

T.R.
GEBZE TECHNICAL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

**INTEGRATED PARTIAL DISASSEMBLY LINE BALANCING
AND MULTI-OBJECTIVE GREEN VEHICLE ROUTING
PROBLEM**

NİDA DURMAZ

**A THESIS SUBMITTED FOR THE DEGREE OF
MASTER OF SCIENCE
DEPARTMENT OF INDUSTRIAL ENGINEERING**

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ASSOC. PROF. DR. AYŞENUR BUDAK**

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T.C.
GEBZE TEKNİK ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ

BÜTÜNLEŞİK KISMİ DEMONTAJ HATTI
DENGELEME VE ÇOK AMAÇLI YEŞİL
ARAÇ ROTALAMA PROBLEMİ

NİDA DURMAZ
YÜKSEK LİSANS TEZİ
ENDÜSTRİ MÜHENDİSLİĞİ ANABİLİM DALI

DANIŞMANI
DOÇ. DR. AYŞENUR BUDAK

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JÜRİ

ÜYE

(TEZ DANIŞMANI)

: Doç. Dr. Ayşenur BUDAK

ÜYE

: Dr. Öğretim Üyesi Veysel ÇOBAN

ÜYE

: Dr. Öğretim Üyesi Celal Özgür ÜNSAL

ONAY

Gebze Teknik Üniversitesi Fen Bilimleri Enstitüsü Yönetim Kurulu'nun

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SUMMARY

Today, serious environmental problems arise with overconsumption. The most effective way of the environmental protection is recycling. To obtain maximum benefit from the recycling activities depends on the balanced design of the disassembly lines. In addition to this, the distribution plan of products to be recycled is as important as the disassembly process. For this reason, this thesis focuses on the integrated optimization of the Partial Disassembly Line Balancing and the Multi-objective Green Vehicle Routing Problem for the first time. The proposed problem is formulated as a Multi-Objective Mixed Integer Linear Programming model. The objectives of the model consist of the minimization of total CO₂ emission and the minimization of the total cost. Firstly, the proposed model is solved with Augmented ϵ -Constraint Method. Pareto optimal solution set is found. Afterward, this model is tested on an example of the printer disassembly line by using and expanding the data sets in the literature. Then, sensitivity analysis and scenarios are created to investigate the effect of using heterogeneous fleet and changing in the proportion of the product to be partially disassembled.

This thesis also contains a decision-making process to rank Pareto optimal solutions obtained from the proposed optimization model based on the various criteria. In this context, the importance of the criteria is determined by the Entropy Weight Method (EWM) and the selection of the best Pareto optimal solution is performed by the Complex Proportional Assessment (COPRAS) Method. This integrated model provides flexible solutions for the simultaneous optimization and its implementation phase.

Key Words: Green Vehicle Routing Problem, Partial Disassembly Line Balancing, Multi Objective Optimization, Augmented ϵ -constraint Method, Complex Proportional Assessment (COPRAS), Entropy Weight Method (EWM).

ÖZET

Günümüzde aşırı tüketim ile ciddi çevre sorunları ortaya çıkmaktadır. Çevreyi korumanın en etkin yolu geri dönüşümdür. Geri dönüşüm faaliyetlerinden maksimum fayda elde etmek demontaj hatlarının dengeli tasarımıyla bağlıdır. Bunun yanı sıra, geri dönüştürülecek ürünlerin dağıtım planı da demontaj işlemi kadar önemlidir. Bu nedenle bu tez çalışması, ilk kez Kısmi Demontaj Hattı Dengeleme ve Çok Amaçlı Yeşil Araç Rotalama Probleminin bütünleşik optimizasyonuna odaklanmaktadır. Önerilen problem, Çok Amaçlı Karışık Tamsayılı Doğrusal Programlama modeli olarak formüle edilmiştir. Modelin amaçları, toplam CO₂ emisyonu minimizasyonundan ve toplam maliyet minimizasyonundan oluşmaktadır. Öncelikle, önerilen model Artırılmış ϵ -Kısıt Yöntemi ile çözülmüştür. Pareto optimal çözüm kümesi bulunmuştur. Ardından, bu model literatürdeki veri setleri kullanılarak ve genişletilerek bir yazıcı demontaj hattı örneği üzerinde test edilmiştir. Daha sonra, heterojen filo kullanımının ve kısmen demonte edilecek ürün oranındaki değişimin etkisini araştırmak için duyarlılık analizleri ve senaryolar oluşturulmuştur.

Bu tez ayrıca, önerilen optimizasyon modelinden elde edilen Pareto optimal çözümleri sıralamak için çeşitli kriterlere dayalı olarak bir karar verme sürecini de içermektedir. Bu kapsamda, kriterlerin önem dereceleri Entropi Ağırlık Yöntemi (EWM) ile belirlenmekte ve en iyi Pareto optimal çözümün seçimi Karmaşık Oransal Değerlendirme (COPRAS) Yöntemi ile yapılmaktadır. Bu bütünleşik model, eşzamanlı optimizasyon ve uygulama safhası için esnek çözümler sunmaktadır.

Anahtar Kelimeler: Yeşil Araç Rotalama Problemi, Kısmi Demontaj Hattı Dengeleme, Çok Amaçlı Optimizasyon, Artırılmış ϵ -Kısıt Yöntemi, Karmaşık Oransal Değerlendirme (COPRAS), Entropi Ağırlık Yöntemi (EWM).

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LIST OF ABBREVIATIONS AND ACRONYMS

<u>Abbreviations</u>	<u>Explanations</u>
<u>and Acronyms</u>	
\$	: Dollar
CO ₂	: Carbon Dioxide
GHG	: Greenhouse Gas
kg	: Kilogram
km	: Kilometer
ABC	: Artificial Bee Colony
ACO	: Ant Colony Optimization
ALBP	: Assembly Line Balancing Problem
ALNS	: Adaptive Large Neighborhood Search
AUGMECON	: Augmented ϵ -constraint Method
COPRAS	: Complex Proportional Assessment
DLBP	: Disassembly Line Balancing Problem
EOL	: End-of-Life
EWM	: Entropy Weight Method
GVRP	: Green Vehicle Routing Problem
MCDM	: Multi-Criteria Decision Making
MILP	: Mixed Integer Linear Programming
MINLP	: Mixed-Integer Non-Linear Programming
MOGVRP	: Multi Objective Green Vehicle Routing Problem
MOO	: Multi Objective Optimization
NSGA	: Non-Dominated Sorting Genetic Algorithm
PDLBP	: Partial Disassembly Line Balancing Problem
PSO	: Particle Swarm Optimization
RSC	: Reverse Supply Chain
SA	: Simulated Annealing
VNS	: Variable Neighborhood Search
VRP	: Vehicle Routing Problem
VRPTW	: Vehicle Routing Problem with Time Window

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1. INTRODUCTION

With the rapid development of science and technology, the amount of consumption is increasing constantly. The increase in the amount of consumption also enhances the number of end-of-life products. End-of-life (EOL) products contain a substantial number of renewable resources. Overconsumption causes environmental problems to increase day by day in today's world. For this reason, it is thought that the most effective way to protect nature and prevent pollution is to save on these renewable resources. In our current conditions, recycling is the most important action that decreases both the production amount and the economic cost of EOL products. With this understanding, important studies on recycling have been started in the world and it is primarily aimed to recover all the recyclable materials of EOL products as energy or material. In line with this awareness, legal obligations have been created and recycling studies have been initiated with the implementation of many waste control regulations in our country. The waste management and recycling sector in Turkey has become a large market with the contributions of the private sector and local governments and with the recycling of various materials, including paper, plastic, glass, textile products and metals [Kaçtıoğlu and Şengül, 2010].

Incorporating recycling in the existing supply chain structures provides various benefits such as recoverable raw materials, energy, and economic savings. Therefore, the recycling stage plays a key role in supply chain networks. The basic start element of the recycling stage is the disassembly process [McGovern and Gupta, 2011]. In this context, the Disassembly Line Balancing Problem (DLBP) arises to organize the disassembly lines and the recycling processes. The basic DLBP is defined as the assignment of the set of disassembly tasks to an ordered sequence of workstations for each product to be disassembled that all the disassembly precedence relations are satisfied, and some measure of effectiveness is optimized [Altekin et al., 2008; Kalaycılar et al., 2015].

Although the DLBP appears to be similar to the Assembly Line Balancing Problem (ALBP), there are operational differences between assembly and disassembly processes. The disassembly process may cause to inventory problems because of the instability related to the demand and the yield of subassemblies. The

disassembly process may be faced with the uncertainty of the quality, structure, and reliability while some quality control activities are done for the parts which will be assembled in an assembly process. In addition to these, the flow processes of the two problems have opposite effect to each other since the balance of assembly lines deal with a convergent process while the balance of disassembly lines deal with a divergent process [Brennan et al., 1994; Güngör and Gupta, 1999]. Thus, unique characteristics of the disassembly environment lead the need to treat DLBP as a different optimization problem independent from ALBP.

To gain the maximum benefit from the recycling activities depends on the optimal design of the disassembly lines. With the optimal design of the disassembly lines, the disassembly of the products to be recycled should be carried out appropriately. The number of workstations to be opened and the idle time at the workstations should be calculated, thus more efficient labor force can be used. It can be determined which work is done in which workstation at which time. Usage of full-capacity workforce helps to provide the maximum benefit from the recycling activities. Maximizing the use of labor helps to reduce non-value added costs. When viewed from this aspect, the recycling processes can be organized with the design of disassembly lines.

The valuable components are separated from waste products with the disassembly process. With the improvement of environmental awareness, the disassembly as an important content of green manufacturing can reduce environmental impacts and save natural resources. In this context, two commonly considered complications in the scope of DLBP are complete and partial disassembly. In the traditional complete disassembly mode, all components and parts are disassembled by minimizing environmental impact. This mode only focuses on disassembly efficiency, which cannot satisfy the needs of environmental protection and economic development. This situation leads to an increase in the disassembly cost and the decrease in the disassembly profit. In the partial disassembly mode, hazardous or high-value parts are disassembled, and the other parts directly crushed and sorted. The environmental impacts are minimized while the disassembly profit is maximized in the partial process. This situation verifies that the studies which have partial disassembly are more realistic [Wang et al., 2019a].

It is known that the partial disassembly is more practical than the complete disassembly in the disassembly process of the waste products [Wang et al., 2019a]. However, in the current literature, most of the research on the DLBP focuses on complete disassembly. The partial DLBP (PDLBP) was first discussed by Altekin et al., [2003]. Altekin et al., [2008] formulated the profit-oriented disassembly line balancing problem by considering the partial disassembly type. In their study, disassembly level (which parts are disassembled through which tasks), number of stations, cycle time and assignment of tasks to disassembly stations are considered as well as partial disassembly. In the literature, there are different studies that include the profit oriented PDLBP.

Components obtained with the disassembly process are accepted as raw materials for different products. The distribution of components to the customers on the purpose of the remanufacturing is as important as the disassembly process. Thus, the Vehicle Routing Problem (VRP) occupies an important position in the distribution plan of products to be recycled [Kenger et al., 2020]. Dantzig and Ramser [1959] introduced the VRP at first. The classical VRP determines an optimal routing plan for homogeneous vehicles to serve a set of customers and satisfies other some constraints.

New constraints added to classical VRP create variants of the VRP. VRP with Time Window (VRPTW) is a type of VRP developed by adding the time interval constraint $[a, b]$, which is defined as the time window to each node in classical VRPs. In the time window a_i represents the earliest starting time to the service, b_i the latest starting time to the service. The purpose of the VRPTW is to find the optimal routes by considering vehicle capacities, service times, time windows, and to determine the order of customers to be visited for each vehicle [Savelsbergh, 1985; Çetin and Gencer, 2011]. VRPTW is divided into two as soft and hard according to time windows. In VRPs with hard time windows, the vehicle that arrives before the earliest starting time waits until the earliest starting time. A vehicle arriving after the latest starting time cannot start the service. In VRPs with soft windows, the vehicle arriving before the earliest starting time waits until the earliest starting time, while the vehicle arriving after the latest starting time may start the service for a penalty cost [Çetin and Gencer, 2010].

The other variant of the VRP is Heterogeneous Fleet VRP. Although it is very common in theory, the vehicle fleets used in practice are generally not homogeneous. In other words, vehicle fleets have different capacities, fixed and variable costs or special containers [Çetin and Gencer, 2011]. Therefore, the Heterogeneous Fleet VRP determines vehicle routes, each starting and ending at the depot, for a heterogeneous fleet of vehicles which services a set of customers with known demands [Choi and Tcha, 2007]. In the circumstances, VRPs with heterogeneous fleets are often showed up in real life applications. VRPTW and Heterogeneous Fleet VRP are NP-hard problems.

Economic developments have brought environmental problems and consumption growth with rapid industrialization. And consequently, unconscious production and consumption frenzy have caused the depletion of natural resources, global warming, and excess pollution. For this reason, environmental awareness has increased and the strategies to reduce the environmental pollution have come into prominence. In particular, the high rate of carbon emissions in atmosphere is one of the most important elements of the environmental problems. Logistics activities also have a negative impact on this issue. Because the road transportation is the primary mode that causes environmental problems like greenhouse gas (GHG) emissions, CO₂ emissions, fuel consumption etc. in logistic sector. At this juncture, the concept of green logistics comes to the fore with the increased importance of environment and sustainability.

Implementing green logistic ideas in VRP and its variants give rise to the Green Vehicle Routing Problems (GVRP). GVRP determines the optimal vehicle routes that meet financially sound by considering environmental sustainability goals [Jabir et al., 2015]. The basic principle of VRPs is to reduce the total distribution costs and times by minimizing the total travel time and distances. The GVRP, which emerged as a new approach in VRP variants, aims to design a route for the distribution plan that will cause the least damage to the environment by considering not only total travel distance, but also other variables such as gas emissions, fuel consumption, fleet selection, vehicle capacities [Figliozzi, 2010; Dişkaya and Dinçer, 2018]. Costs related to fuel consumption and gas emissions are affected by various factors such as travel distance, vehicle load, vehicle speed, time-dependent speed, and road slope. [Lin vd., 2014; Belbağ, 2017].

GVRP is an important cost item for logistics companies as it optimizes distribution network activities by preserving environment and achieving economic benefits [Durmaz and Budak, 2021]. With the GVRPs, it is possible to provide a sustainable business in the logistics sector by organizing distribution management with less fuel use, reducing costs, and increasing profitability with an environmentalist mission. [Figliozzi, 2010; Dişkaya and Dinçer, 2018]. With the GVRPs, it is possible to provide a sustainable business in the logistics sector by organizing distribution management with less fuel use, reducing costs, and increasing profitability with an environmentalist mission. [Figliozzi, 2010; Dişkaya and Dinçer, 2018]. In this way, logistics companies may gain both economic and environmental advantages and social prestige by using the methods of GVRP.

An important study in the literature, which can be considered as one of the firsts on GVRP, was carried out by Erdoğan and Miller-Hooks [2012]. The authors combined alternative fuel vehicles with the VRP. This problem is defined as GVRP. The proposed problem considers the maximum route time and fuel constraint. To solve the problem, two heuristic algorithms, Adapted Clarke and Wright [1964] Savings Algorithm and Density Based Clustering Algorithm, are proposed. In progress of time, the studies that involve multi-objective optimization (MOO) in which more than one objective function is considered have gained importance. Demir et al. [2014a] created a model by considering two conflicting objective functions, fuel consumption and driving time. This model is one of the first examples of the Multi- Objective GVRP (MOGVRP).

As stated previously, to gain maximum advantages from the recycling and post-recycling activities depends on not only the effective balance of the disassembly lines in the disassembly centers but also the optimal route plan for distribution of the usable and valuable components, generated by the disassembly process, from disassembly center to the collection centers, i.e., customers [Kenger et al., 2020]. That is, the distribution plan of the products to be recycled is as important as the disassembly process. In this context, companies in the logistics sector need to handle these DLBP and GVRP as an integrated structure for the complex supply chain optimization, simultaneously to achieve both environmental and economic goals. Thus, one important area of research that needs further study is the integrated design and planning of DLBP and GVRP.

MOO problems have two or more objective functions, which are often conflicting. A MOO problem ensures Pareto optimal solutions that provide a suitable compromise among all objectives without degrading any of them. This situation requires to order the solutions according to significant criteria and to select the most appropriate one of the optimal solutions during the implementation phase of the proposed MOO problem. For this reason, in addition to the MOO process, it is necessary to determine the ranking and selection approaches for the Pareto optimal solutions, to evaluate these solutions from a multi-criteria perspective, to present the most suitable alternative solution to the decision maker, and to provide flexibility and ease of application with the multi-criteria decision making (MCDM) method. This integrated methodology will give greater insight about the process and be useful for the implementation of the best optimal solution [Rangaiah et al., 2015].

1.1. Motivation and Objectives

The motivation of this thesis is to present an integrated structure which determines both optimal balance for the partial disassembly process and optimal distribution plans of vehicles for parts to be partially disassembled satisfying time windows, by considering environmental considerations and economic benefits simultaneously. While these issues are addressed separately in the relevant literature, this is the first time they have been addressed together in this thesis.

Based on this motivation, the proposed integrated problem is established as MOO model. A Mixed Integer Linear Programming (MILP) is proposed to solve the problem. This integrated problem has two objectives for the distribution plan of the disassembled parts. The first objective is the minimization of total CO₂ emissions. The second objective is the minimization of the total cost consists of the cost of opening workstations on the disassembly line, disassembly cost of the components and transportation cost. In this thesis, the Augmented ϵ -constraint Method (AUGMECON) which is a widely used method for the solution of multi-objective problems (especially bi-objective) is used for these conflicting objectives.

This thesis also combines the advantage of MOO, which yields Pareto solutions, with an MCDM model. The best Pareto optimal solution is selected with this MCDM process to enable the proposed integrated problem to be applied in the industry. This MCDM process consists of two stages. First, the key criteria to be

used in decision making are specified based on the MOO results and weighted using Entropy Weight Method (EWM), which is one of the objective weighting methods. Then, by applying the Complex Proportional Assessment (COPRAS) method, Pareto solutions (i.e., alternatives) are ranked according to their utility values, and the selection of the most priority Pareto solution is performed.

In this way, this study determines optimum line balance and vehicle routes, considering both environmental and economic objectives, as well as allows the selection of the best option among Pareto optimum solutions, according to the criteria obtained from the MOO model.

