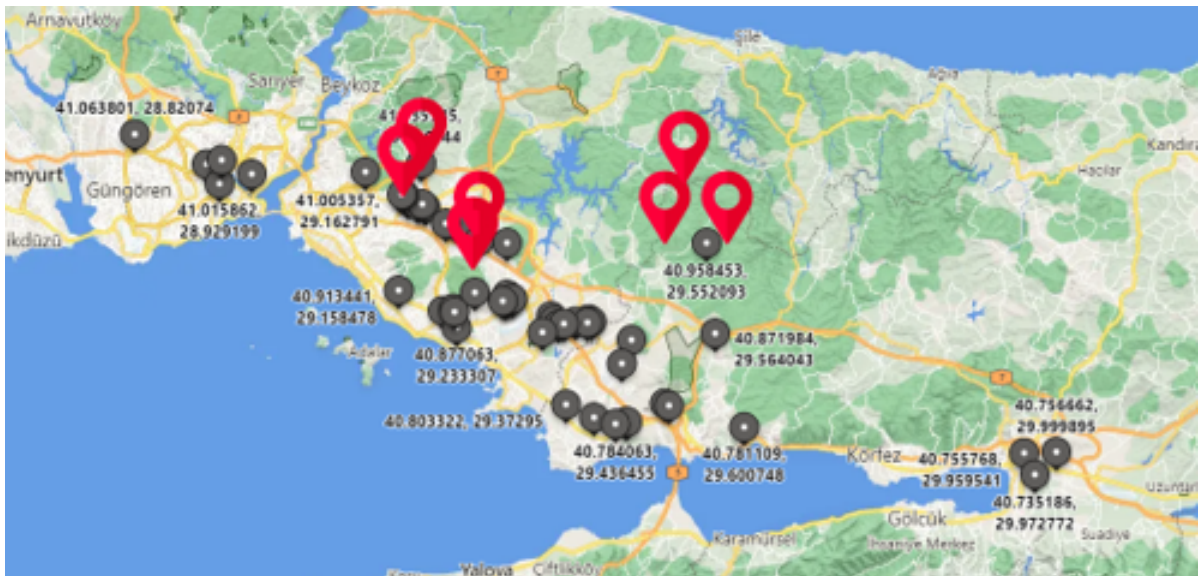


Figure 5: Location of Popular 50 Customers and Residence of Servicemen

CHAPTER IV

MATHEMATICAL MODEL FORMULATION AND SOLUTION APPROACH

We present a comprehensive formulation of the MDVRPTW that is applicable to the real-world after-sales service planning operations of Dalgakiran Compressor Manufacturer Company. The problem is formulated on a Euclidean Graph $G = (V, E)$ where V denotes a collection of nodes, and E indicates a set of arcs or edges that connect node pairs. V is partitioned into two subsets: $V_c = (V_1, V_2, \dots, V_N)$ which corresponds to the customers in need of service, and $V_d = (V_{(N+1)}, V_{(N+2)}, \dots, V_{(N+M)})$ which signifies the depots available for service. Each arc within the set E is assigned a cost function, distance metric, or travel time parameter, denoted by T_{ij} . Distances of these arcs are defined as $Dist_{ij}$ and Q_{ij} indicate whether the customer i can be served with vehicle k . The vehicles commence their routing operations from the respective depots and return to their respective depots upon completing their service operations. The primary objective of the problem is to determine a collection of vehicle routes that meet the following conditions: (i) every vehicle commences and completes its journey at the same depot, (ii) each customer receives service precisely once from a vehicle, and (iii) the overall distribution cost is minimized. The parameters and their respective definitions are provided in the table below.

4.1 Mathematical Model

The definition of parameters, decision variable parameters, and mathematical models are below.

Parameters

Parameter	Description
V_c	Set of customers' node, $V_c = (V_1, V_2, \dots, V_N)$
V_d	Set of servicemen' node, $V_d = (V_{(N+1)}, V_{(N+2)}, \dots, V_{(N+M)})$
K	Sets of all vehicles k , ($\forall k \in K$)
S_i	Service processing time of service requested by customers i ($\forall i \in N$)
T_{ij}	Travel time from node i to node j ($\forall i, j \in N + M, i \neq j$)
$Dist_{ij}$	Distance between node i and node j ($\forall i, j \in N + M, i \neq j$)
Q_{ik}	Indicate if vehicle k can serve customer i , or not ($\forall i \in N, \forall k \in K$)
E_i	Earliest time to visit the customer i ($\forall i \in N$)
L_i	The latest time to visit the customer i ($\forall i \in N$)
M	Big M

