

Logistics Collaboration for Food Bank Operations

by

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Logistics Collaboration for Food Bank Operations

Koç University

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To my family

ABSTRACT

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Supporting Sustainable Development is getting more and more important to leave a better world to the next generations and a sustainable food system is one of the elements in Sustainable Development. This study focuses on developing a sustainable food donation system operated for charitable agencies by an entrepreneurial company. Charitable agencies are mostly in the form of food banks. In the food donation system, donor companies donate their surplus food and the food banks are responsible to collect these donations assigned to them by a digital platform based on their demand. However, not every food bank has vehicles to collect donations on their own. In this study, it is proposed that the vehicles already owned by some of the food banks shall be used mutually to carry out the donation operations for other food banks too. This newly proposed concept is called *logistics collaboration*, and to optimize the system with collaboration, a mathematical formulation is developed. The optimization model assigns the donations timely to the food banks, arranges the daily routes of the vehicles, and decides the pickup and delivery operations to conduct throughout the routes. The model aims to maximize the total monetary savings of the donations rescued while minimizing the total environmental and economic damage caused by vehicle usage. To test the model, 136 real-life based instances are generated with varying sizes. Based on these instances, three case studies are created to evaluate the system with and without the collaboration. For the case studies, a GRASP-ILS metaheuristic implementation is also developed to improve the solution quality obtained by the model and to create starting solutions for the warm-up start procedures. It is shown that around 96% of the food donated can be rescued on average with the logistics collaboration. Furthermore, it is concluded that the model with collaboration outperforms the model without collaboration in terms of the objective function value of the best solutions and also in terms of the amount of rescued donations.

ÖZETÇE

Gıda Bankası Operasyonları için Lojistik İşbirliği

Sude Kocaçiftçi

Endüstri Mühendisliği, Yüksek Lisans

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Sürdürülebilir Kalkınmanın desteklenmesi, gelecek nesillere daha iyi bir dünya bırakmak için giderek daha önemli hale gelmektedir. Sürdürülebilir bir gıda sistemi de Sürdürülebilir Kalkınma'nın önemli bir parçasıdır. Bu tez çalışması, girişimci bir şirket tarafından hayır kurumları için işletilen sürdürülebilir bir gıda bağış sisteminin geliştirilmesine odaklanmaktadır. Sistemdeki hayır kurumlarının büyük bir kısmını gıda bankaları oluşturmaktadır. Gıda bağış sisteminde, bağışçı şirketler fazla yiyeceklerini bağışlamakta ve gıda bankaları da dijital bir platformun talepler doğrultusunda kendilerine tahsis ettiği bağışları toplamaktadır. Ancak, her gıda bankasının bağış toplayabilecekleri araçları bulunmamaktadır. Bu çalışmada, bazı gıda bankalarının sahip olduğu araçların, diğer gıda bankaları için de bağış işlemlerini gerçekleştirmek üzere ortak olarak kullanılması önerilmektedir. Yeni önerilen bu konsepte lojistik işbirliği ismi verilmiş ve bu sistemi işbirliği ile eniyilemek için bir matematiksel model geliştirilmiştir. Eniyileme modeli, bağışları uygun zamanlı olarak gıda bankalarına tahsis etme, araçların günlük rotalarını düzenleme ve bağışların toplama ve teslimat operasyonlarının rotalar üzerinden yürütülmesi işlemlerine karar vermektedir. Model, araç kullanımından kaynaklanan toplam çevresel ve ekonomik zararı en aza indirirken, toplanan bağışlar sayesinde kurtarılan gıdaların toplam parasal tasarrufunu enbüyüklemeyi amaçlamaktadır. Modeli test etmek için, çeşitli büyüklüklerde 136 gerçek yaşama dayanan örnek tasarlanmıştır. Bu örnekler temel alınarak, sistemi işbirliği ile ve işbirliği olmadan değerlendirmek için üç vaka çalışması oluşturulmuştur. Vaka çalışmaları için, meta-sezgisel bir algoritma da geliştirilerek, bir başlatma prosedürü ile modelin elde ettiği çözümlerin kalitesi artırılmıştır. Lojistik işbirliği ile, bağışlanan gıdanın ortalamada yaklaşık % 96'nın kurtarılabildiği gösterilmiştir. Ayrıca, işbirliği modelinin, en iyi çözümlerin amaç fonksiyon değeri ve kurtarılan bağışların oranı açısından işbirliği olmayan alternatif modelden daha iyi sonuçlar verdiği saptanmıştır.

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TABLE OF CONTENTS

List of Tables	x
List of Figures	xiii
Abbreviations	xiv
Chapter 1: Introduction	1
Chapter 2: Literature and Contributions	9
2.1 Pickup and Delivery Vehicle Routing Problems	9
2.2 Charitable Food Logistics	10
2.3 Fuel Consumption and Emissions in Logistics	14
2.4 Contributions of the Study	17
Chapter 3: Solution Approach	20
3.1 Notation and Parameters	20
3.2 Assumptions	21
3.3 Solution Methodologies	23
3.3.1 Mathematical Formulation	23
3.3.2 A GRASP-ILS Implementation	28
3.4 Alternative Models for the Case Studies	37
3.4.1 Case Study 1: Logistics Collaboration in the Donation Oper- ations	37
3.4.2 Case Study 2: Donation Operations with Logistics Collabora- tion and Rental Vehicle Option	37
3.4.3 Case Study 3: Food Bank Operations Without Logistics Col- laboration	39

Chapter 4:	Computational Experiments and Analysis	43
4.1	Emission Model for Fuel and Emissions Cost Function	43
4.2	Data Preparation	46
4.3	Computational Experiments	47
4.3.1	Sensitivity Analysis on Vehicle Fixed Cost	48
4.3.2	Case Study 1: Logistics Collaboration in the Donation Operations	51
4.3.3	Case Study 2: Donation Operations with Logistics Collaboration and Rental Vehicle Option	63
4.3.4	Case Study 3: Food Bank Operations Without Logistics Collaboration	64
4.3.5	Comparison of The Proposed System and The Existing System: FIFO Analysis	69
Chapter 5:	Conclusions	71
	Bibliography	75
	Appendix A: Algorithms	83
	Appendix B: Properties of the Data Sets	87
	Appendix C: Sensitivity Analysis	90
	Appendix D: Case Study 1: Base Run Results	92
	Appendix E: Case Study 1: Metaheuristic Results	101
	Appendix F: Case Study 1: Warm-up Start Results	105
	Appendix G: Case Study 1: Comparison of the Solution Procedures	114
	Appendix H: Case Study 3: Run Results	118

Appendix I: Comparison of Case Study 1 and Case Study 3	127
Appendix J: FIFO Analysis	131



LIST OF TABLES

3.1	Descriptions of sets and parameters	22
3.2	Descriptions of decision variables	24
4.1	Parameters of the emission model [Koç et al., 2016]	44
4.2	A summary of the average results for the sensitivity analysis	49
4.3	A summary of average base run results	51
4.4	Input parameters of the constructive heuristic algorithm in GRASP .	53
4.5	A summary of average metaheuristic results	55
4.6	A summary of warm-up start results	56
4.7	Donation information of instance S_M1W1_5	60
4.8	Demand fulfilment of instance S_M1W1_5	61
4.9	Donation information of instance S_M1W4_5	61
4.10	Demand fulfilment of instance S_M1W4_5	63
4.11	A summary of average results for Case Study 2	64
4.12	A summary of results for Case Study 3	66
4.13	A summary of average results to compare Case Study 1 and Case Study 3	67
4.14	Final comparison of Case Study 1 and Case Study 3	68
4.15	Summary of the average results of FIFO Analysis	70
B.1	The properties of small-sized data sets	87
B.2	The properties of medium-sized data sets	88
B.3	The properties of large-sized data sets	89
C.1	Sensitivity Analysis Results	91
D.1	Base Run Results: Small-sized instances with 5 food banks	93

D.2	Base Run Results: Small-sized instances with 10 food banks	94
D.3	Base Run Results: Small-sized instances with 15 food banks	95
D.4	Base Run Results: Medium-sized instances with 5 food banks	96
D.5	Base Run Results: Medium-sized instances with 10 food banks	97
D.6	Base Run Results: Medium-sized instances with 15 food banks	98
D.7	Base Run Results: Large-sized instances with 10 food banks	99
D.8	Base Run Results: Large-sized instances with 15 food banks	100
E.1	Metaheuristic Results: Small-sized instances	102
E.2	Metaheuristic Results: Medium-sized instances	103
E.3	Metaheuristic Results: Large-sized instances	104
F.1	Warm-up Start Results: Small-sized instances with 5 food banks . . .	106
F.2	Warm-up Start Results: Small-sized instances with 10 food banks . .	107
F.3	Warm-up Start Results: Small-sized instances with 15 food banks . .	108
F.4	Warm-up Start Results: Medium-sized instances with 5 food banks .	109
F.5	Warm-up Start Results: Medium-sized instances with 10 food banks .	110
F.6	Warm-up Start Results: Medium-sized instances with 15 food banks .	111
F.7	Warm-up Start Results: Large-sized instances with 10 food banks . .	112
F.8	Warm-up Start Results: Large-sized instances with 15 food banks . .	113
H.1	Case Study 3 Run Results: Small-sized instances with 5 food banks .	119
H.2	Case Study 3 Run Results: Small-sized instances with 10 food banks	120
H.3	Case Study 3 Run Results: Small-sized instances with 15 food banks	121
H.4	Case Study 3 Run Results: Medium-sized instances with 5 food banks	122
H.5	Case Study 3 Run Results: Medium-sized instances with 10 food banks	123
H.6	Case Study 3 Run Results: Medium-sized instances with 15 food banks	124
H.7	Case Study 3 Run Results: Large-sized instances with 10 food banks	125
H.8	Case Study 3 Run Results: Large-sized instances with 15 food banks	126

I.1	The results of small-sized instances: Comparison of Case Study 1 and Case Study 3	128
I.2	The results of medium-sized instances: Comparison of Case Study 1 and Case Study 3	129
I.3	The results of large-sized instances: Comparison of Case Study 1 and Case Study 3	130
J.1	FIFO Analysis: Small-sized instances	132
J.2	FIFO Analysis: Medium-sized instances	133
J.3	FIFO Analysis: Large-sized instances	134

LIST OF FIGURES

1.1	An illustration of the proposed system	5
4.1	Comparison of the average relative percentage gap found by different solution procedures for (a) small, (b) medium, and (c) large-sized instances	57
4.2	Improvement of the warm-up start procedure in (a) percentage res- cued amount, and (b) percentage rescued value	58
4.3	The optimal solution of instance S_M1W1_5	60
4.4	The optimal solution of instance S_M1W4_5	62
G.1	Comparison of the percentage gap found by different solution proce- dures for small-sized instances with (a) 5, (b) 10, (c) 15 food banks .	115
G.2	Comparison of the percentage gap found by different solution pro- cedures for medium-sized instances with (a) 5, (b) 10, (c) 15 food banks	116
G.3	Comparison of the percentage gap found by different solution proce- dures for large-sized instances with (a) 10, (b) 15 food banks	117