Objectives of this thesis which makes four main scientific contributions to the literature can be summarized as follows:

- The first is to build a partial disassembly structure in which only relevant parts/components are disassembled on the disassembly lines, not all components separated from a product. Because the disassembly profitability decreases and environmental effects are not taken into account due to that all components of a product are disassembled in the complete disassembly process. For this reason, the usage of this model for real life applications is aimed by considering the partial mode for DLBP, which is in the integrated optimization problem structure in this thesis.
- The second is to propose a complex optimization model, consists of PDLBP and GVRP that simultaneously determines the optimum load balance on the disassembly lines and the optimal distribution plan for the parts coming from the disassembly, considering relevant objective functions and constraints. Another advantage of this model is that it is created within the scope of green logistics, and it provides environmental protection as well as economic contribution.
- The third is to present scenarios and sensitivity analysis related to both sections of the integrated problem to test the applicability of the proposed model under different conditions. In practice, there may be a change in the proportion of the product to be partially disassembled during the disassembly process, or the fleet of heterogeneous vehicles may be used to determine distribution routes. Therefore, it is aimed to examine the effects of these changes on the results in detail within the scope of the thesis. In this way, the importance of obtaining

flexible approaches that will be able to generate solutions under all circumstances is emphasized.

- The fourth objective of this thesis is to make the best choice from the many Pareto optimal solutions, known as the non-dominated solutions of the MOO model, with the key criteria evaluated objectively by avoiding human subjective interference. Thus, the actualization of the proposed integrated model with the most appropriate Pareto optimum solution will be able to reveal tactical level decisions in the supply chain and to increase the efficiency of this complex process.

The remainder of this thesis is organized as follows. In Section 2, an extensive literature review related to the DLBP and GVRP is provided. Section 3 presents the problem definition, assumptions about the problem and the proposed MILP model. Then, in Section 4, gathered data for the main model, heterogeneous vehicle fleet model and sensitivity analysis are presented. The MOO and MCDM methods to be used are described and the proposed model is tested with computational experiments. The results of the model are analyzed in Section 5. In this section, the effect of considering heterogeneous fleet, sensitivity analysis and their implementation details are explained. Ranking results of Pareto optimal solutions obtained with the proposed MOO model for both homogeneous and heterogeneous vehicle fleet are also given. Finally, conclusion part summarizing this study along with future research directions is presented in Section 6.

2. LITERATURE REVIEW

As mentioned at the beginning, the logistics sector has gained more importance with the increase in trade volume and the development of globalization in the recent period. These developments force companies to consider complex supply chain optimization problems. For this reason, vehicle routes should be determined by minimizing the environmental impacts that occur during the distribution network. In addition, the integrated structure in which available resources are used efficiently and the disassembly line balancing processes are considered should be tackled. From this point of view, this section of the thesis provides a comprehensive literature review conducted in two main areas, DLBP and GVRP. The following subsections explain used objective functions, constraints, and methods for both areas in detail.

2.1. Disassembly Line Balancing Problem

In the last decades, classical DLBP and its variants have been studied in the literature due to increasing importance of the product recovery. Güngör and Gupta [2001] introduced DLBP, analyzed the task failures and proposed a model to reduce the effects of this failures on disassembly lines with the results of analysis in their study. Güngör and Gupta [2002] discussed the complications that are likely to arise on a disassembly line in another study. They proposed a simple heuristic method to solve DLBP of a personal computer. They contributed to the literature with the unique identification of the characteristics of disassembly lines. Özceylan and Paksoy [2013] focused an integrated structure consists of Reverse Supply Chain (RSC) and DLBP. They proposed a nonlinear mathematical model to minimize the total transportation cost and the total fixed cost of workstations. Özceylan and Paksoy [2014] presented two fuzzy mathematical formulations for the integration of DLBP and RSC in their other study. The authors aimed to optimize a RSC that involves customers, collection/disassembly centers and plants while to balance the disassembly lines in disassembly centers, simultaneously by applying fuzzy modeling. They illustrated accuracy and applicability of the model and benchmarked the fuzzy approaches via a hypotheticalal example. On the other hand, Özceylan et al. [2014] combined Closed-Loop Supply Chain and DLBP. They proposed a nonlinear mathematical model to minimize the total cost. The authors concluded that this

integrated problem yields savings in cost over the case where the two decisions are made sequentially. Habibi et al. [2017] handled RSC and the disassembly of EOL products, simultaneously. At the same time, they solved the integrated study of the collection and disassembly of products in reverse logistics with a two-stage iterative heuristic method. Habibi et al. [2018] also discussed the uncertainty in their study. The quality and demand variables in the returned product contain uncertainty. The authors considered a multi-vehicle stochastic collection-disassembly problem. They proposed a mathematical formulation and sample average approximation to solve this problem. Kannan et al. [2017] dealt the integrated multi-product DLBP and the recovery network. They proposed a Mixed-Integer Non-Linear Programming (MINLP) model. The model has the objective function which focuses the minimization of total cost. Budak [2020], developed the sustainable reverse logistics network with integration of DLBP to examine decisions in view of Triple Bottom Line. The author proposed Multi period Multi-Objective MINLP and solved this integrated problem with Improved Augmented Epsilon Constraint technique.

In the existing literature, most of investigates on the DLBP are focused on complete disassembly. As mentioned earlier, the PDLBP was first handled by Altekin et al. [2003]. Ren et al. [2017] addressed the profit oriented PDLBP. In their study, they first developed a mathematical model for the problem, including cycle time constraints and AND/OR precedence relations constraints. Next, they proposed a new metaheuristic approach based on the Gravity Search Algorithm. They used case studies with different problem sizes to test the performance of the proposed method. The authors compared the performance of the proposed with Particle Swarm Optimization (PSO), Differential Evolution, Artificial Bee Colony (ABC) algorithms and CPLEX's exact solution method. They concluded that the proposed metaheuristic method provides optimal solutions like the CPLEX algorithm for small-sized problem examples and successfully solves the profit-oriented PDLBP. Bentaha et al. [2018] handled the profit oriented DLBP by considering partial disassembly, the presence of dangerous parts, and the uncertainty of the processing times of disassembly tasks. The method developed for problem solving consists of two phases. In the first phase, they proposed a two-stage stochastic MILP and the Sampling Average Approximation. This approach provided lower and upper bounds for the optimum value. In the second phase, they developed a Min-Max formulation

and an Upper Bound Mixed Integer Program to balance the disassembly line generated from the first phase under uncertainty. They evaluated the performances of the method procedure and lower and upper bound complex integer programs, with problem instances obtained from the literature. Results of the first phase showed that all problem instances were solved in less than four hours. They emphasized that this computation time for the design and the balance of disassembly lines is acceptable. Numerical results showed that the solution of the first phase remained optimal in the second phase, resulting in cost reduction.

In recent years, this issue has been addressed as MOO in the relevant literature. Wang et al. [2019a] proposed a PDLB which aims to disassemble only hazardous parts. The authors created a model that optimizes three main economic indicators: number of workstations, workload smoothness and disassembly profit. They designed a new Multi-objective Genetic Simulated Annealing (SA) algorithm that includes encoding, decoding, genetic operations, multi-objective processing method and evaluation index. With this study, they reached that not only environmental effects, but also economic efficiency indicators of disassembly lines can be improved. Wang et al. [2019b] established a stochastic partial disassembly line balancing model which includes uncertain disassembly task times, disassembles only parts with hazardous and remanufacturing value, and optimizes the number of workstations, workload smoothness, energy consumption and disassembly profit simultaneously. They proposed a new Multi-Objective Discrete Flower Pollination algorithm for the problem. Zhu et al. [2020] investigated a partially parallel disassembly line to disassemble the different products simultaneously. The authors created multiple objective functions for the minimization of cycle time, number of workstations, idle index, and the amount of disassembly resources. They proposed a new Multi-Objective Hybrid Group Neighborhood Search Algorithm for the problem. They first applied the proposed algorithm to a partially parallel disassembly line for simultaneous disassembly of two types of waste products in a household appliance disassembly plant. Then, they applied the method for the case where two types of waste products are carried out in two different disassembly lines. The comparison results confirmed the superior performance of the parallel disassembly line in terms of reducing the number of workstations and increasing the disassembly production efficiency. Wang et al. [2020] proposed a partial destructive disassembly

line balancing model by considering the uncertainties of corrosion and deformation of the parts. The model aims to optimize the number of stations, the smoothness index, the energy consumption, and the profit of disassembly. They proposed a new Improved Genetic Algorithm based on task precedence relationship. They tested the proposed model on the waste television disassembly line example. The performance of the proposed method was validated by comparing with Ant Colony Optimization (ACO), PSO, ABC and SA approaches.

Laili et al. [2020] presented a literature review of the latest models to summarize the input data, parameters, decision variables, constraints, and objectives of the DLBP. The study provided a basis for further algorithm design in disassembly line scenarios. With the literature review on the DLBP, the created objective functions and constraints for the model as well as the solution methods were examined. The frequently used objective functions in the DLBP are to maximize the efficiency of each workstation, to maximize the disassembly line efficiency, to minimize the number of hazardous tasks, to minimize the disassembly cost, to maximize the disassembly profit and to minimize the environmental pollution. The frequently used constraints in the literature can be evaluated in three main categories. The first category is cycle time constraints. Cycle time constraints are formed according to whether the cycle time is considered as a decision variable or parameter in the model. The second category is precedence constraints. The execution of tasks in the disassembly line may limit according to process techniques and precedence relationships. Precedence constraints can be varied depending on whether the relation are represented by graph (AND/OR graph) or matrix (precedence relationship matrix). The third category is variable constraints. DLBP may include decision variables related to task selection, task assignment, or equipment allocation according to the type of the model. Considering the structure of the model, variable constraints are created according to the required decision variable.

2.2. Green Vehicle Routing Problem

There are many studies on the VRP and its variants in the literature. With the increase in environmental awareness in recent years, studies have been carried out on the GVRP, which reflects the environmental sensitivity of the VRP by concerning about problems such as GHG/CO₂ emissions, fuel consumption within the scope of

the concept of green logistics. An important study, which can be considered as one of the firsts on this subject, was carried out by Erdoğan and Miller-Hooks [2012]. They integrated alternative fuel vehicles with the VRP. This problem is defined as GVRP. The authors added the maximum route time and fuel constraint in their study.

Some authors focused on review papers for the studies on GVRP in the literature. Margaritis et al. [2016] discussed on the usage of electric commercial vehicles in urban freight transport services within the scope of green logistics. The authors analyzed technical specifications, operational conditions which influence the effectiveness for procedures of the routes and schedules.

Ferreira et al. [2020] conducted a systematic literature review on the MOGVRP in their study. According to their results, cost minimization, fuel consumption minimization, travel time minimization, CO₂ minimization, profit maximization and energy minimization were determined as the objective functions of the MOGVRP studies evaluated within the scope of the research.

Asghari and Mirzapour Al-e-hashem [2021] investigated VRP variants in their study. They provided comprehensive search about the formulation techniques, solution approaches and application areas. Moghdani et al. [2021] presented an extensive literature review regarding to green freight transportation problems, optimization types, model formulations and solution techniques to analyze GVRP studies from different perspectives.

It is necessary to analyze papers which contain GVRP in the literature in detail to design a proper mathematical model for determined type of GVRP. To ensure this, the literature review was conducted in accordance with this manner. GVRP papers generally deal with one specific objective function in their optimization model. This objective function differs according to the structure of the model, the variables researched and the parameters used.

According to Durmaz and Budak [2021], a wide range of papers focuses to minimize total distance, emission cost or total time in the scope of single-objective optimization in GVRP. The environmental objective of the optimization comprises the minimization of CO₂/GHG emissions or fuel consumption. The social objective of the GVRP includes the minimization of total performance that is the sum of differences between the maximum of the networks outputs and the targeted output.

Afterwards, the GVRP literature has started to handle MOO models to achieve both environmental and economic objectives simultaneously [Durmaz and Budak, 2021]. Demir et al. [2014a] proposed a model, one of the first example of the MOGVRP, considering two conflicting objective functions, fuel consumption and driving time. Jabir et al. [2015] presented the MOGVRP involving multi-depot in their study. The authors developed a hybrid meta-heuristic algorithm combining Ant Colony Optimization algorithm and Variable Neighborhood Search algorithm (ACO-VNS) to find non-dominated Pareto optimal solutions.

Durmaz and Budak [2021] subdivided objective functions of MOGVRP into three categories in their study. The authors conclude that some MOO models of GVRP minimize not only CO₂/GHG emissions or fuel consumption but also distance/cost. [El Bozuekri and El Hilali Alaoui, 2014; Molina et al., 2014; Jabir et al., 2015; Gupta et al., 2017; Muñoz-Villamizar et al., 2017; Toro et al., 2017; Liu et al., 2018; Poonthalir and Nadarajan, 2018; Soleimani et al., 2018; Wang et al., 2019; Poonthalir et al., 2020; Abdullahi et al., 2021]. They indicate that some authors investigate the optimization model which includes the minimization of total time and total fuel consumption simultaneously [Xiao and Konak, 2015; Kabadurmuş et al., 2019; Ren et al., 2020]. The authors point out that the social aspect of the MOO models of the GVRP focuses on the minimization of total working time or the maximization of the customer satisfaction besides environmental benefits [Ramos et al., 2014; Xu et al., 2019; Zulvia et al., 2020].

To increase the accuracy of the proposed mathematical model in this thesis, the constraints that are frequently used within the scope of the literature review of the GVRP are also analyzed. The literature review of GVRP shows that the studies mostly include vehicle capacity, time window, fuel tank capacity constraints, battery capacity and charge level, distance, speed, flow conservation, demand satisfaction, sub-tour elimination and variable constraints. [Durmaz and Budak, 2021].

A GVRP may include the homogenous or heterogeneous vehicle fleet. In this part of the literature review, it is concluded that most of the previous studies consider homogeneous fleet since the problem including heterogeneous fleet is more complex [Durmaz and Budak, 2021].

The mathematical model of a GVRP may also include more than one depot that the vehicles are dispatched. In this case, the model is handled as Multiple Depot VRP in the literature [Li et al., 2019; Wang et al., 2019].

The proposed models in the literature on GVRP can be deterministic, as well as fuzzy or stochastic. For this reason, mathematical models constructed under uncertainty contain non-deterministic parameters. In this context, the frequently used uncertain parameters in the GVRP, is service time, travelling time, fuel consumption, CO₂ emission cost, vehicle speed, demand, service level and customer satisfaction.

Table 2.1 is presented below to summarize the literature review of GVRP from a broad perspective regarding and to get a clearer on GVRP [Durmaz and Budak, 2021].



Table 2.1: The summary of literature review on GVRP.

Publication	Objective Function(s)	Constraint(s)	Fleet Type	Number of Depot	Publication	Objective Function(s)	Constraint(s)	Fleet Type	Number of Depot
Ubeda et al. (2011)	Min total CO ₂ emissions	Capacity constraint, Time constraint	HMG	Single	Ćirović et al. (2014)	Min total performance	Capacity constraint	HMG	Single
Erdoğan and Miller-Hooks (2012)	Min total distance	Fuel tank capacity constraint, Time constraint	HMG	Single	El Bozuekri and El Hilali Alaoui (2014)	Min total distance, Min CO ₂ emissions	Capacity constraint, Time window constraint, Schedule constraint	HMG	Single
Li (2012)	Min total fuel consumption	Capacity constraint, Time window constraint	HTR	Single	Liu et al. (2014)	Min total carbon footprint	Capacity constraint, Time constraint	HTR	Single
Kwon et al. (2013)	Min total cost	Capacity constraint, Carbon emission balance constraint	HTR	Single	Molina et al. (2014)	Min total cost, Min GHG emissions	Capacity constraint, Time constraint, Load constraint	HTR	Single

Table 2.1 Continued: The summary of literature review on GVRP.

Felipe et al. (2014)	Min total cost	Battery capacity constraint, Time constraint, Charge level constraint	HMG	Single	Ramos et al. (2014)	Min total distance, Min CO ₂ emissions, Min total working hours	Capacity constraint, Time window constraint, Multiple depots constraint	HMG	Multiple
Ćirović et al. (2014)	Min total performance	Capacity constraint	HMG	Single	Goeke and Schneider (2015)	Min total cost	Capacity constraint, Time window constraint, Charge level constraint	HMG	Single
Tajik et al. (2014)	Min total cost	Capacity constraint, Time constraint, Load constraint	HMG	Single	Jabir et al. (2015)	Min CO ₂ emissions, Min total cost	Capacity constraint, Multiple depots constraint	HMG	Multiple
Zhang et al. (2014)	Min total cost	Capacity constraint, Load constraint	HMG	Single	Küçükoğlu et al. (2015)	Min total fuel consumption	Capacity constraint, Time window constraint	HMG	Single

Table 2.1 Continued: The summary of literature review on GVRP.

Salimifard and Raeesi (2014)	Min total CO ₂ emissions	Capacity constraint	HMG	Single	Tiwari and Chang (2015)	Min total CO ₂ emissions	Capacity constraint	NI	Single
Soysal et al. (2015)	Min total cost	Capacity constraint, Time window constraint, Echelon flow constraint	HMG	Multiple	Koç and Karaoğlu (2016)	Min total distance	Fuel tank capacity constraint, Time constraint	HMG	Single
Zhang et al. (2015)	Min total fuel consumption	Capacity constraint, Load constraint, Three dimensional constraint	HMG	Single	Koç et al. (2016)	Min total cost	Capacity constraint, Multiple depots constraint	HTR	Multiple
Bruglieri (2016)	Min total distance	Fuel tank capacity constraint, Time constraint	NI	Single	Rao et al. (2016)	Min total fuel consumption	Capacity constraint, Distance constraint	HMG	Single

Table 2.1 Continued: The summary of literature review on GVRP.

Hiermann et al. (2016)	Min total cost	Capacity constraint, Time window constraint, Energy capacity constraint	HTR	Single	Xiao and Konak (2016)	Min total CO ₂ emissions	Capacity constraint, Fuel tank capacity constraint, Time window constraint, Distance constraint	HTR	Single
Yin and Chuang (2016)	Min total cost	Capacity constraint, Time constraint	HTR	Single	Kazemian and Aref (2017)	Min GHG emissions	Capacity constraint, Time window constraint, Load constraint	NI	Single
Behnke and Kirschstein (2017)	Min GHG emissions	Capacity constraint, Load constraint	HTR	Single	Leggieri and Haouari (2017)	Min total cost	Capacity constraint, Time window constraint, Energy capacity constraint	HMG	Single
Bruglieri et al. (2017)	Min the total time	Capacity constraint, Time window constraint, Charge level	NI	Single	Muñoz-Villamizar et al. (2017)	Min total cost, Min CO ₂ emissions	Capacity constraint, Time constraint,	HTR	Multiple

Table 2.1 Continued: The summary of literature review on GVRP.