Decision Variables

Variable	Description
$x_{ijk} \in \{0, 1\}$	1, if vehicle k travels from node i to node j ; 0 otherwise ($\forall i, j \in N + M, \forall k \in K$)
$y_{ik} \in \{0, 1\}$	1, if node i is visited by vehicle k ; 0 otherwise ($\forall i \in N, \forall k \in K$)
$st_{ik} \in \mathbb{Z}^+$	Service start time of vehicle k to customer i ($\forall i \in N + M, \forall k \in K$)
$u_{ik} \in \mathbb{Z}^+$	Auxiliary variable for sub tour elimination ($\forall i \in N, \forall k \in K$)

Objective Function

$$\min \sum_{i=1}^{N+M} \sum_{j=1}^{N+M} \sum_{k \in K} Dist_{ij} x_{ijk}$$

The primary objective of the objective function is to minimize the aggregate distance traversed by all vehicles. Additionally, constraints (1) and (2) guarantee that each customer is served by a single vehicle. Constraints (3) and (4) represent indicate which vehicle visits the customer. Constraints (5) represent route continuity. All vehicles can only pass from one customer to another. Constraints (6) and (7) serve to ensure that the vehicle departs and returns to the same depot location. Constraints (8) and Constraints (9) ensure that all vehicles must start from their own depots and return to their own depots. Constraints (10) eliminate sub-tours. Constraints (11)

calculate the service start time of each customer. Constraints (12) ensure that each vehicle can serve the client within the given time window. Constraints (13) satisfy that vehicle k can be assigned to customers i and j if and only if the vehicle is able to serve both customers.

$$\sum_{i=1}^{N+M} \sum_{k \in K} x_{ijk} = 1 \quad (\forall j \in N) \quad (1)$$

$$\sum_{j=1}^{N+M} \sum_{k \in K} x_{ijk} = 1 \quad (\forall i \in N) \quad (2)$$

$$\sum_{j=1}^{N+M} x_{ijk} = y_{ik} \quad (\forall i \in N, \forall k \in K) \quad (3)$$

$$\sum_{j=1}^{N+M} x_{jik} = y_{ik} \quad (\forall i \in N, \forall k \in K) \quad (4)$$

$$\sum_{i=1}^{N+M} x_{ihk} - \sum_{j=1}^{N+M} x_{hjk} = 0 \quad (\forall k \in K, \forall h \in N + M | Q_{hk} = 1) \quad (5)$$

$$\sum_{i=N+1}^{N+M} \sum_{j=1}^N x_{ijk} \leq 1 \quad (\forall k \in K) \quad (6)$$

$$\sum_{j=N+1}^{N+M} \sum_{i=1}^N x_{ijk} \leq 1 \quad (\forall k \in K) \quad (7)$$

$$\sum_{j=1}^{N+M} x_{ijk} = 0 \quad (\forall k \in K, i = N + 1, \dots, N + M) \quad (8)$$

$$\sum_{i=1}^{N+M} x_{ijk} = 0 \quad (\forall k \in K, j = N + 1, \dots, N + M) \quad (9)$$

$$u_i - u_j + (N + M) x_{ijk} \leq N + M - 1 \quad (\forall i, j \in N, \forall k \in K) \quad (10)$$

$$st_{ik} + T_{ij} + S_i - M (1 - x_{ijk}) \leq st_{jk} \quad (\forall i, j \in N, i \neq j, \forall k \in K) \quad (11)$$

$$E_i \leq st_{ik} \leq L_i \quad (\forall i \in N, \forall k \in K) \quad (12)$$

$$x_{ijk} \leq M Q_{ik} Q_{jk} \quad (\forall k \in K, \forall i, j \in N | i \neq j) \quad (13)$$

4.2 Clustering Algorithm

We have devised a simple clustering approach to reduce the number of variables involved in solving large-scale problems. Customers are clustered to a specific depot while minimizing total transportation.