ABBREVIATIONS

ALNS	Adaptive Large Neighborhood Search
CVRP	Capacitated Vehicle Routing Problem
EMVRP	Energy Minimizing Vehicle Routing Problem
FDP	Food Delivery Points
FIFO	First-in-first-out
FRARP	Food Rescue Allocation and Routing Problem
FRP	Food Rescue Program
GRASP	Greedy Randomized Adaptive Search Procedures
GU-PDVRP	Green Unpaired Pickup and Delivery Vehicle Routing Problem
H-PDP	Humanitarian Pickup and Distribution Problem
MILP	Mixed Integer Linear Programming
MOW	Meals on Wheels Program
PDTSP	Pickup and Delivery Traveling Salesman Problem
PDVRP	Pickup and Delivery Vehicle Routing Problem
PRP	Pollution Routing Problem
PVRPB	Periodic Vehicle Routing Problem with Backhauls
RCL	Restricted Candidate List
SDG	Sustainable Development Goals
SOA	Speed Optimization Algorithm
SRAP	Sequential Resource Allocation Problem
TDVRP	Time-dependent Vehicle Routing Problem

TRY	The Turkish Lira (Currency of Republic of Turkey)
UNDP	United Nations Development Programme
U-PDVRP	Unpaired Pickup and Delivery Vehicle Routing Problem
VRP	Vehicle Routing Problem
CO ₂	Carbon Dioxide
1-PDVRP	The Single-product (i.e. 1-Commodity) PDVRP



Chapter 1

INTRODUCTION

Today, there are many environmental problems worldwide that people face and have to cope with. Global warming and climate change, the danger of extinction of living beings and their habitats due to these difficult conditions, unidentified and distorted urbanization, air and water pollution, unhealthy societies and hunger constitute just a small portion of the problems. Unfortunately, these problems are primarily caused by current human activities. These activities can generally be defined within the framework of consumption and settlement practices. As the human population grows rapidly and globalization gains pace, consumption and settlement also increase continuously.

As it is known that these aforementioned problems are on a global level, having cooperation between countries and international organizations is quite essential to deal with them. One of the pioneering initiatives for this cooperation is the Brundtland Report. This report was prepared by the World Commission on Environment and Development in 1987, and it has come up with the concept of *Sustainable Development*, which brings together many globally-defined goals such as preventing poverty, minimizing hunger, responsible consumption of natural resources, conscientious climate action, and many others. In the report, *Sustainable Development* is accounted as “the development that meets the needs of the present without compromising the ability of future generations to meet their own needs” [The General Assembly of United Nations, 1987]. It can be said that this cooperation and the notion of *Sustainable Development* has laid the foundation of the actions carried out in the name of sustainability until the present day. Another fundamental milestone for sustainability is the United Nations Conference on Environment and Development

(also known as *Earth Summit* [United Nations (UN), 1992b]). In this conference, an action plan “Agenda 21”, which aims a global cooperation for sustainable development, was introduced for the first time and adopted by more than 178 governments [United Nations (UN), 1992a]. In 2015, the “Agenda 2030 for Sustainable Development” was introduced in the United Nations Sustainable Development Summit [United Nations (UN), 2015]. This agenda specifies the today’s well known seventeen *Sustainable Development Goals (SDGs)* for the first time [United Nations (UN), 2014]. This agenda carries a significant role as it has inspired lots of actions taken by the governments on sustainable development since then.

One of the goals set for sustainable development is to end hunger. Although the global number of malnourished people has fallen by half in the last 20 years, it is estimated that still around 800 million people are constantly undernourished due to increased environmental pollution, drought and reduced biodiversity [United Nations (UN), 2019]. Despite the significance of the problem, one third of the food produced worldwide is estimated to be lost or disposed of in the garbage, according to the United Nations Food and Agriculture Organization [Food and Agriculture Organization of the United Nations, 2020]. While *food loss* is generally experienced in the transference between the producer and the retailer in the supply chain, *food waste* is caused by neglecting or disposing of the *surplus food* whose nutritive value is safe for consumption. Food waste can occur in a few situations, such as removal and disposal of fresh foods from the supply chain because of several problems including inappropriate shapes and colors of the food. Other examples of these situations are the disposal of products that are close to or past the "best-before" consumption date by retailers or consumers, and the disposal of unused or leftover food made by restaurants and similar businesses that serve daily food. Not only the good food is thrown away, but also food waste accounts for 8% of the world’s carbon emissions [Food and Agriculture Organization of the United Nations, 2020].

It is clear that accurately planned food production and less food waste will create significant benefits for climate change by making more efficient use of both water resources and soil. With this purpose in mind, the formation of food banking has emerged, which aims to store and consume the nutritious *surplus food* for avoiding

waste. While food banking was emerged in the United States for the first time in 1970's, in Turkey, it started nearly 15 years ago and has continued to grow since then. In Turkey, food banks are defined as non-profit associations or foundations that supply all kinds of donated or surplus health-appropriate food, store them in suitable conditions and deliver these products directly or through various aid organizations to the poor and those affected by natural disasters. An entrepreneurial company named *Fazla Gıda* has started to serve the food-suppliers (such as retailers, wholesalers and restaurants), aiming to prevent the surplus food they produce to become waste. Furthermore, the company acquires surplus food to aid the people in need. Basically, *Fazla Gıda* rescues the surplus food from the donors and gives these food as donations to associations such as non-profit agencies, municipalities and food banks (these all will be called “food banks” for short). In 2016, the firm constructed a digital platform to announce the donations coming from the aforementioned donor companies. Since then, they have achieved operations in more than 25 cities and carried out food donations worth millions of Turkish liras. *Fazla Gıda* also advises the donor companies on awareness of the surplus food and further evaluation of the food waste such as biogas production. The firm has adopted the “Zero Hunger”, “Responsible Consumption and Production” and “Climate Action” SDGs in their operations. Moreover, *Fazla Gıda* is being supported by the United Nations Development Programme (UNDP). The number of donors, and also the number of foundations (such as food banks) that join to the network family constructed by *Fazla Gıda* grow day by day. However, the firm faces several weaknesses in the collection and delivery operations. They seek not only to improve these food operations, but also to enhance executing food donation check-ups, allocating demanded donations among the food banks accordingly, and controlling the deliveries of food donations to their owners.

There are several problems *Fazla Gıda* faces in their food rescue operations. In their current system, the donors announce their donations on the digital platform. Then, the food banks create their requests based on the content, amount and other properties of the donations. As the donations are matched with the requests by the platform, food banks must collect their allocated donations from their donors

within a time window. If they cannot collect the donations on time, then the food becomes food waste. Another issue here is that the food banks are obliged to use their own resources for pickup operations. However, some of them may not have vehicles. These obligations can cause food banks fail to collect their donations on time or pickup operations to become extra costly.

The current food donation system of Fazla Gıda essentially consists of three components: donors, donations and food banks. Several retailers, restaurants, producers etc. that intend to donate food to food banks are called as donors for short. As described before, food banks are non-profit charity organizations that aim providing food to people in need to reduce hunger and malnutrition. Food donations must consist of healthy and consumable food. Clearly, consumable food to be donated must be kept in hygienic conditions and also must have sufficient time before its best-before or expiration date to be eligible for human consumption. Thus, donors announce the amount and also the validity (time left to perish, in days) of the donations on the aforementioned digital platform. Then, with the FIFO (*first-in-first-out*) principle, the first food bank to demand a donation is directly matched with the donation. After this matching, the food bank can pickup their donations from the donor within the predetermined days. It is the responsibility of the food bank to collect their matched donations. A more efficient system is sought not only for the transportation, but also for the allocation of the donations as Fazla Gıda wishes to renew the donation system such that each food bank would have the opportunity to benefit from each donation.

In this study, we propose a new system to prevent possible food waste. In the proposed system, the food banks which have available vehicles shall execute collection and distribution operations not only for themselves, but also for the other food banks. Leading to collaboration among food banks, the collection and distribution of the food donations can be managed with a decreased vehicle usage and efficient routing, which is a great saving for the environment. To conclude, logistics collaboration seems to be a beneficial way to improve the donation process in all three dimensions of sustainability, that is, social, environmental, and economic dimensions. An illustration of the proposed system can be seen in Figure 1.1. In the

illustration, the food banks with vehicles are distinguished with colored circles from the ones without vehicles.

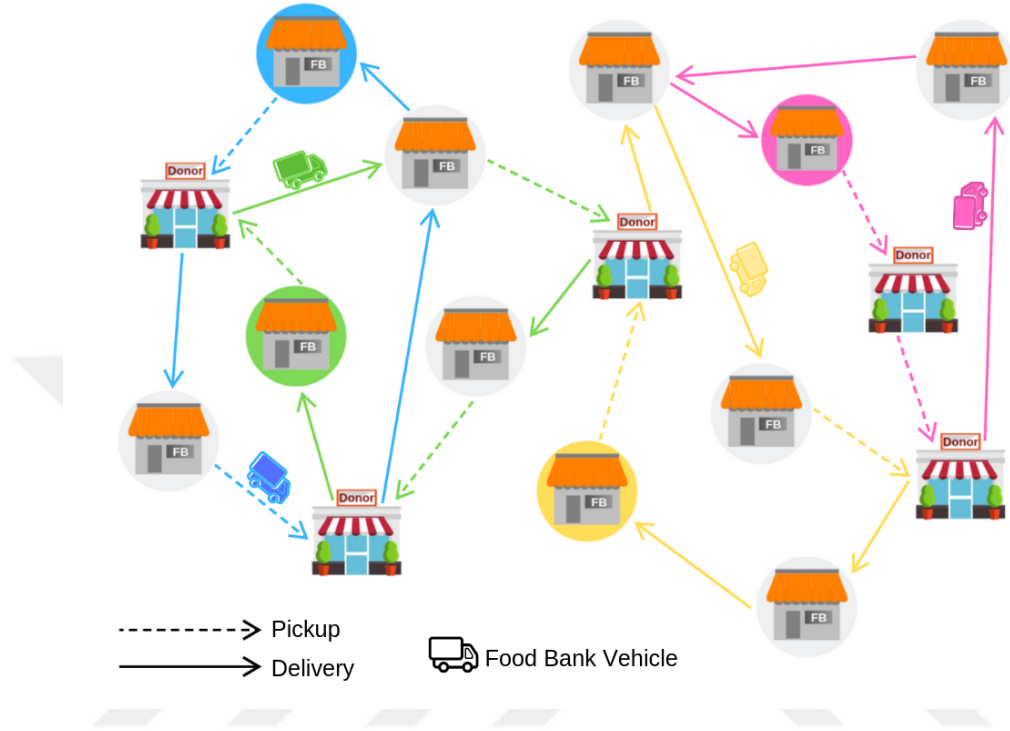


Figure 1.1: An illustration of the proposed system

Carrying out the operations with scarce resources in the most efficient way is critically important for food banks since they are nonprofit organizations. In the context of sustainability, avoiding food waste via making use of healthy and available food is also significant for protecting the environment and supporting the social solidarity among these charitable agencies and also with donor organizations. If food banks share the vehicles among themselves, the collection and distribution operations could utilize the resources more efficiently, which is crucial for all non-profit organizations. In addition, the food banks without vehicles would be able to reduce their logistics costs and reach more people in need.