Gupta et al. (2017)	Min total cost, Min CO ₂ emissions	Capacity constraint, Time constraint	HTR	Single	Toro et al. (2017)	Min total cost, Min CO ₂ emissions	Capacity constraint, Load constraint, Location constraint	HMG	Multiple
Jabir et al. (2017)	Min total cost	Capacity constraint, Multiple depots constraint	HMG	Multiple	Niu et al. (2018)	Min total cost	Capacity constraint, Time window constraint, Speed constraint	HMG	Single
Kancharla and Ramadurai (2018)	Min total fuel consumption	Capacity constraint, Load constraint	HMG HTR	Multiple	Poonthalir and Nadarajan (2018)	Min fuel consumption Min total cost	Fuel tank capacity constraint, Time constraint, Deviation constraint	HMG	Single
Liu et al. (2018)	Min fuel consumption Min total cost	Capacity constraint	NI	Single	Soleimani et al. (2018)	Min fuel consumption Min total cost	Capacity constraint, Multiple depots constraint	HTR	Multiple

Table 2.1 Continued: The summary of literature review on GVRP.

Niu et al. (2018)	Min total cost	Capacity constraint, Time window constraint, Speed constraint	HMG	Single	Poonthalir and Nadarajan (2018)	Min fuel consumption Min total cost	Fuel tank capacity constraint, Time constraint	HMG	Single
Madankumar and Rajendran (2018)	Min total cost	Capacity constraint, Time window constraint, Fuel tank capacity constraint, Operations constraint	HMG	Single	Bruglieri et al. (2019a)	Min total distance	Time constraint, Path constraint	HMG	Single
Soleimani et al. (2018)	Min fuel consumption Min total cost	Capacity constraint, Distribution center constraint, Multiple depots constraint	HTR	Multiple	Bruglieri et al. (2019b)	Min total distance	Time constraint, Fuel level capacity constraint	HMG	Single
Soysal et al. (2018)	Min total cost	Capacity, Load, Speed constraint	HMG	Single	Bruglieri et al. (2019c)	Min total distance	Time constraint, Fuel level constraint	HMG	Single

Table 2.1 Continued: The summary of literature review on GVRP.

Dewi and Utama (2019)	Min total cost	Capacity constraint	NI	Single	Kabadurmuş et al. (2019)	Min CO ₂ emissions Min the maximum travelling time	Time constraint, Fuel tank capacity constraint	HMG	Multiple
Koyuncu and Yavuz (2019)	Min total cost	Capacity constraint, Time window constraint	HTR	Single	Macrina et al. (2019a)	Min total cost	Capacity constraint, Time window constraint, Energy capacity constraint, Fuel tank capacity constraint	HTR	Multiple
Li et al. (2019)	Max revenue, Min total cost, Min travel time, Min CO ₂ emissions	Capacity constraint	HMG	Multiple	Macrina et al. (2019b)	Min total cost	Capacity constraint, Time window constraint, Battery capacity constraint, Pollution emission constraint	HTR	Single

Table 2.1 Continued: The summary of literature review on GVRP.

Yu et al. (2019)	Min CO ₂ emissions	Capacity constraint, Time window constraint, Load constraint	HTR	Single	Shao and Dessouky (2020)	Min total time	Time constraint, Fuel tank capacity constraint, Load constraint	HTR	Single
Poonthalir et al. (2020)	Min total cost, Min CO ₂ emissions	Time constraint, Fuel tank capacity constraint	HMG	Single	Zulvia et al (2020)	Min total cost, Min CO ₂ emissions, Max service level	Capacity constraint, Time window constraint, Product's shelf-life constraint	NI	Single
Ren et al. (2020)	Min total emissions, Min total delay time	Capacity constraint, Time window constraint, Distance constraint	HTR	Single	Abdullahi et al. (2021)	Min total cost, Min CO ₂ emissions	Capacity constraint, Time window constraint, Fuel tank capacity constraint	HMG	Single
NI: Not Informed, HMG: Homogenous, HTR: Heterogeneous									

As stated in the introduction, the distribution plan of the components which obtained from the disassembly process is as important as optimal balance of the disassembly lines to improve efficiency in the logistics sector. For this reason, an integrated problem should be handled to achieve both environmental and economic goals in the complex supply chain optimization. The advantages of this integrated solution may form a roadmap to look at recycling processes holistically.

One important area of research that needs further study is the integrated optimization problem of DLBP and GVRP. There is only one study related to this topic in the literature [Kenger et al., 2020]. The authors modelled the integration of the complete DLBP and VRP. They proposed five different linear and nonlinear mathematical models for one-component distribution, multi-component distribution, inventory cost and multi-period conditions. The objective functions are the minimization of the total cost for all mathematical models. However, in their study, there is no MOGVRP with Time Window approach which designed by considering environmental effects and there is no partial disassembly.

Table 2.2 shows the reviewed literature on GVRP and DLBP, in various aspects of research such as dimension of the objective function, the solution methodology and emphasizes the originality of this study. It is also presented studies that consider mentioned problems simultaneously and differences and similarities of these studies in Table 2.2.

Table 2.2: Review of studies and the originality of this study.

Author	GVRP	Objectives			DLBP	Solution Methodology
		Economic	Environmental	Social		
Jabir et al. (2015)	✓	✓	✓			ACO and VNS
Ren et al. (2017)		✓			✓	Gravitational Search Algorithm
Li et al. (2019)	✓	✓	✓	✓		ACO
Xu et al. (2019)	✓		✓	✓		Non-Dominated Sorting Genetic Algorithm (NSGA)
Wang et al. (2019a)		✓	✓		✓	Genetic SA Algorithm
Kenger et al. (2020)		✓			✓	MINLP
Zhu et al. (2020)		✓			✓	Hybrid Group Neighbourhood Search Algorithm
Zulvia et al. (2020)	✓	✓	✓	✓		Many-Objective Gradient Evolution
Niu et al. (2021)	✓	✓		✓		Membrane-Inspired Multi-Objective Algorithm
This study	✓	✓	✓		✓	AUGMECON

Based on the literature review in Table 2.2, the main contributions of this study to the literature are as follows:

- To our knowledge, there is no study in the literature that includes the integration of the PDLBP and MOGVRP. In this respect, a significant academic gap is filled.
- The mathematical model of this integrated problem is designed as MOO by considering environmental considerations and economic benefits simultaneously. The first objective is the minimization of total CO₂ emissions. The second objective is the minimization of the total cost consisting of the cost of opening workstations on the disassembly line, disassembly cost of the components and transportation cost. In this context, our thesis is the first integrated study in the literature that integrates the GVRP with a time window and the DLBP.
- In the scope of this study, sensitivity analysis and scenarios are created to investigate the effect of using heterogeneous fleet and changing in the proportion of the product to be partially disassembled. Computational experiments are performed on the created scenarios and sensitivity analysis. Thus, the results of the model are examined in detail.
- The advantages of the integrated solution draw a road map for a holistic view. Both economic and environmental concerns are evaluated together. In this field, decision makers and managers will be able to obtain both the PDLBP results and distribution plans. Comprehensive analysis is provided to managers in the logistics sector, considering different scenarios.

3. PROBLEM DEFINITION & MATHEMATICAL MODEL

In this section, the proposed integrated problem is addressed, firstly. The assumptions and the scope of the problem are explained comprehensively. Then, the required notation and the mathematical model are presented. Finally, definitions of the equations related to objective functions and constraints of this mathematical model are clarified.

3.1. Problem Definition and Assumptions

Serious environmental problems arise with overconsumption in our world. The most effective way of the environmental protection is recycling. To obtain maximum benefit from the recycling activities depends on the effective and robust design of the disassembly lines. The valuable components are separated from waste products with the disassembly process. In addition to this, some valuable and usable components obtained from disassembly lines can accept as key items for different processes. At this juncture, it becomes imperative to find the optimal distribution plan of these components. Thus, the determining of the routing plan for usable components and the balancing of disassembly lines should be handled simultaneously. Consequently, logistics companies need to consider complex supply chain optimization problems. Therefore, this study includes the integrated optimization of the PDLP and the MOGVRP for the first time. The integrated structure of the PDLBP and MOGVRP, discussed in this study, is illustrated in Figure 3.1 below. In this figure, the supply chain network is demonstrated from supplier to the remanufacturing center or disposal. This study only focuses on the flow between the disassembly center and the collection center and the VRP is applied for this part.

According to the proposed problem in this thesis, the process starts with the selection of some components from the waste product and the assignment these components to workstations at the disassembly center reasonably. This phase of the integrated problem ensures the partial disassembly. Afterward, these parts obtained with the disassembly need to be transported to the collection centers by vehicles that travel between the collection centers and then go back to the distribution center. For

this reason, optimal distribution routes are determined for these components. Other tasks that come from the disassembly center to the collection centers go remanufacturing centers or disposal. Our model deals with the distribution from the disassembly center to the collection centers shown as Optimization Part in Figure 3.1.

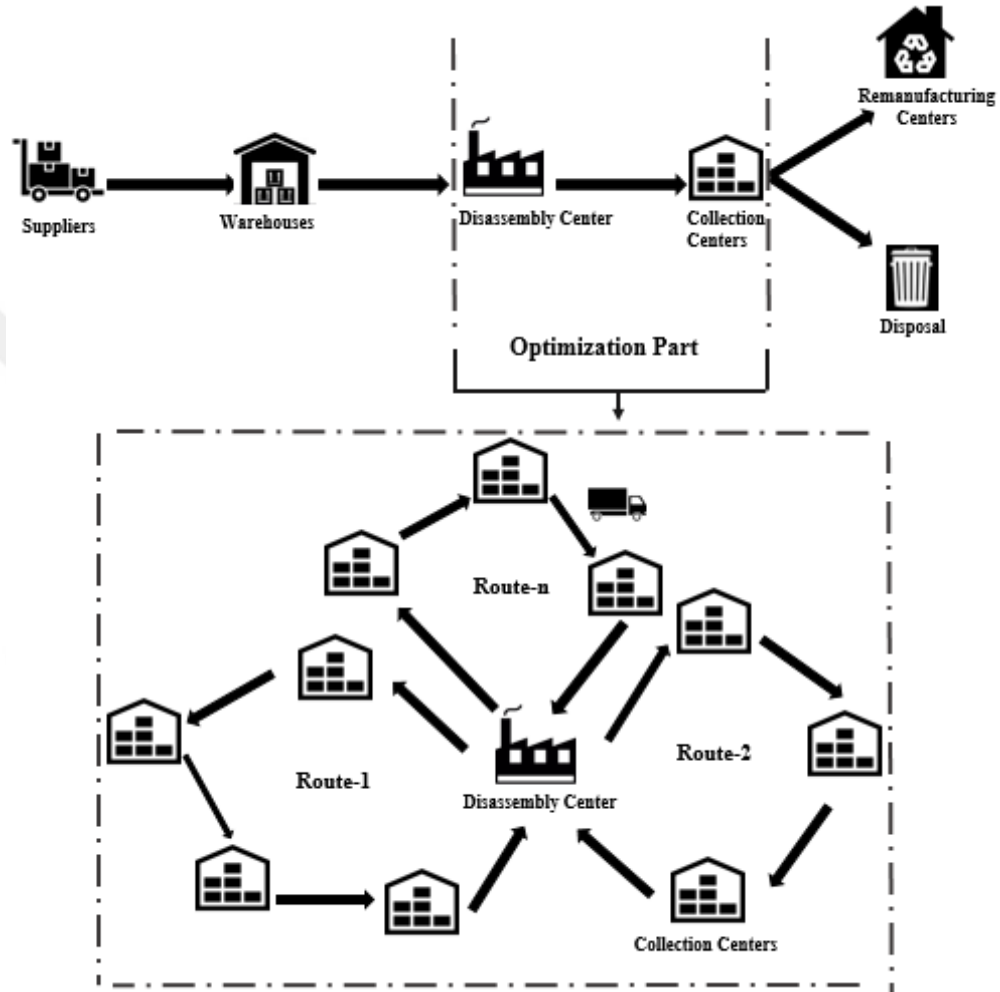


Figure 3.1: The illustration of the proposed integrated structure of PDLP and MOGVRP.

A MILP model is designed for the proposed integrated problem. In the MILP model, more than one objective function is considered. One of the objectives of this MILP model is the minimization of the total CO₂ emissions that occur during the service of the vehicles to the customers (collection centers). The other objective is the minimization of the total cost, which includes the cost of opening a workstation on the disassembly line, the cost of processing the components in the disassembly center, and the cost of transporting the disassembled products on the routes.

In MILP model, the integration of the DLBP and the GVRP is guaranteed with the total demand of the remanufacturing centers. Because the number of parts to be disassembled equals to the total amount of components to be distributed that is total demand. The model respectively determines: (i) total number of opened workstations in disassembly center, (ii) optimal task assignments to workstations in disassembly centers, and non-disassembled tasks, (iii) total workstation times and idle times of each workstation, (iv) optimal distribution routes for all vehicles.

The assumptions that are considered in the proposed model are summarized as follows:

- A task cannot be split among two or more workstations.
- A single type of discarded product is partially disassembled.
- All partially disassembled products are distributed to the collection centers.
- Model does not deal with products which are not disassembled.
- The disassembly tasks which have remanufacturing value in the disassembly line must be disassembled exactly.
- Demand quantities for collection center for a component is deterministic and must be fully satisfied.
- All workstations can process any of tasks and all have the same associated costs.
- A disassembly task may result in removal of one or more parts (or subassemblies).
- Task times and costs are deterministic and independent of the station at which tasks are performed
- Homogeneous and heterogeneous vehicles are used, separately.
- Precedence relations of disassembly tasks are predefined with precedence matrix.
- Each vehicle starts and ends the route at the disassembly center and each collection center can be visited by a specific vehicle.
- The total demand of collection centers allocated to a route should not surpass the vehicle capacity.
- The distances between disassembly center and collection centers are deterministic.

3.2. Mathematical Model

This section describes the MILP model that optimizes the balance of disassembly lines and the distribution routes of vehicles simultaneously. The utilized notations are presented below for this integrated model.

3.2.1. Notations

Sets and Indices:

CC:	set of collection centers $CC=\{2,3,\dots,K\}$
W:	set of workstations
W:	set of workstations
N:	node size $N=\{1,2,\dots,K+1\}$ (1 and $K+1$ indicate the disassembly center)
P:	the disassembly precedence relationship matrix for the disassembly tasks, if the task i immediately precedes the task j , $p_{ij}=1$, else, $p_{ij}=0$
i,j :	disassembly task index $i=\{1,2,\dots,I\}$
s :	station index $s=\{1,2,\dots,S\}$
k,r :	collection center index $k,r=\{2,\dots,K\}$
v :	vehicle index $v=\{1,2,\dots,V\}$

Parameters:

t_i :	the task time of the disassembly task i
U :	number of workstations (upper bound)
d_k :	demand for collection center k
a_k :	the earliest time for collection center k to allow the service
b_k :	the latest time for collection center k to allow the service
V :	the maximum number of vehicles that can be used
trv_{rk} :	the time required for travelling from node r to node k
dis_{rk} :	distance between disassembly center and collection center or between collection centers r and k
ϵ_{rk} :	CO ₂ emission (in kg) between collection centers r and k per km
M :	A sufficiently large number

F:	fixed cost to open a workstation in the disassembly line
T:	transportation cost from collection center r to collection center k
c_i :	cost of the disassembly task i
Q:	the loading capacity of each vehicle
WT:	total working time
R_i :	the demand attribute for the disassembly task i, if the part corresponding to the task i has remanufacturing value $R_i=1$, else, $R_i=0$
CT:	cycle time

Decision Variables:

L_{kv} :	load of the vehicle v upon leaving collection center k
Y_{is} :	$\begin{cases} 1, & \text{if the disassembly task i is assigned to the workstation s} \\ 0, & \text{otherwise} \end{cases}$
Z_{rkv} :	$\begin{cases} 1, & \text{if vehicle v travels from collection center r to collection center k or} \\ & \text{between collection centers} \\ 0, & \text{otherwise} \end{cases}$
G_s :	$\begin{cases} 1, & \text{if the workstation s is opened} \\ 0, & \text{otherwise} \end{cases}$
s_{kv} :	the time vehicle v starts to service collection center k

3.2.2. Objective Functions

$$\min \sum_{\substack{r,k \in N \\ r \neq k}} \sum_{v \in V} \epsilon_{rk} * dis_{rk} * Z_{rkv} \quad (3.1)$$

$$\min \sum_{s=1}^S F * G_s + \sum_{i=1}^I \sum_{s=1}^S c_i * Y_{is} + \sum_{\substack{r,k \in N \\ r \neq k}} \sum_{v \in V} T * dis_{rk} * Z_{rkv} \quad (3.2)$$

Two objectives are proposed for the problem, which is commonly used in the literature related to the DLBP and GVRP. Equations (3.1) and (3.2) represent objective functions. Equation (3.1) minimizes the total CO₂ emission. Equation (3.2) minimizes the total cost. The first term of the Equation (3.2) is the total opening cost

of disassembly workstations. The second term is the total cost of performing the assigned disassembly tasks. The third term is the total travelling cost of vehicles.

3.2.3. Constraints

The constraints in the proposed model may be evaluated in two main groups as PDLBP constraints and VRP constraints. Constraints related to the PDLBP comprise of precedence constraints, disassembly mode constraints, workstation constraints, cycle time constraints and variable constraints while constraints related to the VRP consist of assignment constraints, flow conservation constraints, time window constraints, capacity constraints and binary constraints.