Parameters

Parameter	Description
V_c	Set of customers nodes $V_c = (V_1, V_2, \dots, V_N)$
V_d	Set of depot nodes (servicemen's homes) $V_d = (V_{(N+1)}, V_{(N+2)}, \dots, V_{(N+M)})$
S_i	Processing time of service requested by customer i ($\forall i \in N$)
mT	Maximum service time for a planning day.
avT	Average traveling time between nodes.
$Dist_{ij}$	Distance between node i and node j ($\forall i, j \in N + M, i \neq j$)
Q_{ij}	Indicate if depot j can serve customer i , or not ($\forall i \in V_c, \forall j \in V_d$)
M	Big M

Decision Variables

Variable	Description
$z_{ij} \in \{0, 1\}$	1, if depot j serves customer i ; 0, otherwise ($\forall i \in V_c, \forall j \in V_d$)

Objective Function

$$\text{Min}Z = \sum_{i=1}^N \sum_{j=N+1}^{N+M} Dist_{ij} z_{ij}$$

Constraints (14) enforce the condition that each customer is assigned to only one vehicle. Constraints (15) ensure that the vehicles can only be assigned to customers if the vehicle and service personnel have the competencies to serve the customer. Constraints (16) enforce the vehicle's service time constraint to prevent violations.

$$\sum_{j=N+1}^{N+M} z_{ij} = 1 \quad (\forall i \in V_c) \quad (14)$$

$$z_{ij} \leq M Q_{ij} \quad (\forall j \in V_d, \forall i \in V_c) \quad (15)$$

$$\sum_{i \in N} z_{ij} * (S_i + avT) \leq mT \quad (\forall j \in V_d) \quad (16)$$

CHAPTER V

NUMERICAL EXAMPLES AND RESULTS

This section reports the findings of computational experiments carried out on the real-world problem to evaluate the effectiveness of the mathematical model and heuristic algorithm in terms of their ability to provide high-quality solutions and computational efficiency. The proposed mathematical model is implemented using the Gurobi Python Application Programming Interface (API) and solved using Gurobi Optimizer 10, a commercial optimization software. Each algorithmic model is allocated a time limit of 3600 seconds (1 hour) to generate solutions. All solutions are obtained using a Windows 11 operating system with an Intel R Core TM i9-6500U 2.5 GHz processor and 64 GB RAM. The main objective of this investigation is to devise a mathematical framework capable of addressing the problem at hand. To address the increased complexity of the problem for larger-scale instances, a clustering heuristic algorithm has been developed to generate solutions efficiently within a shorter time frame. The heuristic algorithm clusters customer nodes and minimizes the traveling distance regarding the servicemen's homes while satisfying time constraints. Then clusters obtained are given as inputs for the mathematical model. After identifying the clusters, the location problem is transformed into a traveling salesman problem.

The company meets the 3000-6000 maintenance requests of 10-20 customers on average and the demand of 10-15 additional breakdown service customers on average. Initially, when constructing the model based on data from 20 customers, the desired output was successfully obtained. However, when faced with higher customer demands, it became apparent that additional assistance was required to achieve the desired results. To address this challenge, a straightforward heuristic

approach was developed to tackle larger-scale problems by reducing the number of variables involved. This heuristic approach greatly enhances the algorithm's performance, particularly when dealing with a high number of customers. Under this heuristic approach, customers are consolidated in a specific depot, aiming to minimize total shipping requirements. To illustrate the effectiveness of this approach, the provided table in the appendix was solved using the heuristic algorithm method for a scenario involving 20-30-40 customers. The application of this heuristic approach resulted in the generation of efficient and flexible solutions for problems involving a large number of customers. Upon examining the results, it is evident that the heuristic algorithm successfully forms depot-customer-depot tours, ensuring that job start times are scheduled within the specified time windows. Consequently, the problem of managing maintenance and repair requests has been effectively solved by applying classical heuristics. This approach provides a practical and viable solution, allowing the company to streamline its operations and meet the demands of a growing customer base efficiently.

Table 1: Comparison of Results of Multi Depot VRPTW and Clustering Algorithm

Number of Customer	Number of Depot	Mathematical Model			Clustering Algorithm	
		Solution Time	GAP	Best Bound	Solution Time	Best Bound
20	7	1652		570.401	0.75	882.501
30	7	3600	5.04	599.361	10.81	916.321
40	7	3600	31.2	695.912	135.23	1010.12