Speaking of sustainability, the environmental aspect should also be improved in the new system. In other words, it is quite important to include methodologies that promote to minimize the environmental damage in the solution approaches. A measure to calculate this environmental damage is calculating the carbon emissions

created. Carbon dioxide (and equivalents) emissions can be created by a product, an individual or maybe an organization, via several activities including food consumption, construction, and transportation of the goods. In the study, not only food waste occurrences, but also logistics operations are part of the system. Logistics operations such as freight transport is known to be responsible for a great portion of carbon emissions worldwide. By the year of 2016, carbon emissions from the freight transport sector approached to 16.5% of the total carbon emissions in Turkey [Ministry of Environment and Urbanization, Republic of Turkey, 2018]. Furthermore, road transport accounts for 92.4% proportion of the emissions caused by the freight transport [Ministry of Environment and Urbanization, Republic of Turkey, 2018]. As a prominent firm that encourages sustainability in all senses, Fazla Gıda wishes to minimize the carbon emissions created by food donation operations. It is believed that with the proposed system, decreasing total carbon emissions considerably is strongly possible. Firstly, collecting the available donations as much as possible prevents food waste, since donations become food waste if they are not collected on time. Furthermore, it should be noted that donor organizations also take the advantage of paying less taxes via donating the surplus food. It is also profitable for them to not to waste the excess food as they do not have to take care of the disposal operations. Secondly, using vehicles jointly and improving the utilization of vehicles promote creating less emissions caused by the fuel consumption. However, of course, the proposed system must be able to find the best way to collect the donations correctly and on time, and distribute them to their owners considering the environmental and financial issues. Hence, Fazla Gıda seeks ways to reduce their carbon emissions caused by these logistics operations, meanwhile, keeping the total food waste at the minimum.

In parallel with the identified design considerations, an optimization model for making the allocation, scheduling and routing decisions in the proposed system with the collaboration concept is needed. The new donation system proposed in this thesis can be described as follows. The perishability of the donations will be taken into account while making decisions on their collection and distribution because of the health issues specified before. Incoming donations must be picked and

distributed in a couple of days, maybe within just one day. Therefore, a donation horizon will be considered as a period of time in the system which consists of a few days. At the beginning of each horizon, donors will announce the amount and validity of donations (as start and end dates of their availability) for particularly this donation horizon. Then, food banks will decide in which categories and how much of food they need within the donation period, regardless of a specific donor. The allocation of the specific donations to specific food banks will be one of the required outputs of the system. Another output will be the routes of vehicles. A vehicle will be able to serve more than one food bank with the aforementioned collaboration. If a vehicle of a food bank is used for a specific day, the route plan of the vehicle must be determined. Also, the pickup or delivery amounts at each stop on a route must be determined according to the capacity of the vehicle. These output requirements led us to construct a mathematical programming model to optimize the donation operations. The main goal is to reduce the total food waste while minimizing the carbon emissions created during the transportation operations. Hence, in this study, we develop a mixed integer linear programming model for the unpaired pickup and delivery vehicle routing problem with multiple periods, multiple heterogeneous vehicles, and multiple commodities. The objective of the model is to maximize the total savings on food collection, while minimizing the cost of fuel consumption and emissions.

Since this study focuses on rescuing surplus food as much as possible, it should be noted that equitable assignment of the donations in the context of social sustainability is not considered. However, the system that is proposed can be modified easily with the objective of equitable distribution of rescued food in future studies by using humanitarian approaches.

This study is valuable for seeking better ways of managing charitable operations considering the global sustainability issues. The donation process can be considered as a win-win event for all members of the system. Furthermore, there are several sustainable environmental considerations for improvement beyond the social and economical ones. Optimizing food donation process is also the most beneficial decision made for protecting the environment and minimizing the damage. These points

simply sum up the main motivations behind this work.

The remainder of the thesis is outlined as follows. In Chapter 2, a detailed review of related literature and the contributions of the study are provided. In Chapter 3, the problem is introduced formally and the solution approach is described. In Chapter 4, data is explained and computational experiments are detailed. In Chapter 5, the productivity of the proposed system is discussed, contributions of the study are summarized and possible extensions are described.



Chapter 2

LITERATURE AND CONTRIBUTIONS

Operations on food banks and food rescue have grabbed the attention of many researchers in recent years. While former studies have intensified in America, Australia and Europe, to the best of our knowledge, no studies have been conducted in our country in the literature. In this thesis, a so-called “green” variant of Unpaired Pickup and Delivery Vehicle Routing Problem (GU-PDVRP) is studied for food bank operations. The related literature is reviewed explicitly in three parts. Section 2.1 briefly refers to the studies made on the pickup and delivery vehicle routing problems. Section 2.2 consists of a detailed and comprehensive review of the related studies on charitable food logistics. Section 2.3 examines the studies on fuel consumption and emissions management in the logistics operations. The last section 2.4 is about the contributions of this study to the literature.

2.1 Pickup and Delivery Vehicle Routing Problems

Vehicle Routing Problem (VRP) is a well-known problem and it is studied by many researchers for a long time. Pickup and Delivery Vehicle Routing Problem (PDVRP) extends the classical VRP by including a set of pickup customers and a set of delivery customers. The single-product PDVRP (1-PDVRP) is introduced by Shi et al. [Shi et al., 2009]. They propose a mathematical formulation and a genetic algorithm for the problem.

Unpaired Pickup and Delivery Vehicle Routing Problem (U-PDVRP) is a variant of PDVRP where the pickup and delivery pairing is decided by the model itself. In other words, the supply from a pickup customer can be delivered to one or multiple delivery customers, and the demand of the delivery customers can be met by the products from one or multiple pickup customers. To the best of our knowledge,

U-PDVRP is first introduced by Chen et al., where they formulate the problem with multi-product setting and developed a heuristic algorithm [Chen et al., 2014]. They also assume that pickups and deliveries can be split. Similar setting is also used and extended by Nair et al. for food rescue operations [Nair et al., 2016b, Nair et al., 2016a, Nair et al., 2018]. These works are examined extensively in the next subsection. [Xu et al., 2017] developed a new mathematical formulation for U-PDVRP which allows multi-visits. They also propose several valid inequalities and a tabu search based heuristic algorithm. It can be said that the literature on U-PDVRP is very limited. Thus, there can be a lot of application areas for U-PDVRP such as charitable food logistics operations.

2.2 Charitable Food Logistics

There are various studies for managing the logistics operations of charitable food under the literature of humanitarian logistics. As distinct from profit-based logistics operations on food collection and distribution, charitable food operations are generally being carried out by nonprofit organizations and have a different structure. Thus, the studies working on hunger relief and food rescue operations topics are reviewed in detail in this section which are related to the scope of this study.

One of the pioneer studies on charitable food operations is a vehicle routing problem for Meals on Wheels (MOW) program, which aims to provide prepared meals for people in need. In that study, Bartholdi et al. develop a routing heuristic and aid a nonprofit organization to deliver the meals in a more efficient way [Bartholdi III et al., 1983]. There are further studies on MOW program extending this study. Yıldız et al. approach to MOW program as a location routing problem (LRP) and they implement a genetic algorithm for their planning model [Yildiz et al., 2005]. Furthermore, Yıldız et al. also develop a memetic algorithm for the same problem [Yildiz et al., 2013].

Güneş et al. develop mixed integer programming, constraint programming and constraint-based local search for the 1-Commodity Pickup and Delivery Vehicle Routing Problem (1-PDVRP) to collect excess food and redistribute them [Gunes

et al., 2010]. They obtain their data from a food bank and compare the transportation cost savings under different models they developed.

Solak et al. introduce a new variant of LRP based on the distribution networks of food banks in US [Solak et al., 2014]. The distribution network they define consists of several delivery sites where agencies come and pick their food up from these points. They develop an MILP model to select the delivery sites, assign agencies to these points and construct routes from food bank to these delivery sites with the aim of minimizing the travel costs of the vehicles. They generate data inspired by several food banks, however, they do not consider the collection of food donations. They propose two Benders decomposition based algorithms which they claimed as more practical procedures as opposed to the MILP model.

Similar to previously examined work, Davis et al. propose a novel collection and distribution system for food banks to carry out the donations safer and increase the accessibility of agencies [Davis et al., 2014]. They work on a capacitated set covering problem to determine the food delivery points (FDPs) first, which are chosen from the collection sites (donors). Once FDPs are determined, they implement a periodic vehicle routing problem with backhauls (PVRPB) to create collection and FDP delivery schedules. They assume that a fully loaded truck will go to a single drop-off point. They prepare realistic data inspired from a food bank in US. In their instances, the distances between the nodes in the network are quite long, so they constrain travel time not to violate the perishability of the donations. They also show that the travel time of agencies to collect their donations is reduced considerably with the use of FDPs instead of the single food bank warehouse. However, they do not consider the transportation of donations from FDPs to agencies, as this is agencies' responsibility.

Lien et al. work on a Sequential Resource Allocation Problem (SRAP) for the Food Rescue Program (FRP) of a nonprofit food depository [Lien et al., 2014]. There is a fixed route where the collection and distribution operations are conducted. Donated food is considered as resource and while distributing the collected food, allocation decisions must be made according to demands of the agencies observed. They implement a dynamic programming model where the donation amounts and

demands are unknown and following a probability distribution. With the objective of maximizing the expected minimum fill-rate of an agency, they also consider *equity* among the allocations. They develop heuristic algorithms to set an allocation policy and sequencing visits, which give near-optimal solution quality.

Balçık et al. extend the previous study by Lien et al. [Lien et al., 2014] by modeling the problem for the multi-vehicle case [Balcik et al., 2014]. They add a set partitioning model to cluster the set of donors and agencies to the routes of present vehicles. They develop a decomposition-based heuristic for the clustering, sequencing and allocation decisions. Additionally, they consider minimizing waste as an objective for another benchmark model as well as the objective of equitable allocation. Both studies consider only one food type.