Precedence Constraints:

$$\sum_{s=1}^S (s * Y_{is}) - \sum_{s=1}^S (s * Y_{js}) \leq 0 \quad \forall p_{ij}=1 \quad (3.3)$$

Disassembly Mode Constraints:

$$\sum_{s=1}^S Y_{is} = 1 \quad \forall i \in \{i | R_i = 1\} \quad (3.4)$$

$$\sum_{s=1}^S Y_{is} \leq 1 \quad \forall i \in \{i | R_i = 0\} \quad (3.5)$$

Workstation Constraints:

$$G_s \geq G_{s+1} \quad \forall s, s=1, 2, \dots, S-1 \quad (3.6)$$

$$Y_{is} \leq G_s \quad \forall i \in \{1, 2, \dots, I\}, \forall s \in \{1, 2, \dots, S\} \quad (3.7)$$

$$\sum_{s=1}^S G_s \geq \frac{(\sum_{i=1}^I \sum_{s=1}^S t_i * Y_{is})}{CT} \quad (3.8)$$

$$\sum_{s \in W} G_s \leq U \quad (3.9)$$

Cycle Time Constraints:

$$\sum_{i=1}^I (t_i * Y_{is}) \leq CT * G_s \quad \forall s \in \{1, 2, \dots, S\} \quad (3.10)$$

$$CT = \left(WT / \left(\sum_{k=2}^K d_k \right) \right) \quad (3.11)$$

VRP Assignment Constraints:

$$\sum_{v \in V} \sum_{\substack{k=2 \\ r \neq k}}^{K+1} Z_{rkv} = 1 \quad \forall r \in CC \quad (3.12)$$

Flow Conservation Constraints:

$$\sum_{k \in RC} (Z_{1kv}) = 1 \quad \forall v \in V \quad (3.13)$$

$$\sum_{\substack{r=1 \\ r \neq h}}^K Z_{rhv} - \sum_{\substack{k=2 \\ k \neq h}}^{K+1} Z_{hkv} = 0 \quad \forall h \in CC, \forall v \in V \quad (3.14)$$

$$\sum_{r \in RC} Z_{r, K+1, v} = 1 \quad \forall v \in V \quad (3.15)$$

$$\sum_{v=1}^V \sum_{k=2}^K Z_{1kv} \leq V \quad (3.16)$$

Time Window Constraints:

$$s_{rv} + trv_{rk} - M(1 - Z_{rkv}) \leq s_{kv} \quad \forall r, r=1,2,\dots,K, \forall k, k=2,\dots,K+1, r \neq k, \forall v \in V \quad (3.17)$$

$$a_k \leq s_{kv} \leq b_k \quad \forall k \in N, \forall v \in V \quad (3.18)$$

Capacity Constraints:

$$L_{rv} + d_k * Z_{rkv} - Q * (1 - Z_{rkv}) \leq L_{kv} \quad \forall r, r=1,2,\dots,K, \forall k, k=2,\dots,K+1, r \neq k, \quad (3.19)$$

$$\forall v \in V$$

$$L_{kv} \leq Q \quad \forall k \in CC, \forall v \in V \quad (3.20)$$

$$L_{1v} = 0 \quad \forall v \in V \quad (3.21)$$

$$L_{kv} \geq 0 \quad \forall k \in CC, \forall v \in V \quad (3.22)$$

$$Y_{is}, G_s, Z_{rkv} \in \{0,1\} \quad \forall i,s,r,k,v \quad (3.23)$$

Constraint (3.3) indicates the precedence constraints among all tasks in the partial disassembly line. Precedence relationship matrix for tasks is predetermined. This constraint ensures that if the predecessor task i is not assigned to any workstation, then the successor task j cannot be assigned either.

Constraints (3.4) and (3.5) indicate disassembly mode constraints. Constraint (3.4) guarantees that the disassembly tasks which have remanufacturing value in the disassembly line must be disassembled. Constraint (3.5) ensures that the disassembly tasks which have not remanufacturing value can be selected to be disassembled or not to be disassembled.

Constraints (3.6) - (3.9) indicate workstation constraints. Constraint (3.6) provides that workstations are opened in sequence and that an empty workstation is not allowed. Constraint (3.7) ensures that a workstation opens if and only if a task is assigned to that workstation at least. Constraint (3.8) gives a theoretical lower bound on the total number of workstations to be used. Constraint (3.9) guarantees that the

total number of workstations to be opened cannot exceed the maximum number of workstations.

Cycle time constraints are included in Constraints (3.10) and (3.11). Constraint (3.10) ensures that the disassembly time of each workstation in disassembly line does not exceed the cycle time. Constraint (3.11) indicates the calculation of the cycle time. The cycle time in disassembly centers is calculated by dividing the total working time to the total demand for collection centers. Since the working time and total demand are known.

Constraint (3.12) is general assignment constraint for the VRP. It guarantees that each collection centers must be visited exactly once by one vehicle.

Constraints (3.13) - (3.15) give the flow balance constraints that ensure that each vehicle leaves the disassembly center 1, departs from a collection center that it visited and finally returns to the disassembly center given by node $K+1$.

Constraint (3.16) specifies that there are up to V routes going out of the disassembly center.

Constraints (3.17) and (3.18) are time window constraints. Constraint (3.17) specifies that if vehicle v is travelling from collection center r to collection center k , then the vehicle cannot arrive at collection center k before $s_{rv} + trv_{rk}$.

Constraints (3.19) and (3.20) are vehicle capacity constraints. These constraints limit the vehicle capacity to Q . That is, the transported total load on a vehicle cannot surpass the amount of Q .

Constraint (3.21) initializes load variables, L_{kv} to zero for all vehicles at the disassembly center.

Constraint (3.22) enforces the non-negativity restriction on the decision variables.

Finally, Constraint (3.23) represents the binary variables.

3.2.4. Additional Notations for Heterogeneous Fleet

The proposed main model has homogeneous fleet of the vehicle. Moreover, the effects of considering heterogeneous fleet on the objective functions and optimal solutions are also examined in this study.

In this section, the assumption of "Heterogeneous vehicles are used. The fleet size is limited" is added to previous assumptions. Accordingly, modified notations,

objective functions and constraints are as follows. Other constraints remain same except capacity constraints.

Modified Parameters:

ϵ_{rkv} : CO₂ emission (in kg) between collection center r and k per km for vehicle v

T_v : transportation cost of vehicle v per unit distance ($\frac{\$}{\text{km}}$)

Q_v : the loading capacity of type of vehicle v

Modified Objective Functions:

$$\min \sum_{\substack{r,k \in N \\ r \neq k}} \sum_{v \in V} \epsilon_{rkv} * \text{dis}_{rk} * Z_{rkv} \quad (3.24)$$

$$\min \sum_{s=1}^S F * G_s + \sum_{i=1}^I \sum_{s=1}^S c_i * Y_{is} + \sum_{\substack{r,k \in N \\ r \neq k}} \sum_{v \in V} T_v * \text{dis}_{rk} * Z_{rkv} \quad (3.25)$$

Equation (3.24) minimizes the total CO₂ emission by considering CO₂ emission rate according to types of vehicles. Equation (3.25) minimizes the total cost by considering transportation cost according to types of vehicles.

Modified Capacity Constraints:

$$L_{rv} + d_k * Z_{rkv} - Q_v * (1 - Z_{rkv}) \leq L_{kv} \quad \forall r, r=1,2,\dots,K, \forall k, k=2,\dots,K+1, \quad (3.26)$$

$$r \neq k, \forall v \in V$$

$$L_{kv} \leq Q_v \quad \forall k \in ECC, \forall v \in V \quad (3.27)$$

Constraint (3.26) indicates capacity constraints. Constraint (3.27) ensures that the capacity of each vehicle is not exceeded.

The data generation, used methodology and the application are explained in detail in the next section.

4. METHODOLOGY AND APPLICATION

In this section, the developed MILP model is tested with data prepared for the integrated problem by considering two defined objectives. Afterwards, COPRAS and EWM methods used in the MCDM process, which includes the selection of the best Pareto optimum solution are explained. Figure 4.2 shows the framework of the integrated problem consists of MOO and MCDM processes in detail.

4.1. Data Generation

In the scope of this thesis, the integrated problem structure is discussed to determine the optimal disassembly balance and optimal distribution route plans for the printer disassembly line. For the section of PDLBP of this integrated problem, an example of the printer disassembly line with 55 tasks from Wang et al. [2019a] was used. The precedence graph of disassembly tasks is shown in Figure 4.1.

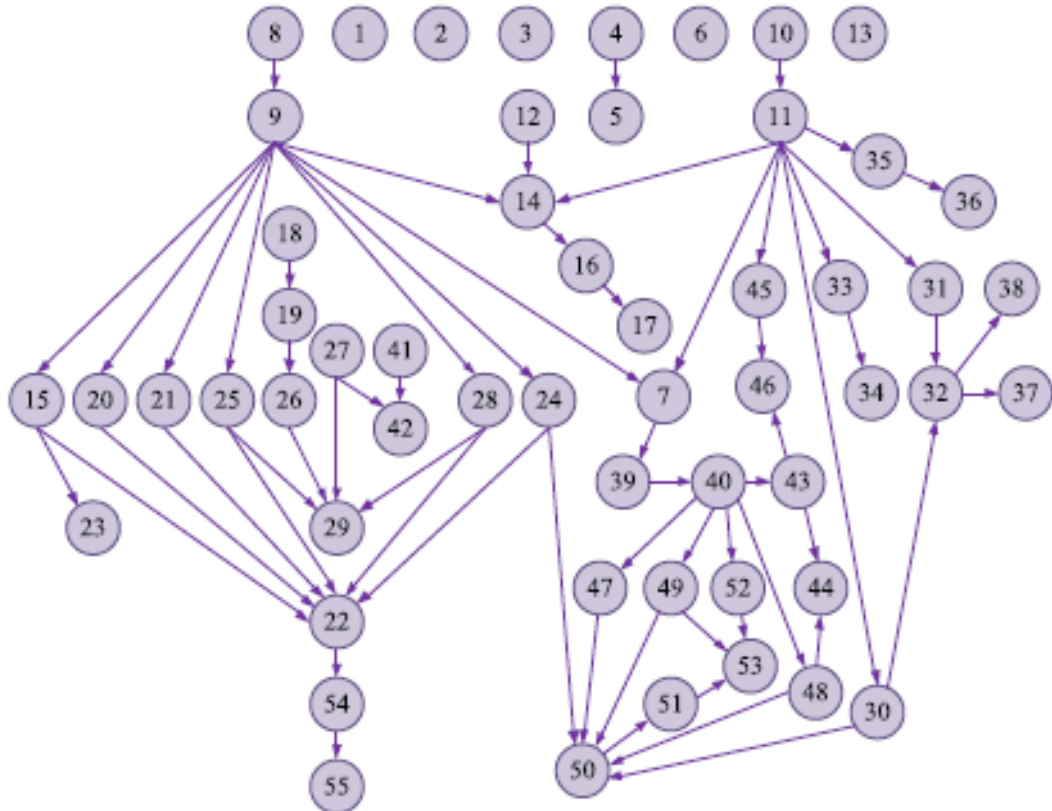


Figure 4.1: The precedence graph of disassembly tasks.

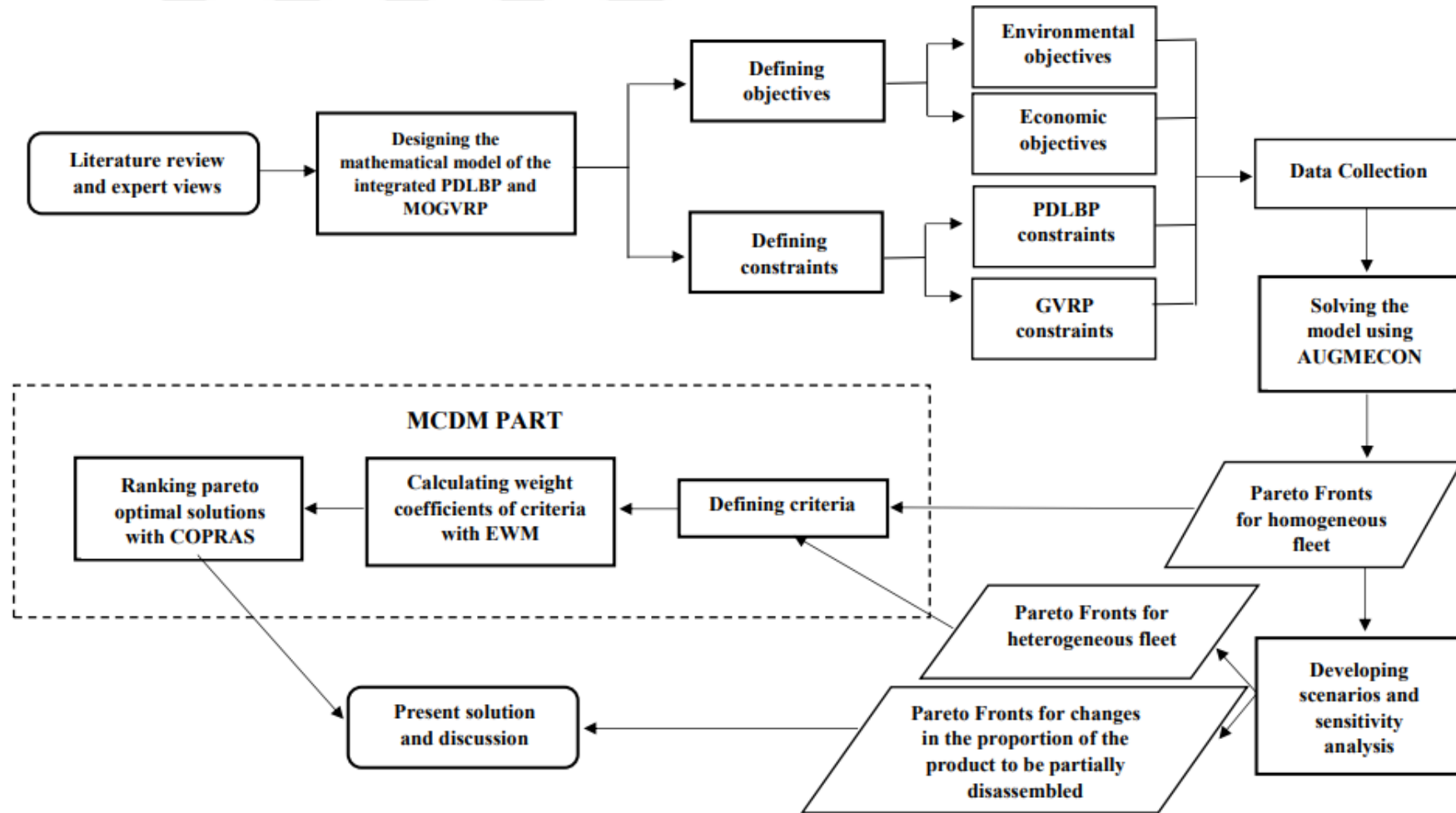


Figure 4.2: The framework of the proposed integrated problem.

To generate our test bed, we modify the printer disassembly tasks instances of Wang et al. [2019a] for the PDLBP part. Table 4.1 presents the information of printer disassembly tasks where 1 in the column of demand attribute denotes that the disassembly task has remanufacturing value and 0 denotes that the disassembly task has not remanufacturing value. Task descriptions, task times and disassembly costs are also included in Table 4.1. Task times and disassembly costs are the same. According to the problem, there is only one disassembly center and the maximum number of workstations that can be opened is 8.

Table 4.1: The information of disassembly tasks.

Task	Description	Task time	Demand attribute	Task	Description	Task time	Demand attribute
1	Power cord	3	0	29	Pickup assembly	15	0
2	Toner cartridge	3	1	30	Take line 2	2	0
3	Paper roll	2	0	31	Gear dust cover screw	40	0
4	Paging device screw	16	0	32	Gear dust cover	3	1
5	Paging device	5	0	33	Relay screw	8	0
6	Input tray	40	0	34	Relay	2	1
7	Front panel	18	0	35	Formatted plate screw	24	0
8	Left plate screw	3	0	36	Format board	2	1
9	Left side panel	3	0	37	Drive gear set	15	1
10	Right side plate screw	8	0	38	Spring group	2	0
11	Right side plate	13	0	39	ECU cover screw	32	0
12	Pull rod	5	0	40	ECU cover	36	0
13	Top cover screw	16	0	41	Base screw	32	1
14	Cover	10	0	42	Base	4	0
15	Cable group	18	0	43	Engine screw	16	0

Table 4.1 continued: The information of disassembly tasks.

16	Heating assembly screw	24	0	44	Engine	3	0
17	Heating component	4	0	45	Right medial plate screw	8	0
18	Screw back	8	0	46	Right medial plate	2	0
19	Back	2	0	47	Laser circuit board screw	8	0
20	Power plate screw 1	16	0	48	Laser circuit board cable 1	2	0
21	Power plate screw 2	32	0	49	Laser circuit board cable 2	2	0
22	Power supply board	15	1	50	Laser circuit board	10	1
23	Plastic block	6	1	51	Laser screw	32	1
24	Take line 1	2	0	52	Laser with cable	2	0
25	Ground	2	0	53	Laser	2	1
26	Pickup assembly screw 1	16	0	54	The left inner plate screw	8	1
27	Pickup assembly screw 2	32	1	55	The left inner plate	2	0
28	Pickup assembly line	4	0				

For the GVRP part of the integrated problem, we modify the instances of Kenger et al. [2020]. The problem has 10 nodes (1 and 10 indicate the same disassembly center and 8 collection centers). All demand characteristics are generated using discrete uniform distributions in the range [5–10]. Table 4.2 and Table 4.3 show the information of demands for collection centers and the distances between collection centers, respectively.

Table 4.2: The information of demand for collection centers.

Collection Center	Demand (kg)
1 (Disassembly Center)	0
2	6
3	8
4	6
5	8
6	5
7	7
8	5
9	10
10 (Disassembly Center)	0

Table 4.3: The distances (km) between collection centers.

COLLECTION CENTRES	1	2	3	4	5	6	7	8	9	10
1	0	20	30	25	15	18	36	17	12	0
2	20	0	24	26	8	16	15	20	8	20
3	30	24	0	12	9	14	21	24	14	30
4	25	26	12	0	13	15	27	30	12	25
5	15	8	9	13	0	13	16	22	10	15
6	18	16	14	15	13	0	14	14	7	18
7	36	15	21	27	16	14	0	9	6	36
8	17	20	24	30	22	14	9	0	15	17
9	12	8	14	12	10	7	6	15	0	12
10	0	20	30	25	15	18	36	17	12	0

Table 4.4 shows that CO₂ emission rates between collection centers. In real-world driving conditions, CO₂ emission rate of a vehicle can be affected by a variety of external factors such as road gradient, traffic conditions, road infrastructure, route difficulty, topography, etc. Due to these factors, CO₂ emission rates differ as kg per km.

Table 4.4: The CO₂ emission rate (kg per km) between collection centers.

COLLECTION CENTRES	1	2	3	4	5	6	7	8	9	10
1	0	0.20	0.30	0.25	0.15	0.18	0.36	0.17	0.12	0
2	0.20	0	0.24	0.26	0.8	0.16	0.15	0.20	0.8	0.20
3	0.30	0.24	0	0.12	0.9	0.14	0.21	0.24	0.14	0.30
4	0.25	0.26	0.12	0	0.13	0.15	0.27	0.30	0.12	0.25
5	0.15	0.8	0.9	0.13	0	0.13	0.16	0.22	0.10	0.15
6	0.18	0.16	0.14	0.15	0.13	0	0.14	0.14	0.7	0.18
7	0.36	0.15	0.21	0.27	0.16	0.14	0	0.9	0.6	0.36
8	0.17	0.20	0.24	0.30	0.22	0.14	0.9	0	0.15	0.17
9	0.12	0.8	0.14	0.12	0.10	0.7	0.6	0.15	0	0.12
10	0	0.20	0.30	0.25	0.15	0.18	0.36	0.17	0.12	0

The fixed cost of opening a workstation in the disassembly line is \$100. Transportation cost is determined as \$0.05 per km. The total working time is set to 5500 minutes. The maximum number of vehicles that can be used is set to 3. The capacity of each vehicle is the same and is equal to 35.