The primary objective of the developed model is to address a real-world problem faced by the company. To ensure the compatibility between the model and the firm's

operations, a comparison was made between the daily maintenance demands of the company and the model's solution. To conduct this analysis, a one-week plan was obtained from the company, and a day-by-day comparison was made between the plan and the model's solution. This comparison aimed to evaluate the effectiveness of the developed model in terms of its ability to provide efficient solutions that meet the company's operational requirements. The comparison involved examining the quality of the solutions generated by the model, the degree of adherence to the specified constraints and objectives, and the level of computational efficiency achieved. To ensure the accuracy and reliability of the comparison, a rigorous and systematic approach was adopted. The performance of the model was assessed based on multiple criteria, including the time taken to generate solutions, the accuracy of the solutions, the ability to handle multiple constraints and objectives, and the ease of use of the model. The results of the comparison demonstrated that the developed model was effective in addressing the company's operational challenges. The model was able to generate high-quality solutions that met the company's requirements while adhering to the specified constraints and objectives. Additionally, the model was able to achieve a high level of computational efficiency, enabling it to handle large-scale problems within a reasonable timeframe.

Overall, the comparison confirmed the effectiveness of the developed model in addressing the real-world problem faced by the company. The model provided a flexible and efficient framework that could be easily integrated into the company's existing operations. The results of the comparison demonstrated the potential of the developed model to enhance the efficiency and effectiveness of the company's maintenance and repair operations, thus improving customer satisfaction and increasing profitability. In order to analyze the improvement, a 5-day data was taken from the company and then compared with the solution of the model.

- On April 24, 2023, a service plan was developed to cater to the needs of 15

customers, which involved a vehicle routing plan covering a total distance of 426.1 kilometers. However, the proposed route model presented in this study suggests an alternative solution that covers a slightly shorter distance, approximately 393.5 kilometers. These optimization results suggest that the daily maintenance service, which was initially planned to be executed using five vehicles, can be carried out more efficiently using only four vehicles while covering a shorter distance. This finding implies that the proposed routing model has the potential to generate more efficient solutions for the company's maintenance and repair order process. By optimizing vehicle allocation and routing, the model can significantly reduce transportation costs, increase resource utilization, and improve the overall service quality by ensuring the timely delivery of maintenance and repair services. The model's ability to accurately schedule appointments and assign technicians to specific tasks can also enhance the company's customer satisfaction and loyalty. The clustering algorithm utilized in this study demonstrated efficient performance with a running time of 0.01 seconds. This algorithm was responsible for grouping the data points into clusters based on specific criteria, enabling a more streamlined and manageable dataset for further analysis. On the other hand, the model employed to solve the optimization problem exhibited a running time of 0.26 seconds. Despite the slightly longer running time compared to the clustering algorithm, the model was able to identify the optimal solution with a value of 393,513 within a mere 0.27 seconds. These findings underscore the effectiveness and efficiency of both the clustering algorithm and the optimization model in addressing the problem at hand, providing valuable insights and solutions within a relatively short computational time.

Table 2: Comparison of The Mathematical Model and The Factory's Solution
(24.04.23)

Mathematical Model		Dalgakıran Planning	
depot2	11	depot2	11
11	2	11	2
2	15	2	15
15	3	15	depot2
3	5	depot1	7
5	8	7	3
8	4	3	5
4	7	5	8
7	depot2	8	depot1
depot3	10	depot3	10
10	12	10	12
12	9	12	9
9	depot3	9	4
depot4	14	4	depot3
14	1	depot4	14
1	13	14	1
13	depot4	1	13
depot6	6	13	depot4
6	depot6	depot6	6
		6	depot6

- Based on the analysis conducted on April 25, 2023, the company successfully provided breakdown and maintenance services to a total of 32 customers. The vehicles were dispatched from 5 depots to meet customer demands and returned to their starting points. The company's vehicle routing plan resulted in a total distance traveled of 612.7 kilometers. However, when comparing this with

the mathematical model, which suggested a total distance of 530.5 kilometers with vehicle departures from 5 depots, a significant gain of 82.2 kilometers was observed. This improvement represents a thirteen percent enhancement over the company's initial solution. The vehicle routing solution of the mathematical model and the planning solution of the company are given in Table.3 below.

The results demonstrate that the mathematical model offers a more efficient and effective solution for daily maintenance services, leading to cost savings for the company and a high level of customer satisfaction. Mathematical model itself required total 49.25 seconds to complete the optimization process.

Overall, the analysis showcases the benefits of utilizing the mathematical model for vehicle routing planning in the context of daily maintenance services. It not only leads to significant distance reductions but also contributes to cost-effectiveness and enhanced customer satisfaction. By optimizing the routing process, the company can improve its operational efficiency, reduce transportation costs, and better serve its customers' needs. Table.3 shows the vehicle route obtained by applying the clustering method of the mathematical model.