Örgüt et al. study effective and equitable models for a food distribution network of a food bank in US [Orgut et al., 2016]. In terms of “equity”, they try to minimize the deviation between the proportion of food sent to a county and that county’s relative need. They define “effectiveness” by minimizing the total amount of undistributed food. Unlike other studies, they define a capacity for each agency of maximum amount of donation that can be received by that agency. Whenever this capacity is exceeded, food waste occurs. They propose two models with these conflicting objectives. The first model is for food distribution while the second one is based on a capacity allocation problem for allocating additional capacity. They observe optimal solutions for the real-life case study. However, they do not consider any transportation costs. In their further studies, they propose stochastic and robust modeling approaches [Orgut et al., 2017, Orgut et al., 2018].

Nair et al. work on a periodic U-PDVRP for a nonprofit food rescue organization in Australia [Nair et al., 2016a]. There is a network based on a wide area, consisting of hundreds of donors and agencies. Because of the perishability of the food, the donations are distributed immediately as they are collected within the same day. The visit frequencies to both donors and agencies are considered. While donors have a fixed schedule of visits, agencies generally have a flexible schedule. There are several schedules to be assigned to days. Since pickups and deliveries are not paired, the demand of the agencies can be met with surplus food collected from one or more

donors. They propose an MILP model which minimizes the total transportation costs of vehicles for routing and weekly scheduling decisions of the organization. They develop a heuristic algorithm to solve larger instances which works in two stages. In the first stage, an initial schedule is generated and improved, then the routes are constructed and improved in the second stage. They consider only one commodity and assume that the agencies are directly served. Nair et al. extend this study by implementing a Tabu Search heuristic algorithm for the problem where they also consider two types of products: perishable products and long-life products [Nair et al., 2018]. They show that the heuristic algorithm can reduce the route cost up to 30%. There is also another study that the authors work with bi-objective models to apply equity and efficient routing at the same time for the same problem [Nair et al., 2016b]. In this study, rather than using only the traditional cost minimization function, they promote fair resource allocation by proposing two additional objective functions, one maximizes the satisfaction of all agencies, while the other maximizes the satisfaction of the least satisfied agency.

In another study, Nair et al. introduce the Food Rescue Allocation and Routing Problem (FRARP) [Nair et al., 2017]. They first implement a multi-objective mathematical model for equitable allocation with efficient routing decisions with goal-programming approach. They also develop a heuristic algorithm for larger instances for the aforementioned nonprofit organization in Australia. Based on this study, Rey et al. propose a novel MILP formulation which promotes envy-free allocation [Rey et al., 2018]. They assume that the total food supply is lower than the total food request. They minimize total transportation costs including the price of envy-freeness as a weight. They develop a cutting plane algorithm which implements Bender's decomposition and valid inequalities as an exact solution method. For larger instances, they develop a heuristic algorithm based on local search and compare these approaches. They also use real-life scenarios to evaluate the performances of the proposed models. The study concludes that using less vehicles can improve the fairness of the allocations. Again, only one commodity is considered in both of the studies and perishability is handled by same-day deliveries.

Eisenhandler et al. introduce single-period, single-product, single-vehicle static

variant of the Humanitarian Pickup and Distribution Problem (H-PDP) for resource allocation and routing decisions of food banks [Eisenhandler and Tzur, 2018]. They propose a novel objective function which conjugates equity and effectiveness of allocations. They divide the problem into two sub-problems: the routing sub-problem and the allocation sub-problem. They propose a heuristic algorithm which can find pickup and delivery quantities efficiently when the route is predetermined. Furthermore, Eisenhandler et al. extend this study by introducing a new segment-based formulation for the H-PDP [Eisenhandler and Tzur, 2019]. They propose a hybrid method implementing their previous formulation and large neighborhood search (LNS) to solve the multi-vehicle and single-vehicle variants of the problem. In both of studies, single food type is considered.

2.3 Fuel Consumption and Emissions in Logistics

One of the main purposes of this study is to construct a sustainable logistics system for the charitable food operations. Therefore, not only the economic cost, but also the environmental cost of transportation must be taken into account while optimizing the logistics expenses. In this section, the studies related to emission modeling in vehicle routing problems are briefly reviewed.

Kara et al. work on one of the several studies that initiate environmental concerns based on fuel consumption in the routing problems [Kara et al., 2007]. In this study, they introduce the Energy Minimizing Vehicle Routing Problem (EMVRP) which is an extension of capacitated VRP (CVRP). They define a weighted vehicle load function which uses vehicle loads and distances to minimize the total energy used in terms of fuel consumption. They use this function as the objective function. They compare their function with the conventional distance-minimizing function on several illustrative examples. However, their function fails to reflect actual energy consumption accurately since it is derived from simple physics laws and it does not include several important factors such as speed and vehicles' technical parameters.

To the best of our knowledge, Bektaş et al. are the first to integrate the emissions and the traditional VRP cost objectives with a comprehensive fuel consumption and

emissions model which includes vehicle loads, speed, distance traveled, technical factors and more [Bektaş and Laporte, 2011]. They introduce the Pollution Routing Problem (PRP) which extends the classical VRP with a new objective function that incorporate fuel consumption and carbon emissions with the mainstream cost calculations. They try to minimize the total cost incurred by fuel costs, emissions and drivers' wages. Another decision included by their model is the speed level to be "used" on different route segments. They test their models on realistically generated data which is based on the cities in United Kingdom. They analyze several performance criterion such as vehicle load, demand variation, including time windows and number of vehicles. According to their experiments, minimizing emissions and minimizing operational costs necessarily do not boil down to the same thing in vehicle routing.

Jabali et al. also propose a new framework to model emissions for the time-dependent VRP (TDVRP) [Jabali et al., 2012]. They model time-dependency by partitioning travel time periods as free-flow periods and congestion periods. They decide on the vehicle speed considering these time periods, e.g. low speed is inevitable during congestion periods. They model the emissions as a function of speed and they analyze different speed profiles. However, they do not consider any other factors such as loads and technical parameters for calculating the emissions. They show that as travel time, fuel and emissions depend on the speed of the vehicle, controlling speed is indeed very effective on minimizing the total cost.

Recently, many studies extend the work of Bektaş et al. [Bektaş and Laporte, 2011] to incorporate fuel consumption and carbon emissions with the mainstream cost calculations in various logistics management and decisions. Demir et al. develop an Adaptive Large Neighborhood Search (ALNS) algorithm for the PRP [Demir et al., 2012]. They also use an additional algorithm called Speed Optimization Algorithm (SOA), which improves ALNS solutions by optimizing vehicle speeds. In another work, Demir et al. introduce the bi-objective PRP [Demir et al., 2012]. They use two conflicting objectives, minimizing fuel consumption and minimizing driving time. The reason behind this choice of objectives is that in their previous work [Demir et al., 2012], they assert that optimal speed is lower than the speed

preferred by the drivers in general. For this problem, they also use ALNS with the speed optimization procedure, which turn out to give good-quality solutions. Kramer et al. develop a matheuristic for the PRP and other green VRP variants [Kramer et al., 2015]. They assert that their methodology improved the solutions which are reported beforehand. Another extension of PRP is the time-dependent PRP (TDPRP) which is introduced by Franceschetti et al. [Franceschetti et al., 2013]. They also consider congestion in their problem and try to optimize departure times of the vehicles and travel speed levels during the tours with a novel SOA. Franceschetti et al. develop an ALNS metaheuristic with new move operators for the TDPRP [Franceschetti et al., 2017].

There are many extensions for the PRP and new solution methodologies adopting similar emission model for other type of problems [Daryanto et al., 2019, Koç, 2019, Li et al., 2018, Xu et al., 2019]. The emission model used in PRP turns out to be very useful in increasing environmental savings as seen in the reviewed studies. On the other hand, even if the congestion is included, these studies focus on the intercity transportation. Koç et al. work on city logistics by using a simplified version of the emission model proposed by Bektaş et al. [Bektaş and Laporte, 2011] for the PRP [Koç et al., 2016]. They investigate the impact of depot locations, fleet composition and vehicle routing decisions on carbon emissions with the consideration of different speed zones in a city. The speed level differs from zone to zone, however, it is taken as a constant while the vehicle is traveling within a zone. They propose an MILP model with the objective of minimizing total cost of depot location cost (it also differs from zone to zone), vehicle cost, and fuel consumption and CO₂ emissions cost. They consider heterogeneous fleet, therefore each vehicle differs in terms of cost and technical parameters. They develop an ALNS metaheuristic for the problem. They conclude that driving faster causes less pollution in cities. They also assert that locating depots outside of the city is more favorable in terms of cost, since that brings a total saving around 34%.

An emission model will be used in this study to be able to contribute decreasing the environmental damage. It is decided to use the emission model of Koç et al. [Koç et al., 2016]. Their emission model can calculate the fuel consumption and

carbon emissions with a fixed speed, including the effects of the distances and the vehicle loads. Also, other technical parameters and types of the vehicles are relevant for the setting of our problem. The modification and usage of this emission model and several assumptions will be explained later in detail in Chapter 4, along with the relevant data.

2.4 Contributions of the Study

The literature review given in the first section shows that PDVRP and problems with similar settings for food bank operations such as allocation and routing are focused on one food bank that coordinates the donations and welfare agencies. In our problem, there are several food banks, municipalities and also non-profit organizations under the name of agencies. Also, the company we are working with, Fazla Gıda, helps the donor organizations to tackle with the surplus food issue. There is no vehicle that Fazla Gıda operates for the donation process. The agencies are responsible for collecting their donations from the corresponding donors. As indicated before, the main goal of this study is to help the welfare organizations and make these processes easy for them as they already have limited resources.

In our setting, only some of the food banks have vehicles. Thus, a multi-depot environment is constructed, which is not studied before for charitable food logistics. Also, a case study will cover a horizontal collaboration among the food banks for charitable food operations. Recently, logistics collaboration in supply chain management gained importance for organizations with the aim of accomplishing economic, social, and environmental sustainability goals [Chen et al., 2017]. However, work on collaborative logistics operations among nonprofit organizations is still limited. Cost savings from collaborative transportation for the food banks are extremely valuable. Furthermore, using less vehicles is expected to cause less environmental damage and cooperation among nonprofit organization will definitely contribute social solidarity in this case, which is priceless.

Another contribution to the literature is the consideration of time limitations of the donations. Perishability is an important issue that concerns lots of organizations

in the food industry. Sustainable food supply chain management also promotes reducing the food waste. There are several studies with perishable products, mostly on supply chain management, inventory, and location routing problems that include sustainability issues in the literature [Govindan et al., 2014, Rohmer et al., 2019, Soysal et al., 2015, Soysal et al., 2018]. In the context of perishability, most of the studies on charitable food logistics assert that each collected donation must be delivered during the same day of its collection. However in our setting, donors set a deadline for the collection of their donations. Thus, the availability of each donation is limited with only a few days or maybe just one day. Considering that the donations are already close to their expiration dates, the time intervals for the donations are important as they have to be collected and used immediately.