4.1.1. Additional Data for Heterogeneous Fleet

One of the aims of this thesis is to analyze the effects of considering heterogeneous fleet for vehicles to optimal solutions in the integrated problem. We have 3 vehicles which have the same capacity in the main model. However, the analysis of considering heterogeneous fleet includes 3 types of vehicles which have different capacities, different transportation costs and different CO₂ emission rates. To this respect, Table 4.5 presents transportation costs and capacities according to

the vehicle type. Table 4.6 shows CO₂ emission rates between collection centers for each vehicle types.

Table 4.5: The information of the transportation cost and the capacity for the heterogeneous fleet.

<i>Vehicle Type</i>	<i>Capacities</i>	<i>Transportation Costs</i>
<i>A</i>	35	0.32
<i>B</i>	50	0.05
<i>C</i>	40	0.17

Table 4.6: The information of the CO₂ emission rate between collection centers for heterogeneous fleet.

Collection Centres			Vehicle Types			Collection Centres			Vehicle Types		
			A	B	C				A	B	C
1	-	1	0	0	0	5	-	6	0.13	0.27	0.18
1	-	2	0.2	0.4	0.3	5	-	7	0.16	0.32	0.25
1	-	3	0.3	0.5	0.4	5	-	8	0.22	0.44	0.34
1	-	4	0.25	0.3	0.28	5	-	9	0.1	0.5	0.37
1	-	5	0.15	0.25	0.23	5	-	10	0.15	0.25	0.23
1	-	6	0.18	0.32	0.24	6	-	1	0.18	0.32	0.24
1	-	7	0.36	0.63	0.48	6	-	2	0.16	0.36	0.18
1	-	8	0.17	0.5	0.36	6	-	3	0.14	0.34	0.22
1	-	9	0.12	0.28	0.22	6	-	4	0.15	0.38	0.24
1	-	10	0	0	0	6	-	5	0.13	0.27	0.18
2	-	1	0.2	0.4	0.3	6	-	6	0	0	0
2	-	2	0	0	0	6	-	7	0.14	0.3	0.22
2	-	3	0.24	0.6	0.42	6	-	8	0.14	0.35	0.26
2	-	4	0.26	0.45	0.35	6	-	9	0.7	0.85	0.75
2	-	5	0.8	0.9	0.85	6	-	10	0.18	0.32	0.24
2	-	6	0.16	0.36	0.18	7	-	1	0.36	0.63	0.48
2	-	7	0.15	0.42	0.34	7	-	2	0.15	0.42	0.34
2	-	8	0.2	0.4	0.22	7	-	3	0.21	0.47	0.35
2	-	9	0.8	0.9	0.82	7	-	4	0.27	0.55	0.38
2	-	10	0.2	0.4	0.3	7	-	5	0.16	0.32	0.25
3	-	1	0.3	0.5	0.4	7	-	6	0.14	0.3	0.22
3	-	2	0.24	0.6	0.42	7	-	7	0	0	0
3	-	3	0	0	0	7	-	8	0.9	0.95	0.92
3	-	4	0.12	0.28	0.25	7	-	9	0.6	0.76	0.66
3	-	5	0.9	0.96	0.92	7	-	10	0.36	0.63	0.48
3	-	6	0.14	0.34	0.22	8	-	1	0.17	0.5	0.36
3	-	7	0.21	0.47	0.35	8	-	2	0.2	0.4	0.22
3	-	8	0.24	0.52	0.36	8	-	3	0.24	0.52	0.36

Table 4.6 continued: The information of the CO₂ emission rate between collection centers for heterogeneous fleet.

3	-	9	0.14	0.36	0.28	8	-	4	0.3	0.65	0.4
3	-	10	0.3	0.5	0.4	8	-	5	0.22	0.44	0.34
4	-	1	0.25	0.3	0.28	8	-	6	0.14	0.35	0.26
4	-	2	0.26	0.45	0.35	8	-	7	0.9	0.95	0.92
4	-	3	0.12	0.28	0.25	8	-	8	0	0	0
4	-	4	0	0	0	8	-	9	0.15	0.42	0.28
4	-	5	0.13	0.46	0.3	8	-	10	0.17	0.5	0.36
4	-	6	0.15	0.38	0.24	9	-	1	0.12	0.28	0.22
4	-	7	0.27	0.55	0.38	9	-	2	0.8	0.9	0.82
4	-	8	0.3	0.65	0.4	9	-	3	0.14	0.36	0.28
4	-	9	0.12	0.4	0.2	9	-	4	0.12	0.4	0.2
4	-	10	0.25	0.3	0.28	9	-	5	0.1	0.5	0.37
5	-	1	0.15	0.25	0.23	9	-	6	0.7	0.85	0.75
5	-	2	0.8	0.9	0.85	9	-	7	0.6	0.76	0.66
5	-	3	0.9	0.96	0.92	9	-	8	0.15	0.42	0.28
5	-	4	0.13	0.46	0.3	9	-	9	0	0	0
5	-	5	0	0	0	9	-	10	0.12	0.28	0.22
10	-	1	0	0	0	10	-	6	0.18	0.32	0.24
10	-	2	0.2	0.4	0.3	10	-	7	0.36	0.63	0.48
10	-	3	0.3	0.5	0.4	10	-	8	0.17	0.5	0.36
10	-	4	0.25	0.3	0.28	10	-	9	0.12	0.28	0.22
10	-	5	0.15	0.25	0.23	10	-	10	0	0	0

4.1.2. Additional Data for Sensitivity Analysis

Another aim of this thesis is to observe the effects of changing in the proportion of the product to be partially disassembled with sensitivity analysis. Three scenarios are created by increasing the total demand of collection centers 10%, 20% and 30% respectively for the changing in the proportion of the product to be partially disassembled. In our main model, the amount of the total demand is equal to 55 (for 8 collection centers). The demand amounts generated for scenarios are shown in Table 4.7. As seen in Table 4.7, the changes in the amount of the demand are made according to the amount of the total demand in the main model. From this point of view, the total demand increased to 61 for 10% change, it increased to 66 for the 20% change and to 72 for the 30% change.

Table 4.7: Demand quantities for sensitivity analysis.

<i>Collection Centers</i>	<i>Base</i>	<i>10% change</i>	<i>20% change</i>	<i>30% change</i>
1	6	7	9	10
2	8	9	8	9
3	6	7	6	9
4	8	8	8	8
5	5	6	10	9
6	7	8	8	9
7	5	6	7	8
8	10	10	10	10
<i>Total demand</i>	55	61	66	72

4.2. Augmented ϵ -Constraint Method (AUGMECON)

Single-objective optimization models can be solved directly to obtain a single result. In MOO models, there are multiple objectives, and the solution of the model does not generally give a single best result. Instead, a solution set that optimizes all objectives is found. In such cases, the most preferable result is evaluated instead of the best result. The best solution in MOO has been replaced by the concept of Pareto optimal or Pareto efficiency. It is not possible to increase the best value of one objective in the model without worsening the values of other objectives in Pareto optimal solutions. The set with Pareto optimal solutions is the Pareto set. In addition to this, direct approach and aggregation or transformation methods can be applied for the solution of MOO models. The solution with the direct approach is quite difficult, especially when there are conflicting objective functions. For this reason, a solution is realized by transforming all objectives in the model into a single objective. In general, weighted sum and utility methods are used to transform MOO models into single-objective models. The weighted sum method transforms all objective functions into a single scalar objective function using the weighted sum of these functions. The weights are determined deterministically in this method. However, uncertainty is considered for the criteria of each alternative in the utility method. In

this respect, the utility method is more realistic because there will always be uncertainty when considering the outcomes for each alternative [Bal, 2019].

As mentioned above, MOO problems involve multiple conflicting objectives. It is generally difficult to find an optimum solution that is best for all objectives. Karsu [2018] emphasizes in her study that the Epsilon-Constraint method is a widely used method in the literature for solving multiple (especially two) objective problems. Demir et al. [2014b] used the Epsilon-Constraint method with the weighting method for the Adaptive Large Neighborhood Search (ALNS) algorithm to minimize fuel consumption and journey time. Ramos et al. [2014] applied Epsilon-Constraint method for the reverse logistics problem of Multi-Depot VRP. The authors considered the minimization of costs and CO₂ emissions and the maximization of working hours in their model. Govindan et al. [2016] proposed a fuzzy multi-objective model to handle the multi-echelon VRP and multi-period reverse logistics in their study. The objective functions of their model were the minimization of costs and environmental impacts. They compared the solution of PSO method with the Epsilon-Constraint method.

The Epsilon-Constraint method get several advantages over other multi-objective solution methods. As stated by T'Kindt and Billaut [2006], the Epsilon-Constraint method provides ease of trade-off to the decision maker. In addition, the value of an objective can be adjusted easily and the effect of this adjustment on the other objective can be investigated interactively. On the other hand, the number of solutions can be prearranged by changing the value of the epsilon. The Epsilon-Constraint method is based on solving a single-objective sub-problem multiple times in which one of the objectives is optimized and the other objective values are constrained by constraints. In each iteration, the objective values controlled by the constraints are more constrained than their values in the previous solution. The algorithm terminates when the sub-problem it is trying to solve becomes infeasible.

AUGMECON is a variation of the method that produces only efficient solutions (no weakly efficient solutions) and also avoids redundant iterations as it can perform early exit from the relevant loops (that lead to infeasible solutions), accelerating the whole process [Mavrotas, 2009]. Based on all these advantages, AUGMECON is used to obtain Pareto optimal solutions and to analyze the tradeoff

between CO₂ emission and cost and in this integrated problem. AUGMECON is applied as shown below:

$$\min(f_1(x) + \epsilon s_2 / r_2) \quad (4.1)$$

$$f_2(x) + s_2 = e_2 \quad (4.2)$$

$$x \in S \text{ and } s_2 \in \mathbb{R}^+ \quad (4.3)$$

where ϵ is an adequately small number usually between 10^{-3} and 10^{-6} (Mavrotas, 2009). s_2 is represented as surplus variable. The above formulation of the ϵ -constraint method produces only efficient solutions [Mavrotas, 2009]. In Equations. (4.1) - (4.3) f_1 and f_2 represent environmental and economic objectives, respectively. To avoid any scaling problems, it is recommended to replace the s_i by s_i/r_i , where r_i is the range of the i th objective function (as calculated from the payoff table).

4.3. MCDM Methods for Pareto Optimal Solutions

As is known to all, MOO gives many alternate optimal/trade-off solutions, which are equally good from the perspective of the objective functions. These solutions are called as Pareto optimal front and as non-dominated solutions. Pareto optimal set provides a suitable compromise among all objectives and deeper insights into the trade-off among these objectives [Wang and Rangaiah, 2017; Erdoğan et al., 2021]. So, in case of MOO, selection of the best optimal solution from the set of alternate solutions is important and required for implementation. This can be done based on the experience of senior engineers/managers (decision makers) or using a Pareto ranking approach, which often requires certain preferences about the objective functions and their changes [Rangaiah et al., 2015]. Pareto ranking selection should therefore be practical for real-time applications.

It is clear that the selection process of the best Pareto optimal solution obtained from MOO can be considered as a MCDM problem. Because this decision making process includes several key criteria to evaluate the Pareto optimal solutions. In this study, a two-stage MCDM method is carried out, firstly, the EWM method is used to identify the criteria weights, and then a ranking of the Pareto optimal solutions is made with the COPRAS method.

4.3.1. Entropy Weight Method (EWM)

For achievement of the best alternative selection goal, the weighting of the criteria is performed by EWM. In MCDM methods, the weighting process, which shows the importance of the criteria, is generally done in two ways as the objective and the subjective weighting. While subjective weighting includes the judgments of the decision maker, the quantitative characteristics of the alternatives are considered in the objective weighting [Bakır and Atalık, 2018; Işık, 2019; Topak and Çanakçıoğlu, 2019].

EWM, one of the objective weighting methods, was first proposed by Zeleny [1982]. This method provides an important information weight model that measures value dispersion in decision-making. Compared with various subjective weighting models, the most important advantages of the EWM are the avoidance of the interference of human factors on the weight of criteria, and the enhancement of the objectivity in the evaluation results. For this reason, the EWM is preferred in decision making process by decision-makers considerably [Ömürbek and Urmak Akçakaya, 2018; Gorgulu et al., 2021].

The EWM evaluates value by measuring the degree of differentiation. The higher the degree of dispersion of the measured value, the higher the degree of differentiation of the index, and more information can be derived. The formulation of the EWM is presented below [Shemshadi et al., 2011; Ghorbani et al., 2012; Wu and Lin, 2012; Gök-Kısa and Perçin, 2018]:

$$X = \begin{bmatrix} X_{11} & X_{12} & X_{1n} \\ X_{21} & X_{22} & X_{2n} \\ \vdots & \vdots & \vdots \\ X_{m1} & X_{m2} & X_{mn} \end{bmatrix} \quad i=1,2,\dots,m; j=1,2,\dots,n \quad (4.4)$$

The decision matrix is constructed as in Equation (4.4). X_{ij} indicates the performance of each alternative i with respect to each criterion j .

$$P_{ij} = X_{ij} / \sum_{i=1}^m X_{ij} \quad (4.5)$$

Since the values in the decision matrix have different measurement units, it is necessary to normalize the decision matrix in order to ensure consistency. The normalized decision matrix is showed in Equation (4.5). P_{ij} represents the elements included in the normalized decision matrix.

$$e_j = -k \sum_{i=1}^m p_{ij} \cdot \ln(p_{ij}) \quad (4.6)$$

Entropy values regarding criteria are as in Equation (4.6), where $k = 1 / \ln(m)$ representing a fixed number.

$$d_j = 1 - e_j \quad (4.7)$$

In Equation (4.7), differentiation degrees for all criteria are determined. Higher d_j values state higher importance of the relevant criterion.

$$w_j = d_j / \sum_{j=1}^n d_j \quad (4.8)$$

Equation (4.8) shows the calculation of the importance of criteria. w_j represents the importance weight of each criterion. As a result, the total value of w_j equals to 1.

4.3.2. COPRAS (Complex Proportional Assessment) Method

To have an effective implementation process in real-life cases, it is inevitable to determine the priorities of the Pareto-optimal solutions obtained by MOO. For this reason, this study contains a MCDM model to select the best performing solution among optimal options based on the various criteria. In the scope of this MCDM model, after calculating the weight values of the selection criteria determined by the EWM, the relative importance values of the alternatives are determined by the COPRAS method, and these alternatives are ranked according to their importance values.

The COPRAS method was first introduced by the researchers Zavadskas and Kaklauskas in 1996 [Zavadskas and Kaklauskas, 1996; Yazdani et al., 2011]. This method is a MCDM method that can evaluate qualitative and quantitative criteria [Özbek, 2017]. The COPRAS method, which allows the ranking and evaluation of alternatives or options, taking into account the maximization and minimization aspects of the criteria, is very simple to use and has short calculation time. The method provides several advantages over other MCDM methods in the decision-making process in terms of these features [Topak and Çanakçıoğlu, 2019].

The COPRAS method uses step-by-step sequencing and evaluation of alternatives in terms of the significance and utility degree of the available alternatives. This method selects the best decision considering both the ideal and the ideal-worst solutions. In other words, how good or how bad an alternative is compared to other alternatives can be expressed as a percentage in the benchmark process of alternatives [Arslan et al., 2018; Gorgulu et al., 2021]. The algorithm of the COPRAS method is presented [Das et al., 2012; Gorgulu et al., 2021]:

$$D=[X_{ij}]=\begin{matrix} & \begin{matrix} C_1 \\ w_1 \end{matrix} & \begin{matrix} C_2 \\ w_2 \end{matrix} & \begin{matrix} C_n \\ w_n \end{matrix} \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} X_{11} & X_{12} & X_{1n} \\ X_{21} & X_{22} & X_{2n} \\ \vdots & \vdots & \vdots \\ X_{m1} & X_{m2} & X_{mn} \end{bmatrix} \end{matrix} \quad (4.9)$$

The decision matrix is constructed as in Equation (4.9). where A_i represents the alternatives, $i=1,2,..,m$; C_j represents j th criterion, $j=1,2,..,n$. The subjective weight of the j th attribute is denoted by w_j and X_{ij} indicates the performance of each alternative A_i with respect to each criterion C_j .

$$X_{ij}^* = X_{ij} / \sum_{i=1}^m X_{ij} \text{ for } j=1,2,3,..,n \quad (4.10)$$

Equation (4.10) shows the normalization of the decision matrix D .

$$D' = [d_{ij}]_{m \times n} = X_{ij}^* w_j \quad (4.11)$$

Determine the weighted normalized decision matrix D' using Equation (4.11). where X_{ij}^* is the normalized performance value of i th alternative on j th criteria.

$$S_{i+} = \sum_{j=1}^k d_{ij} \quad (4.12)$$

$$S_{i-} = \sum_{j=k+1}^n d_{ij} \quad (4.13)$$

The sums S_{i+} and S_{i-} of weighted normalized values are computed for both beneficial and non-beneficial criteria respectively. For beneficial criteria, higher value is better and for non-beneficial criteria, lower value is better for the attainment of goal. These sums S_{i+} and S_{i-} are calculated using the Equations (4.12 and 4.13).

$$Q_i = S_{i+} + \frac{\sum_{i=1}^m S_{i-}}{S_{i-} \cdot \sum_{i=1}^m \frac{1}{S_{i-}}} \quad (4.14)$$

Using Equation (4.14), the relative importance of the relevant alternative Q_i are determined. Among the alternatives, one with the highest relative importance value is the best choice.

$$P_i = \left[\frac{Q_i}{Q_{\max}} \right] \times 100\% \quad (4.15)$$

The performance index P_i of each alternative is calculated using Equation (4.15). $Q_{\max}$ is the maximum relative importance value. This performance index P_i value is utilized to get complete ranking of the candidate alternatives.

5. RESULTS OF THE MATHEMATICAL MODEL

The proposed model is coded and solved by using GAMS® 34.0/CPLEX 20.1 optimization solver and carried out on a computer with Intel Core I7 5500U CPU with 2.40 GHz processor, with 12.00 GB RAM. While there are 1292 constraints in the main model, there are 727 variables. Execution time of the main model is 41.140 seconds to reach Pareto optimum solutions.