Table 3: Comparison of The Mathematical Model and The Factory's Solution
(25.04.23)

Mathematical Model		Mathematical Model		Dalgakıran Planning		Dalgakıran Planning	
depot1	17	8	5	depot1	17	5	8
17	depot1	5	depot3	17	9	8	depot3
depot2	9	depot4	3	9	12	depot4	3
9	12	3	30	12	14	3	30
12	14	30	1	14	depot1	30	1
14	7	1	2	depot2	16	1	2
7	15	2	31	16	18	2	31
15	10	31	depot4	18	6	31	depot4
10	13	depot6	28	6	13	depot6	28
13	6	28	19	13	10	28	32
6	18	19	32	10	15	32	19
18	16	32	23	15	7	19	23
16	depot2	23	20	7	depot2	23	20
depot3	27	20	22	depot3	27	20	22
27	29	22	25	27	29	22	25
29	11	25	21	29	11	25	21
11	26	21	24	11	26	21	24
26	8	24	4	26	5	24	4
		4	depot6			4	depot6

- According to the maintenance and repair vehicle routing of the company on April 26, 2023, the company left 4 different depots and served 22 customers. Vehicles leaving the depots and serving 22 customers and returning to their depots traveled 438.2 km. Vehicles departed from Depot1, Depot2, Depot3, Depot6 starting points and provided maintenance and rate services to 22 customers and returned to their starting points. In the solution of the mathematical

model, it was ensured that by leaving 4 depots, 22 customers were served with 437.3 km and returning to the starting points. The model took 1.19 seconds to run and the optimum solution was calculated as 437.3 km. We can say that the model provides a better solution than factory planning. The vehicle routing for the company showing the service provided to 22 customers and their return to their depots is shown in Table.4. It also shows the vehicle route obtained by applying the clustering method of the mathematical model.

Table 4: Comparison of The Mathematical Model and The Factory's Solution (26.04.23)

Mathematical Model		Mathematical Model		Dalgakıran Planning		Dalgakıran Planning	
depot1	3	16	4	depot1	18	1	depot5
3	2	4	depot2	18	16	depot3	13
2	17	depot3	11	16	4	13	11
17	depot1	11	8	4	depot1	11	8
depot2	9	8	5	depot5	2	8	5
9	19	5	depot3	2	17	5	depot3
19	7	depot6	12	17	3	depot6	20
7	15	12	14	3	9	20	22
15	10	14	21	9	19	22	21
10	1	21	6	19	15	21	6
1	13	6	22	15	7	6	14
13	18	22	20	7	10	14	12
18	16	20	depot6	10	1	12	depot6

- According to the data recorded on April 27, 2023, the company carried out maintenance services on 19 vehicles categorized under 3000-6000 maintenance, and conducted repairs on 16 vehicles on the same day. A total of 35 customers were attended to by a team of 6 employees. The overall distance covered during

the service provision amounted to 996.8 kilometers. The employees commenced their journeys from the starting points, served the 35 customers, and returned to their respective starting points. Table 5 illustrates the vehicle routes of the company based on the depots, alongside the routes determined by the mathematical model. The mathematical model operated for a duration of 61.05 seconds, finalizing the routing plan with a total distance of 944.1 kilometers. This signifies a 5.3 percent enhancement compared to the company's initial model. The primary objective of the model was to optimize the vehicle routes, ensuring minimum distances for the after-sales service provided to customers.

Table 5: Comparison of The Mathematical Model and The Factory's Solution
(27.04.23)

Mathematical Model		Mathematical Model		Dalgakıran Planning		Dalgakıran Planning	
depot1	20	8	11	depot1	20	33	4
20	depot1	11	depot3	20	11	4	5
depot2	7	depot4	39	11	depot1	5	2
7	12	39	6	depot2	16	2	depot4
12	16	6	33	16	12	depot5	18
16	9	33	4	12	7	18	10
9	28	4	5	7	9	10	17
28	18	5	2	9	28	17	15
18	10	2	depot4	28	depot2	15	31
10	17	depot6	22	depot3	1	31	depot5
17	15	22	35	1	30	depot6	22
15	31	35	26	30	32	22	35
31	depot2	26	23	32	14	35	26
depot3	1	23	25	14	29	26	23
1	30	25	24	29	13	23	25
30	32	24	3	13	8	25	24
32	14	3	27	8	depot3	24	3
14	29	27	21	depot4	39	3	27
29	13	21	19	39	6	27	21
13	8	19	depot6	6	33	21	19
						19	depot6