As distinct from other studies in the literature, one of the two primal objectives in this study is to minimize the food waste. Here, each donation has a different amount of food, food type and monetary value. The other primal objective is to minimize the environmental damage caused by the logistics operations. To be able to measure these two different objectives together, their corresponding monetary values will be used. The total monetary value of collected donations should be maximized while the total cost of fuel consumption and CO₂ emissions is minimized. Thus, differently than the equity and effectiveness issues, rescuing the valuable food as much as possible is the main goal set on the charitable operations in this study. In the meantime, the total demand of the food banks is already greater than the total food supply. To the best of our knowledge, this is the first study that addresses several categories of food in the multi-commodity context within the charitable food logistics literature.

Additionally, instead of traditional VRP objectives, an emission model is used in the study to minimize the environmental damage of transportation operations. According to this emission model, fuel consumption directly depends on the vehicle load, which is very unstable for U-PDVRP since pickup and delivery do not follow a stationary pattern. This load issue itself can lead completely different solutions other than the objective of distance minimization only. Many other parameters such as speed and distance will also be included in the model, among the cost of fuel used

and emissions. To the best of our knowledge, this is also the first study that uses an emission model to calculate fuel and emission costs in the objective function. Taking environmental concerns into account within such a problem setting is considered as a big step to contribute sustainable development in all senses.

To conclude, this study embeds sustainability issues into the charitable food logistics problem. The solution methodology of this study considers all three dimensions of sustainability: social, environmental and economic.



Chapter 3

SOLUTION APPROACH

While optimizing the donation system introduced in Chapter 1, a collaboration concept for the logistics operations is proposed to promote sustainability. Since several food banks in the system do not have vehicles, the logistics collaboration aims to use the available vehicles for all of the food banks mutually. Three case studies are developed to examine the effects of collaboration. While the first case study proposes a system with collaborative logistics operations, the second case study proposes a vehicle rental option to the food banks without vehicles in addition to the collaboration. The third case study proposes using shipments, to the food banks without vehicles, while disallowing collaboration.

In this chapter, the case studies and solution methodologies will be explained in detail. This chapter is organized as follows. In Section 3.1, notation for the formulations are introduced. While the assumptions necessary to develop a realistic solution procedure are explained in Section 3.2, the solution methodologies for the system with logistics collaboration are described in Section 3.3. In Section 3.4, alternative models developed for the case studies are provided.

3.1 Notation and Parameters

The problem considered in thesis can be described formally as follows. The proposed donation system has a donation horizon which consists of couple of days. The set of time periods (here, days) is denoted by $\mathcal{T}$. Each donor has a fixed location, thus a donation can be picked up from its owner donor. Each donor location corresponds to a pickup node. Each food bank also has a fixed location and these locations are used for deliveries. Each food bank location corresponds to a delivery node. In the problem, the vehicles belong to food banks. If a food bank owns a vehicle, the

site of the food bank also serves as a depot for their vehicle(s). The set of all food bank nodes are denoted by $\mathcal{F}$ and the set of all donor nodes are denoted by $\mathcal{G}$. The set of vehicles are denoted by $\mathcal{K}$. For each vehicle $k \in \mathcal{K}$, a dummy initial depot represented as node e_k and a dummy final depot represented as node f_k are defined to control the beginning and the end of the tours. Including the dummy nodes, the set of all nodes is denoted by $\mathcal{N}$. Clearly, $|\mathcal{N}| = |\mathcal{F}| + |\mathcal{G}| + 2 \times |\mathcal{K}|$. Each donation consists of one type of food and the set of all food types is denoted by $\mathcal{R}$.

The descriptions of the parameters are given in Table 3.1. In the following subsection, assumptions on the system will be provided.

3.2 Assumptions

The basic characteristics of the proposed system are identified as follows. There are three main components in the donation system: donors, donations and food banks. Donors consist of several retailers, restaurants, producers etc. that intend to donate food to food banks. Food banks are non-profit charity organizations that aim providing food to people in need to reduce hunger and malnutrition. Donations must consist of healthy and consumable food. Clearly, consumable food to be donated must be kept in hygienic conditions and also must have sufficient time before its best-before or expiration date to be eligible for human consumption. Thus, incoming donations must be distributed and used before they perish in a couple of days. Accordingly, a donation horizon consists of a few days. There are multiple categories of donated food to be considered while making the collection and distribution decisions. At the beginning of each horizon, donors announce the amount of donations and their availability duration in the digital platform provided by Fazla Gıda. Then, food banks decide in which categories and how much of food they need. There is no restriction on the amount of demand. Thus, the total amount of demands can exceed the total amount of the donations. The demands and donations are deterministic.

The food banks with the vehicles collect and distribute the donations according to a route (tour). If a vehicle is used, it starts the tour at the location of its owner food bank. After the pickup and delivery operations, the vehicle comes back to

Table 3.1: Descriptions of sets and parameters

Sets	
$\mathcal{F}$	Set of food banks, $\forall i \in \mathcal{F}$
$\mathcal{G}$	Set of donors, $\forall j \in \mathcal{G}$
$\mathcal{N}$	Set of all nodes including dummies
$\mathcal{K}$	Set of vehicles, $\forall k \in \mathcal{K}$
$\mathcal{R}$	Set of food categories, $\forall r \in \mathcal{R}$
$\mathcal{T}$	Set of time periods (days) in the donation horizon $\forall t \in \mathcal{T}$
Parameters	
D_{mn}	Distance (<i>in km</i>) between node (location) m and node n ; $\forall m, n \in \mathcal{N}$
P_{jr}^t	Amount of food (<i>kg</i>) in category r donated by donor j which will be available by day t
B_{jr}^t	Average monetary value of food category r donated by donor j which will be available by day t (<i>TRY</i>)
Q_{ir}	Total amount of food (<i>kg</i>) in category r demanded by food bank i throughout the donation horizon
$W_{jr}^{t\bar{t}}$	Indicator denoting the durability period of a donation. It is equal to 1 if the donation in category r that donor j donated which will be available by day t , is still available on day $\bar{t}$ ($t \leq \bar{t}$), otherwise 0
C_k	Capacity of vehicle k (<i>kg</i>)
L	Maximum tour length (<i>in hours</i>)
H_k	Maximum number of days that vehicle k can be used throughout the donation horizon
ν	Fixed speed level (<i>km/h</i>)

its owner's location. In other words, a tour indicates that a vehicle leaves from its starting location, collects and distributes the donations, and returns back to the starting location. Each vehicle can make just one tour during a day in a donation horizon. As stated before, there can be multiple pickups from several donors and also multiple deliveries to several food banks in a day. Note that pickups and deliveries are allowed to be splittable. However, a vehicle can visit a specific location (a donor or a food bank) just once in a tour. During a tour, the capacity of a vehicle cannot be exceeded. A tour length limit can be specified for a vehicle if its owner requires such a limit. A vehicle can be used even if the owner food bank does not receive any donation on that day. There can be further limitations on the days that a vehicle can be used for these operations during a donation horizon.

In this study, the aim is to propose a collaborative food collection system for the food banks considering the structure described above. In the following section, the mathematical formulation for the proposed system will be given according to the described characteristics.

3.3 Solution Methodologies

3.3.1 Mathematical Formulation

As stated before, the allocation, collection and distribution of the donations and the routing schedules for the vehicles must be determined. To optimize these decisions, a mixed integer linear programming (MILP) model is constructed according to the properties specified in the previous section. The decision variables are described in Table 3.2.

Table 3.2: Descriptions of decision variables

Binary Decision Variables	
x_{kmn}^t	is equal to 1 if vehicle k travels between node m and node n on day t ; 0 otherwise ($\forall m, n \in \mathcal{F} \cup \mathcal{G}$)
z_k^t	is equal to 1 if vehicle k is active (<i>being used</i>) on day t ; 0 otherwise
Integer Decision Variables	
q_{km}^t	The visiting order of node m in the tour of vehicle k on day t
Continuous Decision Variables	
u_{kmr}^t	Amount of food in category r that vehicle k picks up or delivers at node m on day t ($\forall m \in \mathcal{F} \cup \mathcal{G}$, since dummy nodes cannot be used for pickups or deliveries)
$p_{jr}^{t\bar{t}}$	Amount of food in category r that picked up from donor j on day $\bar{t}$ which was available first on day t ($t \leq \bar{t}$)
v_{kmr}^t	The total load of food in category r in vehicle k while leaving node m on day t
l_{kmn}^t	The total load in vehicle k while traveling from node m to node n on day t

MILP Model

$$\text{Maximize } \sum_{\forall t \in \mathcal{T}} \sum_{\forall \bar{t} \in \mathcal{T}} \sum_{\forall j \in \mathcal{G}} \sum_{\forall r \in \mathcal{R}} B_{jr}^t \times p_{jr}^{t\bar{t}} - \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}} \sum_{\forall m \in \mathcal{N}} \sum_{\forall n \in \mathcal{N}} c(m, n, l_{kmn}^t) \times x_{kmn}^t \quad (3.1)$$

subject to

$$\sum_{\forall m \in \mathcal{F} \cup \mathcal{G}} x_{kmn}^t - \sum_{\forall l \in \mathcal{F} \cup \mathcal{G}} x_{knl}^t = 0 \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, n \in \mathcal{F} \cup \mathcal{G} \quad (3.2)$$

$$\sum_{\forall m \in \mathcal{N}} x_{kmn}^t \leq 1 \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, n \in \mathcal{N} \quad (3.3)$$

$$\sum_{\forall m \in \mathcal{F} \cup \mathcal{G}} x_{ke_k m}^t = 1 \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \quad (3.4)$$

$$\sum_{\forall i \in \mathcal{F}} x_{kif_k}^t = 1 \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \quad (3.5)$$

$$q_{kn}^t + |\mathcal{F}| + |\mathcal{G}| \geq q_{km}^t + (|\mathcal{F}| + |\mathcal{G}| + 1) \times x_{kmn}^t \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{N}, n \in \mathcal{N} \quad (3.6)$$

$$\sum_{\forall m \in \mathcal{N}} \sum_{\forall n \in \mathcal{N}} \frac{D_{mn}}{\nu} \times x_{kmn}^t \leq L \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \quad (3.7)$$

$$\sum_{\forall r \in \mathcal{R}} v_{kmr}^t \leq C_k \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{N} \quad (3.8)$$

$$\sum_{\forall r \in \mathcal{R}} u_{knr}^t \leq \sum_{\forall m \in \mathcal{N}} C_k \times x_{kmn}^t \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, n \in \mathcal{F} \cup \mathcal{G} \quad (3.9)$$