In the scope of this thesis, it was aimed to analyze the effects of considering heterogeneous fleet and the change in the proportion of the product to be partially disassembled in the integrated problem. Therefore, using additional decision variables, data and constraints, the model was run for the heterogeneous vehicle fleet and for the sensitivity analysis consisting of 3 scenarios, separately. Accordingly, the execution time of the model which has heterogeneous fleet is 32.235 seconds. Regarding to sensitivity analysis, execution time is 15.5 seconds for the scenario of 10% change, 12.547 seconds for the scenario of 20% change and 22.203 seconds for the scenario of 30% change, respectively.

The Pareto optimal solutions obtained of the main model are presented in Figure 5.1.

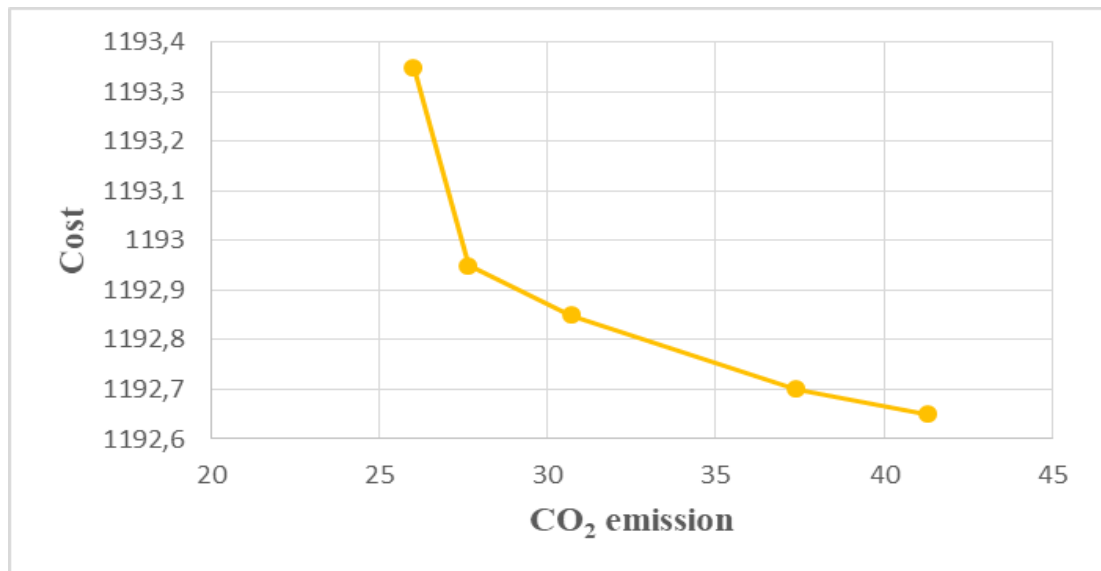


Figure 5.1: Pareto optimal solutions of the main model.

As can be seen in Figure 5.1, 5 non-dominated solutions are obtained. The solution with the minimum CO₂ emission has \$1193.350 of total cost and 26.01 kg of CO₂ emission. The solution with the minimum total cost has 41.31 kg of CO₂

emission and \$1192.650 of total cost. According to the graph, if the main focus is the reduction of CO₂ emission rate, it should be borne more cost to provide environmental benefits. In the same way, ensuring minimum total cost in this network increases environmental impact. For this reason, the decision maker should pay attention to these aspects.

Comparing the results obtained for the main model, where a homogeneous vehicle fleet is used, with the results obtained when the heterogeneous vehicle fleet is considered and a sensitivity analysis involving 3 different scenarios is performed, will provide strategic decisions to decision makers. In this respect, it is very important to clearly observe the change in objective functions, assignment of tasks, number of opened workstations, vehicle routes and capacity utilization. For this reason, the 3rd Pareto optimum solution was chosen to make comparisons in this study.

According to the 3rd Pareto solution, results of the optimal partial disassembly line are given in Table 5.1. The calculation of the cycle time for disassembly line is shown in Equation (5.1) below:

$$\text{Cycle Time} = \frac{\text{Total Working Time}}{\text{Total Demand}} = \frac{5500}{55} = 100 \text{ minutes} \quad (5.1)$$

The 3rd Pareto solution has 30.7 kg of CO₂ emission and \$1192.85 of the cost. Table 5.1 demonstrates total number of opened workstations, assignment of the disassembly tasks to the workstations, tasks not disassembled, total workstation times and idle time of each workstation for 3rd Pareto solution. As seen in Table 5.1, 6 out of 8 workstations are opened. 2nd, 3rd, 4th workstations have no idle time. Total idle time is equal to 15 minutes for this Pareto solution. The maximum workstation time can be equal to 100 for each workstation since the cycle time is equal to 100, and this constraint is ensured as can be seen in Table 5.1. Based upon the assumption, the disassembly tasks which have remanufacturing value in the disassembly line must be disassembled exactly, tasks which have 2, 22, 23, 27, 32, 34, 36, 37, 41, 50, 51, 53, 54 numbers are assigned to related workstations. On the other part, 9 tasks which have no remanufacturing value out of 55 tasks are not assigned to any workstations.

Table 5.1: DLB results at the 3rd Pareto solution for the main model.

Workstation No	Disassembled Tasks	Workstation Time	Idle Time
1	7, 8, 9, 10, 11, 25, 28, 30, 33, 34	98 minutes	2 minutes
2	2, 12, 18, 19, 24, 39, 40, 47, 48, 49	100 minutes	-
3	14, 16, 43, 45, 50, 51	100 minutes	-
4	15, 20, 23, 26, 29, 35, 44, 46	100 minutes	-
5	27, 31, 32, 37	90 minutes	10 minutes
6	17, 21, 22, 36, 41, 52, 53, 54	97 minutes	3 minutes
Tasks not disassembled	1, 3, 4, 5, 6, 13, 38, 42, 55		

The results of the proposed integrated problem also include optimal vehicle routes. Figure 5.2 illustrates optimal distribution of components at the 3rd Pareto solution for the main model. There are 3 vehicles in our model. According to the results of the optimal routes, each vehicle starts and ends its route at the disassembly center and each collection centers are visited by a specific vehicle. In addition to this, capacity and time window constraints are satisfied for all routes. Capacities at each collection centers and how many products received from each customer for each vehicle are shown in Table 5.2.

The logistics sector has gained more importance with the increase in trade volume and the development of globalization. These developments force companies to consider complex supply chain optimization problems. In this study, an integrated model is proposed that considers both reduction of the environmental impacts and reduction of the economic impacts. In addition, the model does not only analyze the DLB process but also creates effective distribution plans for components of the waste product. With this study, it is aimed to help to decision makers who interested in logistics activities to generate flexible solutions.

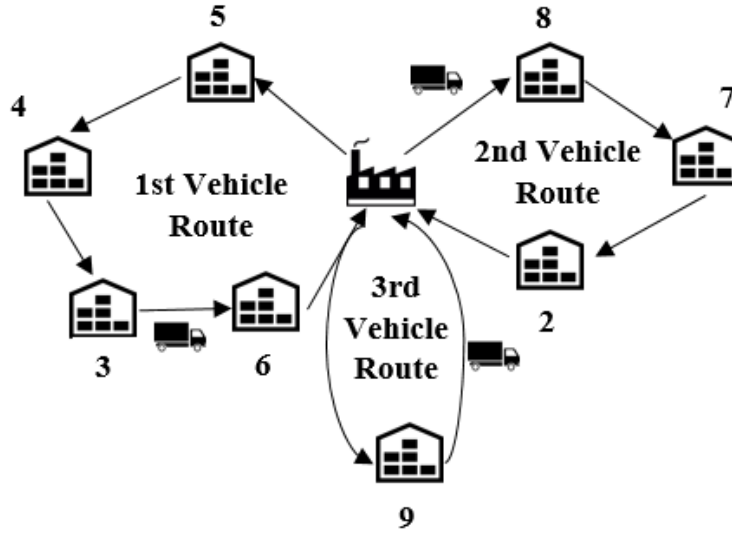


Figure 5.2: Optimal vehicle routes at the 3rd Pareto solution for the main model.

Table 5.2: Vehicle capacities at the 3rd Pareto solution for the main model.

Vehicles	Collection Centers in Route	Vehicle Capacities	Total Distance Traveled
1	1 (Disassembly Center)	35	72 km
	5	27	
	4	21	
	3	13	
	6	7	
	10 (Disassembly Center)	7	
2	1 (Disassembly Center)	35	61 km
	8	30	
	7	23	
	2	17	
	10 (Disassembly Center)	17	
3	1 (Disassembly Center)	35	24 km
	9	25	
	10 (Disassembly Center)	25	

5.1. The Effect of Considering Heterogeneous Fleet

Although homogeneous vehicle fleet is often used in theory, heterogeneous fleet with different capacities or costs are encountered for VRP in real life applications. For this reason, it was answered questions like what kind of results can be achieved in the case of a heterogeneous vehicle fleet, what changes can be observed in the model, how much could the cost and CO₂ emission value increase or decrease. These comprehensive analyzes provided flexible solutions for simultaneous optimization in supply chain management and logistics sector in Turkey by considering different conditions.

In this section, it is aimed to analyze the effects of considering heterogeneous fleet for vehicles in the proposed integrated problem. There are 3 vehicles which have the same capacity in the main model. However, the analysis of heterogeneous fleet usage includes 3 types of vehicles (A, B, C) which have different capacities, different transportation costs and different CO₂ emission rate as mentioned Section 4.1.1. While capacities are 35, 50 and 40 for the type of A, B, C, respectively, transportation costs are 0.32, 0.05 and 0.17.

Pareto optimal solutions obtained by considering the heterogeneous vehicle fleet in the model, are presented in Figure 5.3. As shown in Figure 5.3, 13 non-dominated solutions are obtained.

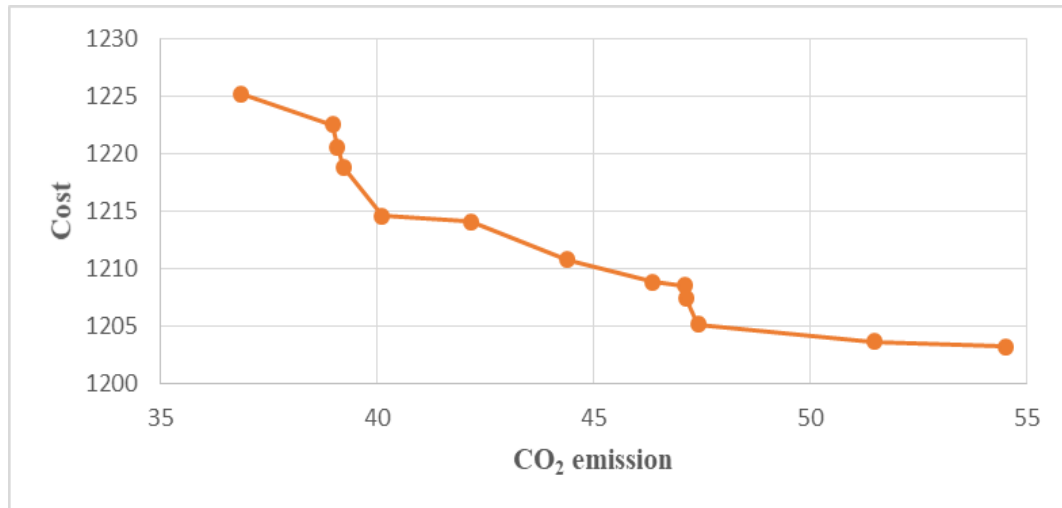


Figure 5.3: Pareto optimal solutions for the heterogeneous fleet.

The solution with the minimum CO₂ emission increases to \$1225.250 of total cost and 36.84 kg of CO₂ emission as against the main model. Furthermore, the

solution with the minimum total cost increase 54.51 kg of CO₂ emission and \$1203.18 of total cost. Changes in the vehicle capacity, transportation cost and CO₂ emission rate affect to the values of objective functions and the number of Pareto optimal solutions.

Changes made in the heterogeneous vehicle fleet usage have also caused differentiations in the optimum disassembly balance. According to the 3rd Pareto solution of the heterogeneous fleet, results of the optimal workload balance in disassembly line are given in Table 5.3. The 3rd Pareto solution has 39.08 kg of CO₂ emission and \$1220.63 of the cost. It can be seen that the number of opened workstations, total idle time and tasks not disassembled did not change in Table 5.3. 6 out of 8 workstations are opened. 2nd, 3rd, and 4th workstations have no idle time. Total idle time is equal to 15 min for this Pareto solution. The tasks numbered 2, 22, 23, 27, 32, 34, 36, 37, 41, 50, 51, 53, and 54 which must be disassembled are assigned to related workstations. On the other part, 9 tasks which have no remanufacturing value out of 55 tasks are not assigned to any workstations.

Table 5.3: DLB results at the 3rd Pareto solution for the heterogeneous fleet.

Workstation No	Disassembled Tasks	Workstation Time	Idle Time
1	2, 8, 9, 10, 11, 12, 14, 18, 19, 28	94 minutes	6 minutes
2	7, 30, 39, 40, 47, 48, 49	100 minutes	-
3	15, 21, 41, 43, 52	100 minutes	-
4	16, 17, 31, 33, 35	100 minutes	-
5	20, 22, 24, 25, 32, 34, 37	97minutes	3 minutes
6	23, 26, 27, 29, 36, 44, 45, 46, 53, 54	94 minutes	6 minutes
Tasks not disassembled	1, 3, 4, 5, 6, 13, 38, 42, 55		

Based on the Table 5.3, it can be concluded that the task assignment in the disassembly line and the values of objective functions change as against the main model because of usage of the heterogeneous fleet. In the real life, heterogeneous fleet is more realistic to determine the vehicle routes. Therefore, this situation necessitates to endure more environmental impacts and economic cost.

Figure 5.4 illustrates optimal vehicle routes for the 3rd Pareto optimal solution of the heterogeneous fleet. As seen in Figure 5.4, due to that the vehicle capacities are not same, vehicle routes have been changed as regards the main model in the presence of the heterogeneous fleet. Table 5.4 shows that the capacities at each collection centers and how many products received from each collection centers for each vehicle by considering heterogeneous fleet.

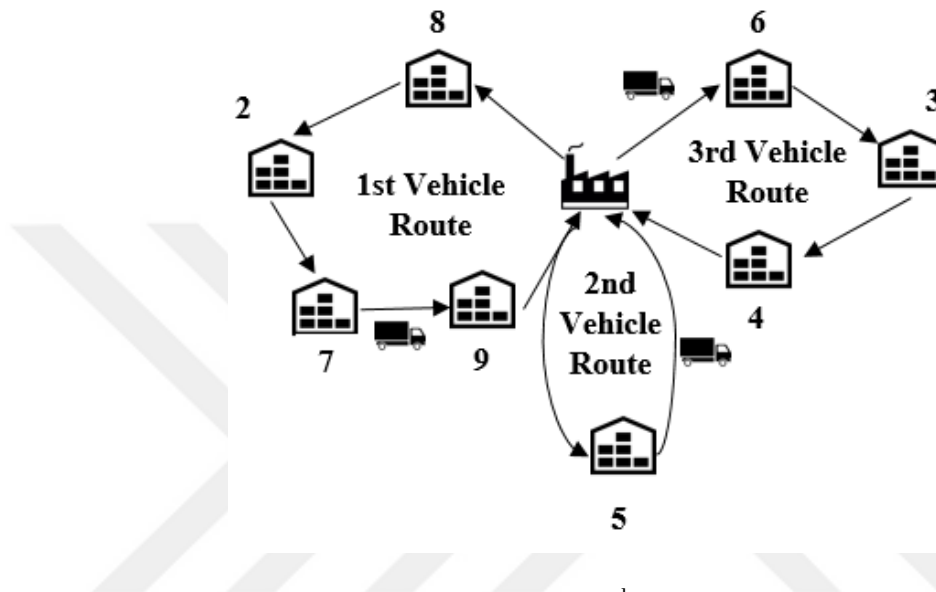


Figure 5.4: Optimal vehicle routes at the 3rd Pareto solution for the heterogeneous fleet.

Table 5.4: Vehicle capacities at the 3rd Pareto solution for the heterogeneous fleet.

Vehicles	Collection Centres in Route	Vehicle Capacities	Total Distance Travelled
1	1 (Disassembly Center)	35	72 km
	8	30	
	2	24	
	7	17	
	9	7	
	10 (Disassembly Center)	7	
2	1 (Disassembly Center)	50	30 km
	5	42	
	10 (Disassembly Center)	42	
3	1 (Disassembly Centre)	40	69 km
	6	35	
	3	27	
	4	21	
	10 (Disassembly Center)	21	

As in the main model, each vehicle starts and ends its route at the disassembly center and each collection centers are visited by a specific vehicle. In addition to this, capacity and time window constraints are satisfied for all routes by considering the heterogeneous fleet.

5.2. Sensitivity Analysis

In this section, sensitivity analysis is carried out to analyze the effects of the model in the long term. Scenarios are created for the changes in the proportion of the product to be partially disassembled and the effect of this on the solution is analyzed. Three scenarios in the sensitivity analysis are generated by increasing the proportion of the product to be partially disassembled. Scenario 1, 2, 3 represents 10%, 20% and 30% changes respectively. Accordingly, changes in the CO₂ emission rate, changes in the total cost, the number of workstations to be opened at the disassembly center, idle times of workstations, tasks assigned to these workstations and changes in the vehicle routes are specified in detail for each scenario.

In our main model, the amount of the total demand is equal to 55 (for 8 collection centers). The need to change in the amount of the demand for sensitivity analysis are met according to the total demand in the main model. From this point of view, the total demand increased to 61 for 10% change, it increased to 66 for 20% change and to 72 for 30% change as mentioned in Section 4.1.2. These changes observed in the amount of the total demand cause the differentiation of optimal solutions in the sensitivity analysis. When each scenario is analyzed separately, the following results are obtained.

Figure 5.5 shows Pareto optimal solutions for the first scenario with 10% change. As can be seen in Figure 5.5, 5 non-dominated solutions are obtained. By comparison with the main model, it can be concluded that the CO₂ emission rates remain the same. In addition to this, the total cost increases up \$100 for each Pareto optimal solutions.