- According to the data collected on April 28, 2022, the Company provided maintenance services for 21 vehicles in the 3000-6000 maintenance category and conducted breakdown maintenance on 18 vehicles on the same day. Due to the holiday period, the service employees had to work at a significantly intense

pace throughout that week. A total of 39 customers were served by a team of 7 personnel. The distance covered for the provision of the service was calculated to be 639.8 kilometers.

Optimize the vehicle routing and scheduling, a mathematical model was employed, which took 25.25 seconds to execute. The model generated a revised vehicle routing plan with a total distance of 580.7 kilometers, resulting in a 9 per improvement compared to the Company's initial plan. By achieving this objective, the model aimed to generate cost savings and enhance customer satisfaction. Table 6 presents the routing solution of the Company's plan and the mathematical model's solution. The proposed routing model aims to minimize the total distance traveled while meeting all operational constraints and customer demands, thus providing cost savings and increased customer satisfaction. The results of this study highlight the potential benefits of using mathematical models and optimization techniques to improve the efficiency of logistics operations, especially in the context of vehicle routing problems.

Table 6: Comparison of The Mathematical Model and The Factory's Solution
(28.04.23)

Mathematical Model		Mathematical Model		Dalgakıran Planning		Dalgakıran Planning	
depot1	14	34	36	depot1	14	7	3
14	30	36	33	14	30	3	37
30	27	33	12	30	27	37	9
27	29	12	depot4	27	18	9	10
29	18	depot5	7	18	15	10	5
18	15	7	9	15	29	5	2
15	17	9	10	29	depot1	2	38
17	22	10	37	depot2	25	38	1
22	depot1	37	5	25	24	1	depot5
depot2	25	5	2	24	17	depot6	16
25	24	2	38	17	22	16	26
24	depot2	38	1	22	depot2	26	19
depot3	11	1	depot5	depot3	8	19	13
11	8	depot7	35	8	11	13	6
8	28	35	3	11	28	6	depot6
28	6	3	4	28	depot3	depot7	35
6	13	4	21	depot4	34	35	4
13	19	21	31	34	36	4	20
19	26	31	20	36	33	20	31
26	16	20	32	33	12	31	21
16	depot3	32	23	12	depot4	21	32
depot4	34	23	depot7	depot5	7	32	23
						23	depot7

A comprehensive analysis has been conducted to evaluate the breakdown and

repair requests received by Dalgakıran Company from its customers. The analysis includes an assessment of the company’s routing solution as well as the solution provided by the mathematical model. Weekly data was examined to assess the performance of the mathematical model in various customer scenarios.

The results indicate that the mathematical model consistently outperforms the company’s routing solution, showing an improvement ranging from 5 to 15 percent. Notably, the improvement becomes more significant when the number of customers exceeds 30. The mathematical model demonstrates effective performance up to a customer count of 20; however, for larger customer counts, additional support is required to achieve optimal results. To address this challenge, the model has been enhanced with the inclusion of a clustering algorithm for improved support and performance.

Table 7 provides a detailed comparison between the company’s implemented solution, including the distance traveled, and the solution proposed by the mathematical model. The table serves as a visual representation of the performance differences between the two approaches, highlighting the advantages of the mathematical model in terms of optimizing the routing process and reducing overall distance traveled.

By utilizing the mathematical model, Dalgakıran Company can benefit from improved efficiency and cost savings in their daily maintenance and repair operations. The model’s ability to generate more optimized routes enhances the company’s ability to meet customer demands within specified time windows while minimizing transportation costs.

In summary, the analysis demonstrates the effectiveness of the mathematical model in improving the company’s routing solution for breakdown and repair services. The model’s performance surpasses the company’s solution, particularly in scenarios with a larger number of customers. By leveraging the model’s capabilities, Dalgakıran Company can achieve greater operational efficiency, cost savings, and improved customer satisfaction.