$$x_{kmn}^t = 1 \Rightarrow v_{knr}^t = v_{kmr}^t + u_{knr}^t \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, n \in \mathcal{N}, m \in \mathcal{G}, r \in \mathcal{R} \quad (3.10)$$

$$x_{kmn}^t = 1 \Rightarrow v_{knr}^t = v_{kmr}^t - u_{knr}^t \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, n \in \mathcal{N}, m \in \mathcal{F}, r \in \mathcal{R} \quad (3.11)$$

$$Q_{ir} \geq \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}} u_{kir}^t \quad \forall i \in \mathcal{F}, r \in \mathcal{R} \quad (3.12)$$

$$P_{jr}^t \geq \sum_{\bar{t}=t}^{|\mathcal{T}|} p_{jr}^{\bar{t}\bar{t}} \times W_{jr}^{\bar{t}\bar{t}} \quad \forall t \in \mathcal{T}, j \in \mathcal{G}, r \in \mathcal{R} \quad (3.13)$$

$$W_{jr}^{\bar{t}\bar{t}} = 0 \Rightarrow p_{jr}^{\bar{t}\bar{t}} = 0 \quad \forall t, \bar{t} \in \mathcal{T}, j \in \mathcal{G}, r \in \mathcal{R} \quad (3.14)$$

$$\sum_{\forall k \in \mathcal{K}} u_{kjr}^t = \sum_{\bar{t}=0}^t p_{jr}^{\bar{t}\bar{t}} \quad \forall t \in \mathcal{T}, j \in \mathcal{G}, r \in \mathcal{R} \quad (3.15)$$

$$\sum_{\forall k \in \mathcal{K}} \sum_{\forall i \in \mathcal{F}} u_{kir}^t = \sum_{\forall k \in \mathcal{K}} \sum_{\forall j \in \mathcal{G}} u_{kjr}^t \quad \forall t \in \mathcal{T}, r \in \mathcal{R} \quad (3.16)$$

$$\sum_{\forall r \in \mathcal{R}} v_{kmr}^t \geq l_{kmn}^t \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{N}, n \in \mathcal{N} \quad (3.17)$$

$$C_k \times x_{kmn}^t \geq l_{kmn}^t \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{N}, n \in \mathcal{N} \quad (3.18)$$

$$l_{kmn}^t \geq \sum_{\forall r \in \mathcal{R}} v_{kmr}^t - C_k \times (1 - x_{kmn}^t) \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{N}, n \in \mathcal{N} \quad (3.19)$$

$$\sum_{\forall r \in \mathcal{R}} v_{kekr}^t = \sum_{\forall r \in \mathcal{R}} v_{kfkr}^t = 0 \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \quad (3.20)$$

$$|\mathcal{N}| \times z_k^t + 2 \geq \sum_{\forall m \in \mathcal{N}} \sum_{\forall n \in \mathcal{N}} x_{kmn}^t \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \quad (3.21)$$

$$\sum_{\forall t \in \mathcal{T}} z_k^t \leq H_k \quad \forall k \in \mathcal{K} \quad (3.22)$$

$$x_{kmn}^t \in \{0, 1\} \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{N}, n \in \mathcal{N} \quad (3.23)$$

$$z_k^t \in \{0, 1\} \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \quad (3.24)$$

$$q_{km}^t \in \{0, 1, \dots, |\mathcal{F}| + |\mathcal{G}| + 1\} \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{N} \quad (3.25)$$

$$u_{kmr}^t \in [0, C_k] \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{F} \cup \mathcal{G}, r \in \mathcal{R} \quad (3.26)$$

$$p_{jr}^{t\bar{t}} \in [0, \max_{\forall k \in \mathcal{K}} C_k] \quad \forall t, \bar{t} \in \mathcal{T} : t \leq \bar{t}, j \in \mathcal{G}, r \in \mathcal{R} \quad (3.27)$$

$$v_{kmr}^t \in [0, C_k] \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{N}, r \in \mathcal{R} \quad (3.28)$$

$$l_{kmn}^t \in [0, C_k] \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{N}, n \in \mathcal{N} \quad (3.29)$$

The objective function (3.1) in the model aims to maximize the total monetary value. The total monetary value is defined as the difference between the monetary value saved from collecting the donations from donors and the cost of fuel consumption and emissions from vehicle use during the donation horizon. The cost function uses the emission model proposed by Koç et al. (2016) [Koç et al., 2016]. Details and parameters of the cost function will be explained in the next chapter. Then, it can be said that food waste and carbon emissions are being minimized. Constraints (3.2) are well-known flow balance Constraints. In other words, the number of entries to a node and the number of exits from that node by a vehicle must be equal to each other on a day. Note that traveling from a node to the same node is not allowed. Constraints (3.3) imply that a node can be visited just for once by a vehicle on a day. While Constraints (3.4) ensure that a vehicle must leave its starting dummy node, Constraints (3.5) ensure that a vehicle must return to the end dummy node on a day. Note that if a vehicle is not used on a day, it is expected that this vehicle visits only its original node, which means it does not move to any other locations. Also, a vehicle cannot visit any other dummy node except its. Constraints (3.6) are well-known Miller-Tucker-Zemlin subtour elimination constraints and they assign the visiting order of the nodes on the route of a vehicle on a day [Miller et al., 1960]. Constraints (3.7) place a tour length limit for each vehicle on a day. Constraints (3.8) ensure that the capacity of a vehicle can never be exceeded during the day. Constraints (3.9) imply that pickup and delivery operations can be done on a node if and only if that node is visited. The operations are also limited by the capacity of the vehicle. Constraints (3.10) control the load of the vehicle if a pickup operation is made on a donor node. Similarly, constraints (3.11) control the load of the vehicle if a delivery operation is conducted on a food bank node. Constraints (3.10) and (3.11) can be linearized commonly as inequalities. Constraints (3.12) ensure that

the amount of total deliveries to a food bank node throughout the donation horizon, cannot exceed their total demand. Similarly, Constraints (3.13) ensure that collection of each donation cannot exceed the donation amount. Note that a donation on a specific day by a specific donor in a specific food type is unique. A donation can be collected in coming days, however, the donation must be still consumable. Thus, Constraints (3.14) ensure that if the donation is not available or perished already on a day, it cannot be collected. Constraints (3.15) set the relationship between the pickup variables u and p , to determine the total collections of a food type from a donor on a day. Constraints (3.16) are the balance constraints for equalizing total collection with total distribution. Constraints (3.17) - (3.19) ensure that if an edge is traveled, then the total load carried by the vehicle on this edge is calculated accordingly. Constraints (3.20) ensure that initial load and final load of a vehicle must be zero. In other words, a vehicle must be empty while leaving the initial dummy depot node and entering the final dummy depot node. Constraints (3.21) imply that a vehicle can visit other nodes on a day if and only if it is active on that day. Constraints (3.22) ensure that the days in which a vehicle is in use, cannot exceed the maximum number of days a vehicle can be used. Finally, Constraints (3.23) to (3.29) define the domains of the decision variables.

3.3.2 A GRASP-ILS Implementation

Since this study deals with a large-scale vehicle routing based real life problem, finding an exact solution is quite hard and time consuming with a mathematical model. To accelerate this process, a problem-specific GRASP (Greedy Randomized Adaptive Search Procedures) with ILS (Iterated Local Search) metaheuristic algorithm is developed.

The nature of the problem studied actually cover several problems. These problems include deciding the time and amount of donations to pick up, matching the donations picked with the food banks while considering their demands, and constructing capacitated vehicle routes while deciding the schedule of delivery and pickup operations. The objective function includes two critical decisions; one is

maximizing the value of donations picked, and the other is minimizing the fuel and emissions cost at the same time. It should be noted that the operations and vehicles available keep changing day by day. Hence, the decision made at an earlier stage, highly affects the decisions to be made in the forthcoming stages.

GRASP (Greedy Randomized Adaptive Search Procedures) Implementation

Greedy Randomized Adaptive Search Procedures metaheuristic (GRASP) consists of two basic phases: construction and local search. The construction phase is formed as a multi-start metaheuristic, several random feasible solutions are being generated in this phase. These solutions are constructed with a greedy randomized approach. If the constructed solution is infeasible, then a repair procedure is applied to make it feasible. The construction phase ends after feasible initial solutions are constructed. After a feasible solution is obtained, local search is applied to improve an initial solution. Local Search basically keeps moving from the current solution to a better neighbour solution until it is terminated. If the incumbent solution is improved, then it is updated. GRASP terminates if a stopping condition is satisfied, such as maximum number of iterations or target objective value [Resende and Ribeiro, 2014].

The general framework of the constructive heuristic algorithm can be summarized as follows. The algorithm starts to process the donation operations from the day specified by the *starting day* parameter of the donation horizon. In the beginning of a day, the donations which are available to be picked are determined. These available donations are called as *active* donations. In other words, the donations that are within the time windows of their available days are active, therefore they are eligible to be collected and distributed on the specified day. If a donor has an active donation on the specified day, then the donor is also called as an *active* donor. If a food bank has still an unfulfilled demand on the specified day, then it is called *active* food bank. First operation is the assignment of the active donors. The active donors are assigned alternately to one of the available vehicles on that day. After feasibility operations, active food banks are also assigned to the available vehicles.

On a route, the donor nodes come first, then the food bank nodes come in the visit schedule of the *active* vehicle. In other words, delivery operations come after pickup operations during a tour. These assignment operations are made according to several criteria which will be explained in the remainder of this section. After nodes to be visited by a vehicle are determined, pickup and delivery operations are decided. Finally, the final routes are arranged for that day. Then, the components are updated for the next day and operations are again formed for the current day. The pseudo-code of the constructive heuristic algorithm is given in Algorithm 3.1.