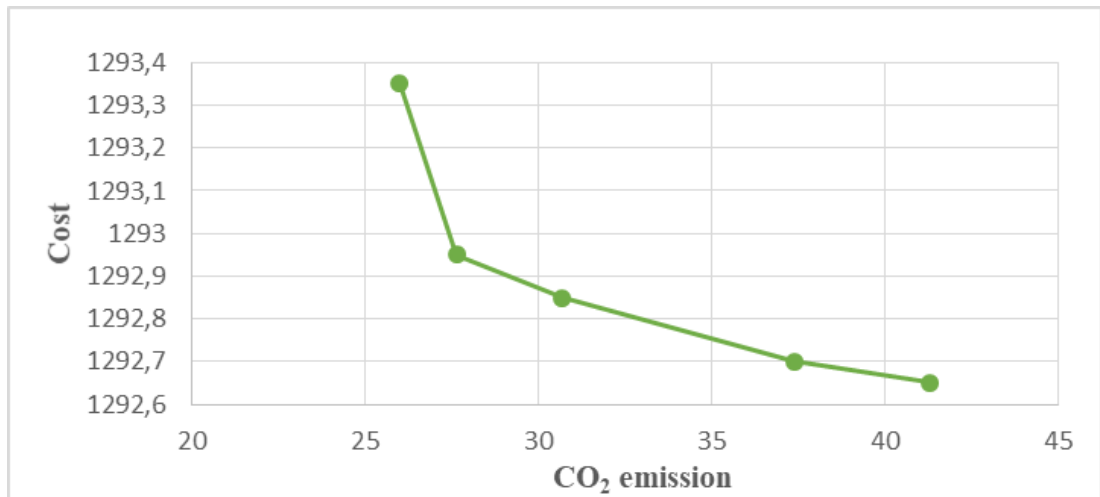


Figure 5.5: Pareto optimal solutions for the first scenario.

Figure 5.6 shows the Pareto Optimal solutions for the second scenario with 20% change. As can be seen in Figure 5.6, 5 non-dominated solutions are obtained. By comparison with the main model, it can be concluded that the CO₂ emission rates remain the same. In addition to this, the total cost increases up \$200 for each Pareto optimal solutions.

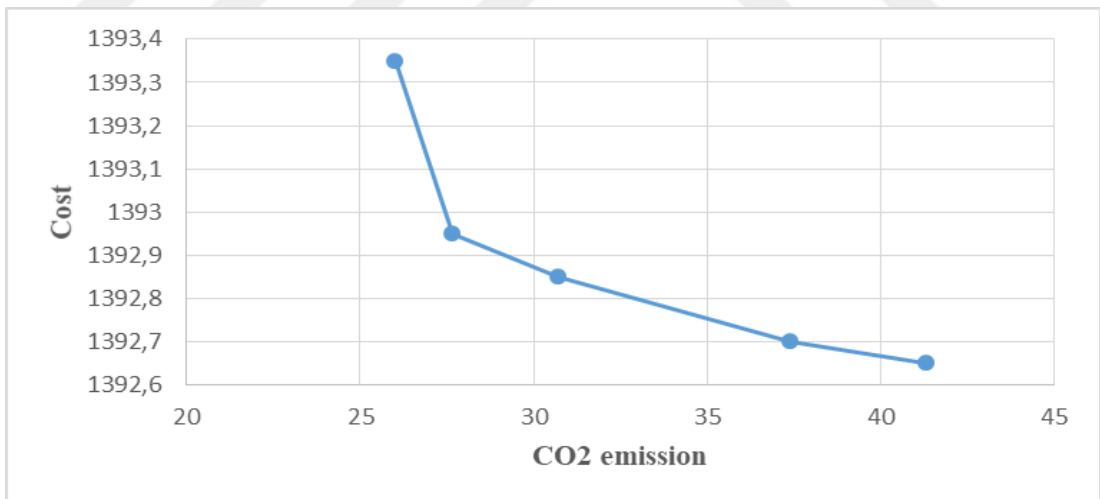


Figure 5.6: Pareto optimal solutions for the second scenario.

Finally, Figure 5.7 shows Pareto optimal solutions for the third scenario with 30% change. As shown in Figure 5.7, 4 non-dominated solutions are obtained. By comparison with the main model, it can be concluded that the CO₂ emission rates remain the same. However, the Pareto Optimal solution which has 26.01 of CO₂

emission rate cannot be obtained for this scenario. In addition to this, the total cost increases up \$200 for each Pareto Optimal solution.

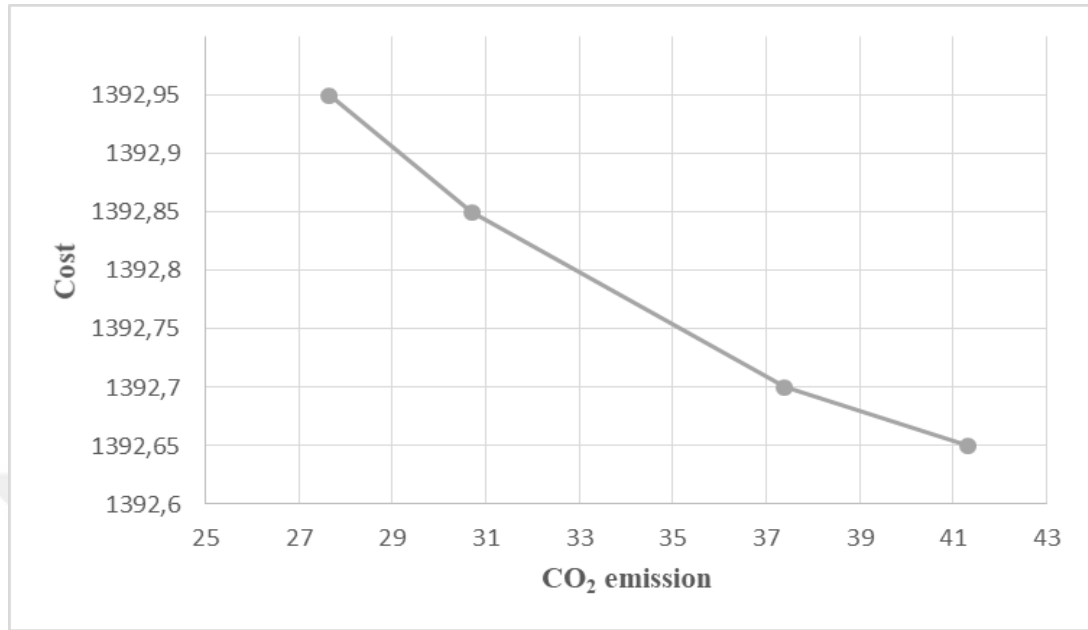


Figure 5.7: Pareto optimal solutions for the third scenario.

The 3rd Pareto solution has 30.7 kg of CO₂ emission and \$1292.85 of the cost at the first scenario, 30.7 kg of CO₂ emission and \$1392.85 of the cost at the second scenario. Due to that the third scenario has 4 non-dominated solutions, the selected 3rd Pareto solution has 37.4 kg of CO₂ emission and \$1392.7 of the cost. Considering the change in the proportion of the product to be partially disassembled in the long term, it has been observed that the objective function values are redetermined according to each scenario with the sensitivity analysis made. This situation has revealed that it is necessary to examine the optimal solutions of line balance and vehicle routes of sensitivity analysis in detail to provide more realistic decisions to the decision maker.

Since the amount of the total demand increases for all scenarios, the cycle times are recalculated for all changes in the amount of the total demand. Table 5.5 shows the calculation of the cycle times according to the changes in the amount of the product to be disassembled separately.

Table 5.5: The calculation of the cycle times for three scenarios.

Scenario	Changes	Total working time	Total demand	Cycle time
1	10% change	5500 min	61	90.164 min/component
2	20% change	5500 min	66	83.333 min/component
3	30% change	5500 min	72	76.389 min/component

According to the 3rd Pareto solution of scenarios, the results of the optimal workload balance in the disassembly line are given in Table 5.6. The number of opened workstations and total idle time do not remain the same because of the recalculation of the cycle time in every scenario.

For the Scenario 1 (10% change), 7 out of 8 workstations are opened. There are no workstations which have not idle time. Total idle time increases from 15 minutes to about 46 minutes as regards the main model. Therefore, it is concluded that the change in the cycle time causes the variances on the total cost and the workload balance.

For the Scenario 2 (20% change), the number of opened workstations is equal to 8. There are no workstations which have not idle time. Total idle time increases from 15 minutes to about 80 minutes as regards the main model.

For the Scenario 3 (30% change), the number of opened workstations is equal to 8. There are no workstations which have not idle time. Total idle time increases from 15 minutes to about 26 minutes as regards the main model.

The tasks numbered 2, 22, 23, 27, 32, 34, 36, 37, 41, 50, 51, 53, and 54 which must be disassembled are assigned to related workstations for all changes in the sensitivity analysis. On the other part, 9 tasks which have no remanufacturing value out of 55 tasks are not assigned to any workstations. In addition, the decreases in the cycle time have affected the workload balance. This situation has resulted as increases in the total idle time of the workstations. Based on the results of Table 5.5, it can be said that a more balanced assignment is made in the disassembly line for the 30% change in the sensitivity analysis.

Table 5.6: DLB results at the 3rd Pareto solution for three scenarios in sensitivity analysis.

Scenario	Workstation No	Disassembled Tasks	Workstation Time (minute)	Idle Time (minute)
1	1	2,8,9,10,11,24,25	77	13.164
	2	7,12,14,15,33,34,35	85	5.164
	3	20,28,39,40,48	90	0.164
	4	16,17,30,31,43,46	88	2.164
	5	21,23,32,36,41,44,47	86	4.164
	6	18,19,22,27,49,52,54	69	21.164
	7	26,29,37,50,51,53	90	0.164
	Tasks not disassembled	1,3,4,5,6,13,38,42,55		
2	1	2,7,8,9,10,11	83	0.333
	2	39,40,49,52	72	11.333
	3	12,15,18,19,23,24,35,47,48	75	8.333
	4	25,26,30,33,50,51,53	72	11.333
	5	14,20,28,31	70	13.333
	6	21,27	64	19.333
	7	22,29,32,34,36,37,43,54	76	7.333
	8	16,17,41,44,45,46	73	10.333
	Tasks not disassembled	1,3,4,5,6,13, 38,42,55		
3	1	2,8,9,10,11,18,25	75	1.389
	2	7,12,14,30,31	75	1.389
	3	21,28,32,41	71	5.389
	4	19,24,39,40,48,49	76	0.389
	5	15,26,29,33,34,47	67	9.389
	6	16,35,43,50,52	76	0.389
	7	23,27,36,51,53	74	2.389
	8	17,20,22,37,44,45,46,54	71	5.389
	Tasks not disassembled	1,3,4,5,6,13, 38,42,55		

Figures 5.8, 5.9 and 5.10 illustrate the optimal vehicle routes for the related Pareto optimal solution with 10% change, 20% change and 30% change, respectively. Since the CO₂ emission rates are same for Scenario 1 and Scenario 2, the total distance travelled by vehicles also did not change. Therefore, only the visit sequences of collection centers have changed in the vehicle routes. The total distance travelled by the vehicles changed at the Scenario 3 because of the change in its CO₂ emission rate. Each vehicle starts and ends its route at the disassembly center and each collection centers are visited by a specific vehicle for all scenarios.

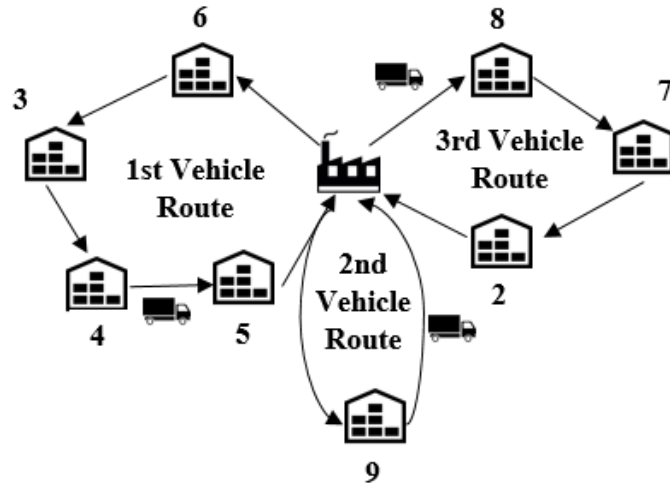


Figure 5.8: Optimal vehicle routes at the 3rd Pareto solution for the first scenario.

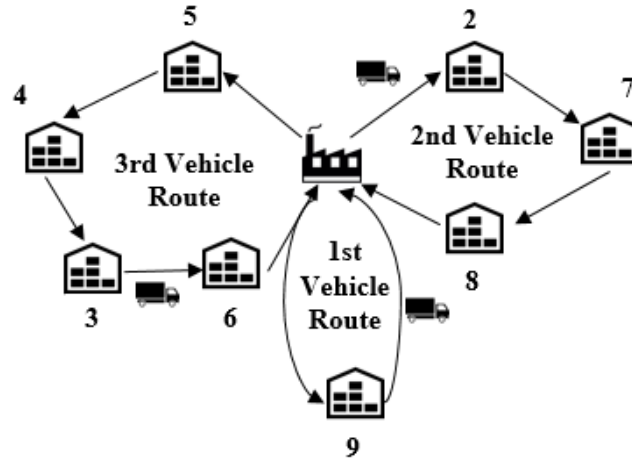


Figure 5.9: Optimal vehicle routes at the 3rd Pareto solution for the second scenario.

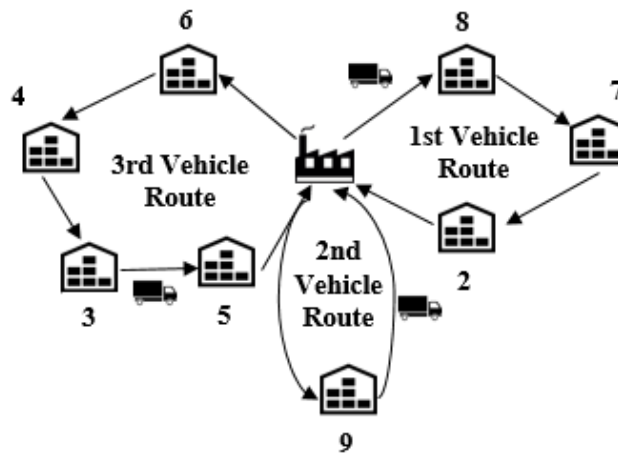


Figure 5.10: Optimal vehicle routes at the 3rd Pareto solution for the third scenario.

Table 5.7: Vehicle capacities at the 3rd Pareto solution for three scenarios.

Scenarios	Vehicles	Collection Centers in Route	Vehicle Capacities	Total Distance Traveled
Scenario 1	1	1 (Disassembly Center)	35	72 km
		6	29	
		3	20	
		4	13	
		5	5	
		10 (Disassembly Center)	5	
	2	1 (Disassembly Centre)	35	24 km
		9	25	
		10 (Disassembly Centre)	25	
	3	1 (Disassembly Centre)	35	61 km
		8	29	
		7	21	
		2	14	
		10 (Disassembly Centre)	14	
Scenario 2	1	1 (Disassembly Centre)	35	24 km
		9	25	
		10 (Disassembly Centre)	25	
	2	1 (Disassembly Centre)	35	61 km
		2	26	
		7	14	
		8	7	
		10 (Disassembly Centre)	7	
	3	1 (Disassembly Centre)	35	72 km
		5	27	
		4	21	
		3	13	
		6	3	
		10 (Disassembly Centre)	3	
Scenario 3	1	1 (Disassembly Centre)	35	61 km
		8	27	
		7	18	
		2	8	
		10 (Disassembly Centre)	8	
	2	1 (Disassembly Centre)	35	24 km
		9	25	
		10 (Disassembly Centre)	25	
	3	1 (Disassembly Centre)	35	69 km
		6	26	
		4	17	
		3	8	
		5	0	
		10 (Disassembly Centre)	0	

Vehicle capacities at the 3rd Pareto solution for three scenarios are shown in Table 5.7 above. The capacities of all vehicles are varied due to the changes in the proportion of the product to be partially disassembled. As can be seen in Table 5.7, the third vehicle in the third scenario runs with full capacity. Besides, the capacity constraints are satisfied for all vehicles at all scenarios.

5.3. Ranking Results of Pareto Optimal Solutions

In this section, the results of the MCDM methods applied to the solutions of the MOO are presented. Within the framework of the proposed approach, EWM and COPRAS Method are used to evaluate the Pareto optimal solutions obtained via AUGMECON method. First, the criteria to be used in the decision-making process are specified by analyzing each Pareto optimal solution separately. Then, the calculations are performed to determine criteria importance by EWM. Finally, applying COPRAS Method, the priority and the importance of considered alternatives (i.e., Pareto optimal solutions) are calculated. As the MOO is applied for both homogeneous and heterogeneous vehicle fleets within the scope of this thesis, the prioritization of Pareto optimal solutions is carried out for each vehicle fleet type individually. EWM and COPRAS Method are coded in MATLAB R2021b.

5.3.1. EWM and COPRAS Method Results for Homogeneous Fleet

It may be noted that once a set of Pareto optimal solutions is obtained with the MOO, all the solutions can be considered as equivalent, as these solutions are non-dominated in nature. However, the compromise among the objectives is different for each solution. Hence, the solution that has the best compromise among the objectives can be considered as the best solution [Rao and Lakshmi, 2021].

In this study, 5 non-dominated solutions are obtained by using the AUGMECON Method for the main model that includes the homogeneous vehicle fleet. These solutions are described as alternatives for the decision-making process. 4 key conflicting criteria that reflect solution-specific characteristic features are calculated by the MOO model. These 4 criteria are described as either benefit or cost perspectives in Table 5.8.

Table 5.8: The evaluation criteria for homogeneous fleet.

Criteria Code	Criteria Name	Unit	Type
C ₁	Cost	dollars/km	Cost
C ₂	CO ₂ emission	kg/km	Cost
C ₃	Number of full-capacity workstations	-	Benefit
C ₄	Execution time	seconds	Cost

Cost and CO₂ emission, C₁ and C₂, are the objective functions of the mathematical model to be minimized. Number of full-capacity workstations, C₃, refers to the number of workstations whose workstation time is equal to the cycle time, that is, no idle time. Since the value of variables for each alternative are different, execution time, C₄, varies ranging from solution to solution.

In the decision-making process, the importance of criteria is determined using EWM firstly. The weights of the criteria demonstrate what criteria are the most important in comprising with other criteria. For determining criteria importance, the data regarding the selection criteria are acquired from every Pareto optimal solution. Initial criteria for evaluation of Pareto optimal solutions and data are presented in Table 5.9.

Table 5.9: Criteria and initial statistic data for homogenous fleet.

Alternatives	Cost	CO ₂ emission	Number of full-capacity workstations	Execution Time
	min	min	max	min
Pareto-1	1193.35	26.01	2	1.219
Pareto-2	1192.95	27.65	1	2.016
Pareto-3	1192.85	30.7	3	1.500
Pareto-4	1192.7	37.4	1	1.578
Pareto-5	1192.65	41.31	2	2.094

After the decision matrix is created, the entropy values, degrees of difference and importance weights of the criteria are calculated according to the steps of the EWM and presented in Table 5.10.