Table 7: Comparison of a Weekly Mathematical Model Solution With The Factory's Solution

Date	Number of Customer	Clustering Algorithm			Dalgakıran Planning		Rate of Change
		Number of Depot	Solution Time	Distance(km)	Number of Depot	Distance(km)	
24.04.2023	15	4	0.27 sec	393.51	5	426.11	-7.7%
25.04.2023	32	5	49.25 sec	530.54	5	612.70	-13.4%
26.04.2023	22	4	1.19 sec	437.38	4	438.23	-0.2%
27.04.2023	35	5	61.05 sec	944.14	6	996.82	-5.3%
28.04.2023	39	6	25.25 sec	580.71	7	619.8	-9.2%

CHAPTER VI

CONCLUSION

A solution method has been developed for this real-life problem. The mathematical model is initially developed to address the vehicle routing problem of Dalgakıran Compressor Manufacturer Company. However, due to the complexity of the problem, particularly with an increasing number of customers, the mathematical model may not provide a reasonable solution; thus, a heuristic algorithm is implemented for larger-sized instances. The proposed heuristic algorithm can efficiently meet all the constraints outlined in the study and is highly adaptable to various situations without requiring any adjustments. Furthermore, it can efficiently generate solutions for problem instances with many customers. As a result, the problem is effectively solved by applying classical heuristics.

Practitioners in the Turkish industry tend to overlook scientific methods and instead plan distribution routes in non-scientific ways, resulting in increased transportation costs and customer dissatisfaction. An actual data set in Istanbul is used to reflect a real-life road network. As the problem size increases, it has been observed that the mathematical model fails to generate results in a reasonable amount of time and with the desired quality. In light of this, a clustering algorithm has been developed to supplement the mathematical model. This approach includes a clustering algorithm that takes into account constraints such as customer distances and vehicle capacities.

This research analyzes current industry VRPs that many companies suffer from disorganized after-sales service planning problems. The model is intended to help everyday logistic operations. Moreover, considering the information gathered and

produced for this research, it intends to contribute to the VRP literature through many good-quality solutions generated from the algorithm. Furthermore, the research enables academia and practitioners to observe the performance of a heuristic model that tries to solve a real-life case. As a result, the developed algorithm provides accuracy, simplicity, fastness, and flexibility. Besides, it can be easily adapted to the solution of different VRPs described in the literature. Therefore, it is hoped that this research will make a significant contribution to the industry and the literature in terms of providing cost savings by determining more suitable distribution routes for the companies and shedding light on the other studies to be conducted as a reference and pioneer.

REFERENCES

- [1] Q. Feng and Q. Zhao, "Routing problem in after-sales delivery service: A model based on customer satisfaction," in *16th International Conference on Service Systems and Service Management (ICSSSM)*, pp. 1–3, IEEE, 2019.
- [2] M. M. Lele, "After-sales service-necessary evil or strategic opportunity?," *Managing Service Quality: An International Journal*, vol. 7, no. 3, pp. 141–145, 1997.
- [3] G. Asugman, J. L. Johnson, and J. McCullough, "The role of after-sales service in international marketing," *Journal of international marketing*, vol. 5, no. 4, pp. 11–28, 1997.
- [4] L. Zhen, C. Ma, K. Wang, L. Xiao, and W. Zhang, "Multi-depot multi-trip vehicle routing problem with time windows and release dates," *Transportation Research Part E: Logistics and Transportation Review*, vol. 135, p. 101866, 2020.
- [5] D. Xu and Y. Tian, "A comprehensive survey of clustering algorithms," *Annals of Data Science*, vol. 2, pp. 165–193, 2015.
- [6] J. K. Lenstra and A. R. Kan, "Complexity of vehicle routing and scheduling problems," *Networks*, vol. 11, no. 2, pp. 221–227, 1981.
- [7] B. Golden, A. Assad, L. Levy, and F. Gheysens, "The fleet size and mix vehicle routing problem," *Computers & Operations Research*, vol. 11, no. 1, pp. 49–66, 1984.
- [8] S. Liu, "A hybrid population heuristic for the heterogeneous vehicle routing problems," *Transportation Research Part E: Logistics and Transportation Review*, vol. 54, pp. 67–78, 2013.
- [9] L. Liu, K. Li, and Z. Liu, "A capacitated vehicle routing problem with order available time in e-commerce industry," *Engineering Optimization*, vol. 49, no. 3, pp. 449–465, 2017.
- [10] I. Moon, J.-H. Lee, and J. Seong, "Vehicle routing problem with time windows considering overtime and outsourcing vehicles," *Expert Systems with Applications*, vol. 39, no. 18, pp. 13202–13213, 2012.
- [11] J. H. Lee and K. H. Kim, "An auction-based dispatching method for an electronic brokerage of truckload vehicles," *Industrial Engineering and Management Systems*, vol. 14, no. 1, pp. 32–43, 2015.
- [12] Y. Arda, Y. Crama, D. Kronus, T. Pironet, and P. Van Hentenryck, "Multi-period vehicle loading with stochastic release dates," *EURO Journal on Transportation and Logistics*, vol. 3, no. 2, pp. 93–119, 2014.