Algorithm 3.1 GRASP Constructive Heuristic - *construct_solution()*

Input: Seed e , Threshold parameter α_t , Number of iterations $max_iterations$, Starting day t'

```

1: Solution  $s \leftarrow null$ 
2: for day  $t = t', \dots, |\mathcal{T}|$  do
3:    $update\_active\_donations(t)$ ;  $\triangleright$  find active donations for the specified day
4:    $assign\_donors(e, \alpha_t)$ ;  $\triangleright$  assign donors to available vehicles
5:    $assign\_food\_banks(e, \alpha_t, max\_iterations)$ ;
6:    $\triangleright$  assign food banks to active vehicles
7:   for vehicle  $k = 1, \dots, |\mathcal{K}|$  do
8:     if vehicle  $k$  is active then
9:        $route_{tk}.pick\_up()$ ;  $\triangleright$  arrange donations to pick up
10:       $route_{tk}.deliver()$ ;  $\triangleright$  deliver the donations collected
11:       $s.add(route_{tk})$ ;  $\triangleright$  add the specified route to the solution  $s$ 
12:     end if
13:   end for
14: end for
Output:  $s$ 

```

The components of the Algorithm 3.1 can be explained as follows. The active donations are determined with the $update_active_donations()$ function at the beginning of a day. This function simply selects the non-empty donations that are eligible

to be collected on the day specified in the function. For example, if the specified day is between the first and the last available days of a donation, then this donation is added to the active donations. After that, active donors are also determined as the owners of the active donations. If a vehicle has one or more days left to serve within the donation horizon, then it is considered to be available. While assigning donors to the available vehicles, the donor assignment function *assign_donors()* uses a greedy randomized algorithm to minimize the distance between the chosen nodes and the depot of that vehicle. This assignment is simply made between the available vehicles and active donors who have available donations on the day specified. After donors are assigned, feasibility for the route length constraint is checked. Whenever this constraint is violated, the function excludes donors with lower-valued donations from the route to be able to rescue more valuable donations from the remaining donors. After feasible active routes are constructed with the active donors, the assignment of the food banks to these routes is made. Food banks are inserted to the routes of randomly selected active vehicles after the donor nodes with *assign_food_banks()* function. The vehicle-owner food banks are assigned directly to one of their active vehicles. Again, a closer food bank is sought for the vehicle by a greedy randomized algorithm, and as soon as a feasible insertion is found, the food bank with non-zero demand is inserted to one of the routes. At the end of this step, feasible routes are constructed. The pseudo-codes of the assignment algorithms are given in Appendix A.

To understand the structure of greedy randomized algorithms in general, there are several concepts to outline. Different than the pure greedy algorithms, greedy randomized algorithms use randomization to construct different solutions at different runs, and they are widely used in metaheuristics such as GRASP, genetic algorithm and scatter search [Resende and Ribeiro, 2014]. These algorithms commonly use a Restricted Candidate List (RCL) to evaluate the corresponding components, i.e. elements, and to restrict the number of candidates while constructing a solution. Candidate elements to be added to the current (or partial) solution, which is being constructed, are restricted with a greedy function. These elements can be defined with respect to the problem (elements can be nodes, edges, tasks, variables, etc.).

At each step, a candidate element is selected from RCL randomly and added to the partial solution. This procedure is repeated until there are no further candidates. For example, the greedy randomized algorithm used in this study evaluates the distances between the depot of the vehicle in consideration, and the candidate nodes. In the aforementioned algorithm, RCL is constructed by using the definition given below:

$$RCL = \{c \in C \mid r(c) \leq r_min + \alpha_t(r_max - r_min)\} \quad (3.30)$$

In (3.30), parameter α_t is called as the “threshold parameter” and it takes values between 0 and 1. $r(c)$ represents the evaluation of the candidates according to the greedy randomized function, and r_max and r_min represent the maximum and minimum number of evaluations at an iteration. Note that when $\alpha_t = 1$, the construction becomes fully randomized, and when $\alpha_t = 0$, the construction becomes fully greedy. This simply sums up the main structure of the greedy randomized algorithm used within the constructive heuristic. The pseudo-code of the greedy randomized algorithm is given in Appendix A.

After node assignments are done, if an available vehicle has at least one donor assigned, it remains active. Then, the donations available on each route are picked from their donors and delivered to the food banks. To avoid the vehicle capacity constraints or the demand fulfillment constraints from being violated, the most valuable donations are picked primarily according to the total demands of the food banks on the route with *pick_up()*. With the *deliver()* function, the demand of the first food bank to be visited is fulfilled as much as possible, then the demands of other food banks on the route are fulfilled in order. After the allocations, if a food bank on the route of an active vehicle is not served, then it is removed from the route. After organizing the route of each active vehicle with this removal process, the solution is formed.

This constructive heuristic algorithm creates different solutions when used with different parameter values and it is dependent on randomization. It should be noted that the solutions constructed with this algorithm are always feasible.

In the construction phase, the routes are constructed by the components de-

terminated with a greedy randomized algorithm. This algorithm uses the distances between the candidate nodes, considering the total length of the route to ensure feasibility. After the construction phase, a local search algorithm is implemented to complete the components of the GRASP metaheuristic.

In the local search phase, each route constructed with the constructive heuristic is improved to enhance the quality of the whole solution that is provided. Since a solution is composed of several routes, each route contributes to the objective function value by the route operations. The contribution of a single route can be calculated by the monetary gain of the rescued donations that are collected and distributed on the route, and the fuel and emissions cost of the route. Local search algorithm basically uses node exchanges to re-organize the nodes visited on a route. If the exchange increases the total monetary value of the route, then it is accepted. It should be noted that a decrease in the fuel and emissions cost of the route yields such an increase, since any donation operation is not executed by the local search. In other words, the neighbour solution is accepted if and only if the cost of the route that is changed is decreased.

The general framework of the local search phase can be summarized as follows. For the route that is organized, a random node on the route is selected. Then, another node on the route is selected to perform the exchange operation. Then, the visit orders of these two nodes are exchanged. After the exchange operation, route is re-organized to calculate the route length and vehicle loads between the nodes. If the new route is feasible and its cost is decreased, then it is updated since the solution is improved. Otherwise, the route remains the same to maintain feasibility. It should be noted that the exchange operation is made between the nodes that are the same type to maintain the organization of the route according to the constructive heuristic. In other words, if a food bank node is selected, then it can be exchanged with another food bank node on the route. The same also holds for the donor nodes. The exchange operations are applied to each route in a solution for a number of iterations. The pseudo-code of the local search phase is given in Algorithm 3.2. After this phase, GRASP implementation is completed.

Algorithm 3.2 GRASP Local Search - *local_search()***Input:** Solution s , Maximum number of iterations $max_iterations_LS$

```

1:  $i \leftarrow 1$ 
2: while  $i \leq max\_iterations\_LS$  do
3:   for day  $t = 1, \dots, |\mathcal{T}|$  do
4:     for vehicle  $k = 1, \dots, |\mathcal{K}|$  do
5:       if vehicle  $k$  is active then
6:          $neighbour_{tk} \leftarrow s.route_{tk}.exchange(random\_node);$ 
7:          $\triangleright$  perform an exchange operation on a random node
8:         if  $neighbour_{tk}.obj > s.route_{tk}.obj$  and  $neighbour_{tk}$  is feasible then
9:            $s.route_{tk} \leftarrow neighbour_{tk}$ 
10:           $\triangleright$  whenever a contribution is improved, update the route
11:        end if
12:      end if
13:    end for
14:  end for
15:   $i \leftarrow i + 1$ 
16: end while

```

Output: s *ILS (Iterated Local Search) Implementation*

Iterated Local Search (ILS) simply generates new solutions which are found by iterating through solution perturbations and an improvement method. Perturbation modifies a previously found solution to diversify in the search space, as well as, to escape local optimum. After the perturbation operation, a local search is again applied to the new solution, and the solution is updated according to an acceptance criterion [Stützle and Ruiz, 2018].

The ILS metaheuristic algorithm developed for this study is outlined as follows. First, a perturbation is applied to a solution that is initially constructed by GRASP. This perturbation operation simply removes a portion of routes from the solution.

These routes to be removed are determined according to their monetary contribution to the objective function value of the solution, the routes which have poorer contributions are destroyed. If a route is destroyed, the pickup and delivery operations on that route are also revoked within the solution. After perturbation, remaining non-empty donations are randomly paired with the food banks which have unfulfilled demand. In the local search phase of the ILS implementation, it is aimed to insert these pairs to the possible available routes.

After pairing donations and demands, candidate routes to insert this pair are determined. For example, if a vehicle conducts donation operations on a day such that the donation is eligible to be collected, then the route is considered as a candidate since it is feasible for that route to collect the donation. As the candidate routes are determined, new routes are constructed by the possible insertions of the pair to the candidate routes. The best-improved and feasible new route is determined among these new routes and the corresponding candidate route is updated in the solution. The pseudo-code of the ILS implementation is given in Algorithm 3.3.

The components of the Algorithm 3.3 can be explained as follows. First, *perturb()* function destroys the specified portion of the routes, starting from the least-contributing routes in the given initial solution. After that, *new_pairs()* function pairs the remaining non-empty donations with the remaining demands of the food banks randomly. Each demand that belongs to one food bank in a specific food category can be matched with only one donation. After pairs are constructed, for each pair, a local search which uses a pair insertion move is applied. Furthermore, this procedure starts from the most valuable pair. For the pair that is considered, candidate routes are determined primarily to detect the feasible routes to collect the donation of the pair. It should be noted that a donation can be collected only within its availability time windows to consider its perishability. Then, for a predetermined number of iterations, various insertions are performed to construct new routes. The function *insert_pair()* selects one of the candidate routes randomly and tries to insert the donor and the food bank nodes to the selected route if they are not already present on the route. While inserting the nodes, the feasibility of the route is checked in terms of route length, and also vehicle capacity usage. If a newly constructed route

Algorithm 3.3 Iterated Local Search - *ILS()*

Input: Solution s , Perturbation $x\%$, Number of iterations max_it_pair ,
 max_it_insert

```

1:  $s \leftarrow s.perturb(x\%);$ 
2:            $\triangleright$  destroy  $x\%$  of the routes, starting from the least-contributing routes
3:  $i \leftarrow 1$ 
4: while  $i \leq max\_it\_pair$  do
5:    $pairs \leftarrow s.new\_pairs();$ 
6:            $\triangleright$  set random pairs from remaining donations and demands
7:   for pair  $p = 1, \dots, |pairs|$  do
8:      $candidate\_routes \leftarrow s.available\_routes(pair\ p);$ 
9:            $\triangleright$  find feasible routes to insert the pair
10:     $new\_routes \leftarrow null$ 
11:    for  $j = 1, \dots, max\_it\_insert$  do
12:       $new\_route \leftarrow insert\_pair(pair\ p, candidate\ route\ c);$ 
13:            $\triangleright$  construct new routes with the insertion of the pair
14:       $new\_routes.add(new\_route);$ 
15:    end for
16:     $improved\_route \leftarrow new\_routes.find\_best\_improvement();$ 
17:     $s.candidate\_route \leftarrow improved\_route$ 
18:   $\triangleright$  find the newly constructed route which improves the objective function value
    the most and update it
19:  end for
20:   $i \leftarrow i + 1$ 
21: end while

```

Output: s

is infeasible, then it is eliminated. After these new feasible routes are constructed, the best-improving route in terms of the objective function value of the solution is found. If there is such an improving move, the candidate route is updated with

the new route. The same local search procedure is performed for each pair created. Until a maximum number of iterations is reached, donation-demand pairing and insertions are performed on the given solution. The detailed pseudo-code of the pair insertion function *insert_pair()* is provided in Appendix A.