As can be seen in Table 5.10, the criterion with the highest importance of 0.701499 is the number of full-capacity workstations, and the criterion with the lowest importance of 0.000522 is the cost. EWM derives the weights of the criteria logically and the decision-maker has no role to play regarding his individual preferences in this method.

Table 5.10: Entropy levels, differentiation degrees and criteria weights for homogeneous fleet.

	Cost	CO ₂ emission	Number of full-capacity workstations	Execution Time
e_j	0.99996	0.990177	0.946265	0.988028
d_j	0.00004	0.00982318	0.0537348	0.0119719
w_j	0.000522	0.128239	0.701499	0.156291

After creating the decision matrix (Table 5.9), normalization process is done at the first stage. Normalization process is performed to make the values in different criteria a standard between 0 and 1 since the criteria do not have the same units. Table 5.11 shows the normalized decision matrix.

Table 5.11: Normalized decision matrix for homogenous fleet.

Alternatives	Cost	CO ₂ emission	Number of full-capacity workstations	Execution Time
Pareto-1	0.200075	0.159502	0.222222	0.144998
Pareto-2	0.200008	0.169559	0.111111	0.2398
Pareto-3	0.199992	0.188263	0.333333	0.178423
Pareto-4	0.199966	0.229349	0.111111	0.187701
Pareto-5	0.199958	0.253327	0.222222	0.249078

The sum of evaluated normalized maximizing value, the sum of evaluated normalized minimizing value, the relative importance, utility value, final priority and ranking for each alternative (i.e., Pareto Optimal solution) obtained by applying the relevant steps of the COPRAS Method are given in Table 5.12.

As can be seen in the Table 5.12, the ranking order for all alternatives is found to be Pareto-3 > Pareto-1 > Pareto-5 > Pareto-4 > Pareto-2. It can conclude that in the decision-making evaluation made according to the selected criteria for the integrated structure of DLB and VRP, the best alternative is the 3rd Pareto optimal

solution with 100% utility value. According to AUGMECON results, the 3rd Pareto optimal solution has more full-capacity workstation compared to other alternatives. The execution time of this solution is 1.5 seconds, which is one of the minimum computation times. This Pareto solution has 30.7 kg of CO₂ emission and \$1192.85 of the cost. In this respect, the 3rd Pareto optimal solution is found to be the most appropriate solution in terms of cost and benefit criteria in the MCDM process.

Table 5.12: Ranking of Pareto optimal solutions for homogenous fleet.

Alternatives	S_{i+}	S_{i-}	Q_i	P_i	Rank
Pareto-1	0.155889	0.0432207	0.229049	77.7791	2
Pareto-2	0.0779443	0.0593271	0.131243	44.5666	5
Pareto-3	0.233833	0.0521329	0.294486	100	1
Pareto-4	0.0779443	0.0588518	0.131673	44.7128	4
Pareto-5	0.155889	0.0715194	0.200101	67.9491	3

The results demonstrate that the inclusion of the MOO model outputs into the decision-making process can reveal distinguishing features in Pareto optimal types. For this reason, when this proposed integrated structure is intended to be implemented by considering the homogeneous vehicle fleet, the usage of the 3rd Pareto optimal solution in terms of the application perspective has a critical importance in terms of the criteria considered.

5.3.2. EWM and COPRAS Method Results for Heterogeneous Fleet

In the scope of this thesis, 13 non-dominated solutions are obtained by using the AUGMECON Method for the model that considers heterogeneous vehicle fleet. These solutions are described as alternatives for the decision-making process.

This model includes 3 types of vehicles (A, B, C) which have different capacities. For this reason, the average vehicle capacity usage criterion is included in the decision-making process in addition to the criteria set for the main model. The sequence of visiting to collection centers of each vehicle and the number of collection centers visited change in every Pareto optimal solution. Since the capacities of the vehicles are not equal, the average capacity usage percentages of the vehicles vary for each Pareto optimum solutions. From this point of view, the average vehicle capacity usage criteria are included to the decision matrix to

investigate the effect of this variability to the MCDM process. These 5 criteria are described as either benefit or cost perspectives in Table 5.13.

Table 5.13: The evaluation criteria fort the heterogeneous fleet.

Criteria Code	Criteria Name	Unit	Type
C ₁	Cost	dollars/km	Cost
C ₂	CO ₂ emission	kg/km	Cost
C ₃	Average vehicle capacity usage	%	Benefit
C ₄	Number of full-capacity workstations	-	Benefit
C ₅	Execution time	seconds	Cost

To determine the importance weights of the criteria with EWM, the results of the model that considers heterogeneous vehicle fleet usage are used and an initial decision matrix consisting of 6 evaluation criteria and 13 alternatives created as in Table 5.14.

Table 5.14: Criteria for evaluation of Pareto optimal solutions and statistic data for heterogeneous fleet.

Alternatives	Cost	CO ₂ emission	Average vehicle capacity usage	Number of full-capacity workstations	Execution Time
	min	min	max	max	min
Pareto-1	1225.25	36.84	48.33	1	1.937
Pareto-2	1222.53	38.97	47.95	0	0.890
Pareto-3	1220.63	39.08	47.83	3	1.140
Pareto-4	1218.85	39.22	44.57	1	1.703
Pareto-5	1214.59	40.11	44.76	3	0.688
Pareto-6	1214.07	42.16	45.69	1	1.640
Pareto-7	1210.74	44.39	42.93	2	1.671
Pareto-8	1208.84	46.36	41.93	1	0.953
Pareto-9	1208.49	47.09	41.93	2	3.328
Pareto-10	1207.43	47.13	39.1	1	1.594
Pareto-11	1205.11	47.41	39.76	1	2.594
Pareto-12	1203.61	51.47	40.36	2	0.297
Pareto-13	1203.18	54.51	42.86	2	0.328

After creating the decision matrix, normalization process is performed to make the values in different criteria a standard between 0 and 1. With reference to this matrix, the entropy values, degrees of difference and importance weights of the

criteria are calculated according to the steps of the EWM and presented in Table 5.15.

Table 5.15: Entropy levels, differentiation degrees and criteria weights for heterogeneous fleet.

	Cost	CO ₂ emission	Average vehicle capacity usage	Number of full-capacity workstations	Execution Time
e_j	0.999993	0.997384	0.999076	0.965459	0.933399
d_j	0.000007	0.00261551	0.000923557	0.0345408	0.0666012
w_j	0.00006686	0.0249839	0.00882202	0.329941	0.636189

After the calculation of entropy values, the next step is to calculate the degree of differentiation. Finally, by dividing the differentiation degree of each criterion by the total differentiation degree the importance degree of each criterion is obtained. As can be seen in Table 5.15, the most important criterion is execution time with the highest weight of 0.636189 and the least important criterion is cost with the lowest weight of 0.00006686 for the heterogeneous vehicle fleet usage.

Pareto optimal solutions for heterogeneous fleet are ranked according to their utility using COPRAS method after determining the weights of the criteria by EWM. With reference to the initial decision matrix in Table 5.14, the normalized decision matrix is obtained for the heterogeneous vehicle fleet as shown in Table 5.16.

Table 5.16: Normalized decision matrix for heterogeneous fleet.

Alternatives	Cost	CO ₂ emission	Number of full-capacity workstations	Execution Time
Pareto-1	0.200075	0.159502	0.222222	0.144998
Pareto-2	0.200008	0.169559	0.111111	0.2398
Pareto-3	0.199992	0.188263	0.333333	0.178423
Pareto-4	0.199966	0.229349	0.111111	0.187701
Pareto-5	0.199958	0.253327	0.222222	0.249078

The sum of evaluated normalized maximizing value, the sum of evaluated normalized minimizing value, the relative importance, utility value, final priority and ranking for each alternative of heterogeneous fleet model obtained by applying the relevant steps of the COPRAS Method are given in Table 5.17.

Table 5.17: Ranking of Pareto optimal solutions for heterogeneous fleet.

Alternatives	S_{i+}	S_{i-}	Q_i	P_i	Rank
Pareto-1	0.015748	0.0672837	0.0413233	24.2537	12
Pareto-2	0.0307394	0.0318761	0.0847236	49.7264	5
Pareto-3	0.0457348	0.0403575	0.0883739	51.8689	4
Pareto-4	0.0156896	0.059453	0.0446335	26.1966	11
Pareto-5	0.0456872	0.0250765	0.11431	67.0911	3
Pareto-6	0.015707	0.0574446	0.0456629	26.8007	9
Pareto-7	0.0306614	0.0585926	0.0600304	35.2333	7
Pareto-8	0.0156486	0.0343334	0.0657691	38.6015	6
Pareto-9	0.0306459	0.114893	0.0456233	26.7775	10
Pareto-10	0.0156046	0.0561009	0.046278	27.1617	8
Pareto-11	0.0156149	0.0900197	0.0347307	20.3843	13
Pareto-12	0.0306215	0.0123128	0.170379	100	1
Pareto-13	0.0306603	0.013496	0.158165	92.8311	2

Based on the results obtained in the Table 5.17, it is seen that 12th Pareto optimal solution is the most efficient alternative according to performance indices of alternatives. Pareto-12 has the biggest utility value. The ranking order of all alternatives for the heterogeneous vehicle fleet is found to be Pareto-12 > Pareto-13 > Pareto-5 > Pareto-3 > Pareto-2 > Pareto-8 > Pareto-7 > Pareto-10 > Pareto-6 > Pareto-9 > Pareto-4 > Pareto-1 > Pareto-11.

In case of the implementation of the proposed integrated problem consists of PDLB and GVRP to the real-life application, final selection of one optimal solution from the set of alternate solutions is very important. When it is decided to use a heterogeneous vehicle fleet for the model created within the scope of this thesis, it is recommended to implement the 12th Pareto optimal solution according to the determined criteria and the obtained AUGMECON results. The execution time of the 12th pareto-optimal solution is 0.229, and it is the fastest calculated solution among

the alternatives of heterogeneous vehicle fleet. This Pareto solution has 51.47 kg of CO₂ emission and has one of the lowest costs with the value of \$1203.61. Its average vehicle capacity usage is 40.36% and it has 2 full-capacity workstations.

In summary, when the heterogeneous fleet that includes 3 types of vehicles which have different capacities, different transportation costs and different CO₂ emission rates is considered in the decision-making process, the selection of the 12th Pareto solution will make the process effective with important entropy-based criteria.



6. CONCLUSIONS AND FUTURE RESEARCH

With the increase in the amount of consumption continuously, recycling is gaining more and more importance. To incorporate recycling in existing supply chain structures provides many advantages such as raw material recovery and energy savings. For this reason, disassembly, which is one of the most important stages of recycling, comes to the fore. After the disassembly process, planning the distribution of the obtained components is also very important for supply chain companies. For this reason, it is thought that modelling and solving complex optimization problems can provide significant benefits to such decision makers. With this study, the opportunities of the integrated DLBP and GVRP structure, which is created by considering both economic factors and environmental effects, are revealed for decision makers. In this context, this study differs from other studies in the literature in that it includes a partial disassembly mode and is a multi-objective integrated model.

Based on this idea, a MOO problem that combines the PDLBP and the GVRP is proposed in this study. The model has two objectives consist of CO₂ emission minimization and cost minimization by considering both environmental benefit and economic impact. Within the scope of this thesis, the disassembling of valuable parts is taken into consideration instead of disassembling all subparts in the PDLBP. The solution of the Multi Objective MILP model is solved by using AUGMECON method and GAMS® software.

The solution of the Multi Objective MILP model is solved by using AUGMECON method and GAMS® software. According to the MOO results, 5 Pareto optimal solutions are obtained for the main model which has homogeneous vehicle fleet. The proposed mathematical model is revised with the additional data of heterogeneous vehicle fleet and the effects of considering heterogeneous fleet to the main model are examined. 13 non-dominated solutions are calculated for heterogeneous vehicle fleet model. In addition to these, three scenarios in the sensitivity analysis are generated according to 10%, 20% and 30% increase in the amount of product to be disassembled. The effect of changing the amount of the total demand of collection centers on the results are also investigated. Main findings related to the MOO part of this thesis are summarized as follows:

- Integrated DLBP and GVRP has been successfully applied as a new practical optimization problem and provides several insights for the optimal workload balance on the line and optimal distribution routes.
- It is concluded that for all scenarios, if the main focus is reduction of CO₂ emission rate, it should bear more cost to provide environmental benefits. In the same way, ensuring minimum total cost in the network increases environmental impact.
- According to the heterogeneous fleet results, the number of the Pareto optimal solutions, total CO₂ emission and total cost have increased as regards the main model. The number of opened workstations has remained the same. However, assignment of the tasks to the workstations and optimal vehicle routes have changed because of the change in the fleet type of vehicle.
- According to three scenarios in sensitivity analysis, total CO₂ emission has remained the same for 10% and 20% change. This rate has increased for 30% change. Besides, the number of opened workstations has increased, incrementally. This situation has caused to be on the rise in the total cost. The number of the Pareto optimal solutions has remained the same for the 10% and 20% change in the amount of the product disassembled. It has also decreased for the 30% change.
- A slight change in the demand for collection centers has affected the line balance and vehicle routes. Since the CO₂ emission rates did not change for scenarios which have 10% and 20% changes in sensitivity analysis, the total distance travelled by the vehicles also did not change. Therefore, only the visit sequences of collection centers have changed in the vehicle routes for these scenarios. In addition to this, the total distance has decreased in the third scenario which have 30% change since its CO₂ emission rate has not remained same with the other scenarios.

MOO provides many optimal solutions known as Pareto optimal front and as non-dominated solutions. The selection of one optimal solution from the Pareto-optimal front is crucial for industrial implementation. Outputs obtained from the MOO problem are identified as inputs of the decision matrix of the MCDM problem. Pareto optimal solutions are alternatives of this decision matrix. Key criteria are defined with the overall analysis of the decision variables and objective functions for

every Pareto optimal solution. In this thesis, EWM and COPRAS Method are used to evaluate the Pareto optimal solutions obtained via AUGMECON method. First, the importance weights of the criteria are determined by EWM. Then, using COPRAS Method, the prioritization and the ranking of obtained Pareto optimal solutions are performed. These MCDM techniques are applied for both homogeneous and heterogeneous vehicle fleets and the prioritization of Pareto optimal solutions is carried out for each vehicle fleet type individually. EWM and COPRAS Method are coded in MATLAB R2021b.

In the decision-making process for homogeneous vehicle fleet, 4 key criteria consist of cost, CO₂ emission, number of full-capacity workstations, and execution time are identified. The EWM results show that the highest important criterion is the number of full-capacity workstations, and the lowest importance criterion is the cost.

The COPRAS Method results present that the best alternative is the 3rd Pareto optimal solution with the highest utility value for homogeneous fleet. This solution has more full-capacity workstation compared to other alternatives. The execution time of this solution is 1.5 seconds, which is one of the minimum computation times. This Pareto solution has 30.7 kg of CO₂ emission and \$1192.85 of the cost.

When the problem is considered with heterogeneous vehicle fleet, the average vehicle capacity usage criterion is added in the decision-making process in addition to the criteria set for the main model. While the least important criterion for the heterogeneous vehicle fleet remains the same, the most important criterion changes and is found as execution time.

Based on the results of COPRAS Method, it is found that 12th Pareto optimal solution is the most efficient alternative for heterogeneous fleet according to performance indices of alternatives. The execution time of this solution is 0.229, and it is the fastest calculated solution among other alternatives. It has 51.47 kg of CO₂ emission and has one of the lowest costs with the value of \$1203.61. The average vehicle capacity usage of this solution is 40.36% and it has 2 full-capacity workstations.

With the growing importance of sustainable supply chains, companies have considered the green logistics activities. Their primary priorities have been to address the imperatives, policies and related objectives of green logistics practices. For this reason, strategic decisions should be taken by considering economic and

environmental aspects, simultaneously. This thesis reveals these important managerial insights:

- By integrating the PDLBP with GVRP, decision makers and managers can take important strategic decisions that will get the highest efficiency from this integrated process. Besides, they can gain competitive advantages within the job practices.
- Managers will be able to optimize disassembly line processes in the integrated works like this. The optimum number of opened workstations and tasks assigned to workstations can be analyzed. Idle times of workstations can be examined to evaluate their efficiency.
- The effective distribution plans for disassembled components can be established and disassembly profit can be increased significantly by considering the partial disassembly mode.
- Environmental benefits can be provided by minimizing CO₂ emissions arising from the transportation between collection centers.
- Logistics companies that provide distribution networks will be able to obtain flexible approach that can generate solutions under all circumstances such as the heterogeneous vehicle fleet, the percentage change in the amount of disassembled product.
- Managers will have a practical and useful decision-making process in the implementation of the integrated model to the sector by realizing more economical and more efficient sustainable logistics concepts.
- The findings of this study will provide a saving of time, labor income, monetary expansion, and heightened awareness in the actualization phase for managers. The determination and the implementation of highly prioritized Pareto solution will be useful in improving tactical or strategical performance.

This thesis provides a recent and robust perspective for to be done scientific research in the future. As future works, various multi-objective solution methods such as NSGA, NSGA II, ALNS and PSO can be developed for large-size instances. More realistic benchmark instances can be generated. Fuzzy methods can be used in

cases where the parameters of the problem like demand, cost are uncertain, and stochastic versions of the model can be considered.

Based on the MCDM part, to determine the prioritization of the Pareto optimal solutions found with the MOO model and to select the most important optimal solution, other frequently used MCDM techniques such as Technique for Order of Preference by Similarity to Ideal Solution, Linear Programming Technique for Multidimensional Analysis of Preference or Preference Ranking Organization Method for Enrichment of Evaluations can be applied to the model. Besides, subjective weighting methods can be included in the MCDM process where the judgment of the decision maker is essential.



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BIOGRAPHY

Nida DURMAZ completed her bachelor's degree in Industrial Engineering at Dokuz Eylül University with a third degree in 2019. In the same year, she was accepted to Graduate Programme of Industrial Engineering at Institute of Natural and Applied Sciences in Dokuz Eylül University. In 2020, she was assigned as a research assistant at Department of Industrial Engineering in Gebze Technical University and continued her Master of Science Programme there. Since 2020, she has been working at Gebze Technical University Industrial Engineering Department as a research assistant.



APPENDICES

Appendix A: Publications Based on This Thesis

Durmaz N., Budak A., (2021), “A Review of Recent Research on Green Vehicle Routing Problem”, 4th European Conference on Industrial Engineering and Operations Management Rome, 472-484, Rome, Italy, 2-5 August.

Durmaz N., Budak A., (2022), “Multi-Objective Optimization Model for an Integrated Disassembly Line Balancing and Green Vehicle Routing Problem”, 12th Annual International Conference on Industrial Engineering and Operations Management, Istanbul, Turkey, 7-10 March.