- [13] J.-F. Cordeau, M. Gendreau, and G. Laporte, “A tabu search heuristic for periodic and multi-depot vehicle routing problems,” *Networks: An International Journal*, vol. 30, no. 2, pp. 105–119, 1997.
- [14] A. Atamtürk and M. W. Savelsbergh, “Integer-programming software systems,” *Annals of Operations Research*, vol. 140, pp. 67–124, 2005.
- [15] J. R. Montoya-Torres, J. L. Franco, S. N. Isaza, H. F. Jiménez, and N. Herazo-Padilla, “A literature review on the vehicle routing problem with multiple depots,” *Computers & Industrial Engineering*, vol. 79, pp. 115–129, 2015.
- [16] H. Bae and I. Moon, “Multi-depot vehicle routing problem with time windows considering delivery and installation vehicles,” *Applied Mathematical Modelling*, vol. 40, no. 13-14, pp. 6536–6549, 2016.
- [17] G. Laporte and Y. Nobert, “A vehicle flow model for the optimal design of a two-echelon distribution system,” in *Advances in Optimization and Control: Proceedings of the Conference “Optimization Days 86” Held at Montreal, Canada, April 30–May 2, 1986*, pp. 158–173, Springer, 1988.
- [18] R. Baldacci, P. Toth, and D. Vigo, “Recent advances in vehicle routing exact algorithms,” *4or*, vol. 5, pp. 269–298, 2007.
- [19] B. C. Shelbourne, M. Battarra, and C. N. Potts, “The vehicle routing problem with release and due dates,” *INFORMS Journal on Computing*, vol. 29, no. 4, pp. 705–723, 2017.
- [20] N. De Jaegere, M. Defraeye, and I. Van Nieuwenhuyse, “The vehicle routing problem: state of the art classification and review,” *FEB Research Report KBI.1415*, 2014.
- [21] P. Toth and D. Vigo, “Guest editorial to the special issue” routing and logistics”(verolog 2012),” *European Journal of Operational Research*, vol. 236, no. 3, pp. 787–788, 2014.
- [22] K. Kim, J. Sun, and S. Lee, “A hierarchical approach to vehicle routing and scheduling with sequential services using the genetic algorithm.,” *International Journal of Industrial Engineering*, vol. 20, 2013.
- [23] S. Salhi, N. Wassen, and M. Hajarati, “The fleet size and mix vehicle routing problem with backhauls: Formulation and set partitioning-based heuristics,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 56, pp. 22–35, 2013.
- [24] D. Reyes, A. L. Erera, and M. W. Savelsbergh, “Complexity of routing problems with release dates and deadlines,” *European journal of operational research*, vol. 266, no. 1, pp. 29–34, 2018.

- [25] B. Crevier, J.-F. Cordeau, and G. Laporte, “The multi-depot vehicle routing problem with inter-depot routes,” *European journal of operational research*, vol. 176, no. 2, pp. 756–773, 2007.
- [26] J. C. Molina, J. L. Salmeron, I. Eguia, and J. Racero, “The heterogeneous vehicle routing problem with time windows and a limited number of resources,” *Engineering Applications of Artificial Intelligence*, vol. 94, p. 103745, 2020.
- [27] H. M. Marlan, “An integer programming model for solving periodic heterogeneous vehicle routing problem with time windows in food material distribution,” *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 7, p. 11, 2018.
- [28] I. Sim, T. Kim, J. Cha, and H. Lee, “A design and analysis of scheduling for the dual of appliances delivery and installation services,” *J. Korean Soc. Supply Chain Manag*, vol. 11, pp. 41–53, 2011.
- [29] X. Li, P. Tian, and S. C. Leung, “Vehicle routing problems with time windows and stochastic travel and service times: Models and algorithm,” *International Journal of Production Economics*, vol. 125, no. 1, pp. 137–145, 2010.

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