3.4 Alternative Models for the Case Studies

One aim of this study is to analyze the effects of logistics collaboration. To this end, three case studies are developed. In the first case study, the solution approaches are developed for a system where collaboration exists as described in the original problem. In the second case, a food bank that does not have any vehicle, gets a chance to rent a vehicle just for itself on a particular day within the donation horizon. However, the available vehicles continue to serve all of the food banks in the system with collaboration. In the third case, the operations are executed without logistics collaboration. In this section, the case studies are introduced and solution approaches to be used in the experiments are provided.

3.4.1 Case Study 1: Logistics Collaboration in the Donation Operations

In this case study, the mathematical model developed for the original problem is used, since logistics collaboration exists in that donation system. The solution approaches provided in Section 3.3 are already designed for this case study. Therefore, the mathematical formulation in Subsection 3.3.1 and the heuristic algorithm in Subsection 3.3.2 are used as solution approaches to test the effects of collaboration.

3.4.2 Case Study 2: Donation Operations with Logistics Collaboration and Rental Vehicle Option

In this case, every food bank without any vehicles has an outsourcing option by renting vehicles. If a food bank has at least one vehicle, then its vehicles can still serve for any other food bank. The mathematical formulation in Subsection 3.3.1 is modified according to the characteristics of this system.

First change made on the MILP model is to add one dummy vehicle for each food

bank not having a vehicle. The set of dummy vehicles is represented with $\mathcal{K}^{dummy}$ and it is also added to the set of original vehicles, $\mathcal{K}$. In other words, $\mathcal{K}^{dummy}$ is a subset of $\mathcal{K}$. For the dummy vehicles, it is prohibited to stop by any other food bank but the owner. This modification is provided with the constraints in (3.31) and (3.32) on the decision variable x , which determines the route.

$$x_{kmn}^t = 0 \quad \forall t \in \mathcal{T}, k \in \mathcal{K}^{dummy}, m \in \mathcal{F} \setminus \{d_k\}, n \in \mathcal{N} \quad (3.31)$$

$$x_{knm}^t = 0 \quad \forall t \in \mathcal{T}, k \in \mathcal{K}^{dummy}, m \in \mathcal{F} \setminus \{d_k\}, n \in \mathcal{N} \quad (3.32)$$

Note that in node d_k in (3.31) and (3.32) is an element of the set of food banks $\mathcal{F}$ and it denotes the original food bank node which can rent dummy vehicle k . Furthermore, a rental cost C_{rent} is defined and used in the objective function as in Term (3.33), for only dummy vehicles representing the rented vehicles.

$$- \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} C_{rent} \times z_k^t \quad (3.33)$$

This term is added to the objective function (3.1) in Subsection 3.3.1 with a minus ($-$) sign since it represents a cost function in a maximization problem.

Other constraints of the model in Subsection 3.3.1 remain unchanged. Note that any feasible solution for the original MILP in Subsection 3.3.1, is also feasible for this MILP model, since the collaboration among the original vehicles and other properties are still valid and available here. The MILP model for Case Study 2 is obtained as follows.

MILP Model for Case Study 2

$$\begin{aligned} \text{Maximize } & \sum_{\forall t \in \mathcal{T}} \sum_{\forall i \in \mathcal{T}} \sum_{\forall j \in \mathcal{G}} \sum_{\forall r \in \mathcal{R}} B_{jr}^t \times p_{jr}^{t\bar{t}} - \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}} \sum_{\forall m \in \mathcal{N}} \sum_{\forall n \in \mathcal{N}} c(m, n, l_{kmn}^t) \times x_{kmn}^t \\ & - \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} C_{rent} \times z_k^t \end{aligned} \quad (3.34)$$

subject to

Constraints (3.2) - (3.29), (3.31), and (3.32)

3.4.3 Case Study 3: Food Bank Operations Without Logistics Collaboration

This case study aims to show the benefits of a system that includes logistics collaboration over a system that does not. In this case, it is assumed that food banks which have vehicles can execute the donation operations just for themselves, with the same restrictions for the vehicles. For the food banks without vehicles, they can transport their matched donations within the day via using a door-to-door express delivery service.

There are several reasons behind creating such a scenario for the case study. First of all, it is known that the pickup operations are in the responsibility of their owner food banks. Whenever a food bank is matched with a donation, the food bank must collect it from the specified donor. Since several food banks in the system do not have vehicles, they should find a way to collect the donations easily. Renting a vehicle just as in Case Study 2 can be considered as an option, however, there are several challenges to be faced while using this option frequently such as finding a proper vehicle in the specified date and time. Besides renting vehicles, using in-city express shipment services is another option for the food banks that do not own vehicles. In this scenario, the matched donations must be picked from the donor and delivered directly to the food bank. This type of shipment is also known as *door-to-door delivery*.

In a typical door-to-door delivery service, the courier driver picks up the shipment on the specified pick-up address and then delivers it to the delivery address. This specified type of delivery service is actually suitable with the aforementioned conditions of the food banks without vehicles. In this service, both sides, donors and food banks, do not have to deal with transportation of the donations. However, as always, shipment and also delivery costs occur whenever the service is used. It should be remembered that since the food banks are responsible of the pickup operations, they are the ones to make the payments. Therefore, the cost of shipments must always be minimized.

Usually, in door-to-door delivery services for close distance shipments, there are two types of cost that occur: shipment cost itself and additionally, delivery cost.

There is also a particular type of shipment cost for a special case in the delivery services. Once the amount to ship exceeds a threshold (e.g. 100 kilograms), this extra weight cost occurs for only once. These types of cost are all included in the case study.

The base MILP model formulation in Subsection 3.3.1 is again modified to represent the system described for this case study. As in the previous case study, a set of dummy vehicles $\mathcal{K}^{dummy}$ are defined for each food bank without vehicles. Again, $\mathcal{K}^{dummy}$ is a subset of $\mathcal{K}$. Also, the route duration constraints (3.7) are not included in the model for the dummy vehicles. Thus, these constraints are modified as in (3.35).

$$\sum_{\forall m \in \mathcal{N}} \sum_{\forall n \in \mathcal{N}} \frac{D_{mn}}{\nu} \times x_{kmn}^t \leq L \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \setminus \mathcal{K}^{dummy} \quad (3.35)$$

Furthermore, for any vehicle in the system, it is not allowed to visit another food bank than the owner. Therefore, constraints in (3.36) and (3.37) are added to the model.

$$x_{kmn}^t = 0 \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{F} \setminus \{d_k\}, n \in \mathcal{N} \quad (3.36)$$

$$x_{knm}^t = 0 \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, m \in \mathcal{F} \setminus \{d_k\}, n \in \mathcal{N} \quad (3.37)$$

An additional binary decision variable y_k^t is defined as in (3.38) to represent the special case of extra weight.

$$y_k^t = \begin{cases} 1, & \text{if the amount shipped by dummy vehicle } k \text{ exceeds the weight} \\ & \text{threshold } T_{weight} \text{ once on day } t \\ 0, & \text{otherwise} \end{cases} \quad (3.38)$$

The objective function (3.1) in the base MILP model is also modified for this case. The part that maximizes the monetary gain remains the same. First, the part subtracting the logistics costs is modified as in (3.39) to represent these costs accurately only for the available vehicles in the system.

$$- \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K} \setminus \mathcal{K}^{dummy}} \sum_{\forall m \in \mathcal{N}} \sum_{\forall n \in \mathcal{N}} c(m, n, l_{kmn}^t) \times x_{kmn}^t \quad (3.39)$$

Second, the shipment and the delivery costs are added to the objective function. These costs are represented by C_{ship} and $C_{delivery}$ functions respectively. Both of these are linear functions of the decision variables u and z . The functions are provided in (3.40). Details and parameters of these functions will be explained in Subsection 4.3.4.

$$- \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} \sum_{\forall i \in \mathcal{F}} \sum_{\forall r \in \mathcal{R}} C_{ship}(u_{kir}^t, z_k^t) - \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} \sum_{\forall i \in \mathcal{F}} \sum_{\forall r \in \mathcal{R}} C_{delivery}(u_{kir}^t, z_k^t) \quad (3.40)$$

Furthermore, to represent the case of extra weight shipment, a special cost is added to the objective function as in (3.41). The cost is denoted by C_{extra} .

$$- \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} C_{extra} \times y_k^t \quad (3.41)$$

It should be noted that all the terms (3.39) - (3.41) are added to the objective function with a minus (-) sign since they all represent cost functions in a maximization problem.

Finally, the constraints in (3.42) are added to the MILP model for the evaluation of the decision variable y_k^t . In (3.42), M represents a very big value to force the decision variable to take the value of 1 when the amount to be shipped exceeds the weight threshold T_{weight} , and hence to incur the cost regarding extra weight used. This big value can be set to be equal to the total demand of the specified owner food bank of the vehicle.

$$\sum_{\forall i \in \mathcal{F}} \sum_{\forall r \in \mathcal{R}} u_{kir}^t - T_{weight} \leq M \times y_k^t \quad \forall t \in \mathcal{T}, k \in \mathcal{K}^{dummy} \quad (3.42)$$

In the end, the following MILP model for Case Study 3 is obtained.

MILP Model for Case Study 3

$$\begin{aligned} & \text{Maximize} \sum_{\forall t \in \mathcal{T}} \sum_{\forall i \in \mathcal{T}} \sum_{\forall j \in \mathcal{G}} \sum_{\forall r \in \mathcal{R}} B_{jr}^t \times p_{jr}^{tt} - \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K} \setminus \mathcal{K}^{dummy}} \sum_{\forall m \in \mathcal{N}} \sum_{\forall n \in \mathcal{N}} c(m, n, l_{kmn}^t) \times x_{kmn}^t \\ & - \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} \sum_{\forall i \in \mathcal{F}} \sum_{\forall r \in \mathcal{R}} C_{ship}(u_{kir}^t, z_k^t) - \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} \sum_{\forall i \in \mathcal{F}} \sum_{\forall r \in \mathcal{R}} C_{delivery}(u_{kir}^t, z_k^t) \\ & - \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} C_{extra} \times y_k^t \end{aligned} \quad (3.43)$$

subject to

Constraints (3.2) - (3.6), (3.8) - (3.29), (3.35), (3.36), (3.37), and (3.42)



Chapter 4

COMPUTATIONAL EXPERIMENTS AND ANALYSIS

In this chapter, computational experiments made to validate and test the model will be shared. This chapter is organized as follows. First, the calculation of fuel consumption and emission costs with the emission model are explained in Section 4.1. Then, data and its preparation are introduced in 4.2. In Section 4.3, the computational experiments executed on data with the related cases are analyzed.

4.1 *Emission Model for Fuel and Emissions Cost Function*

As explained in the previous chapters, to calculate fuel and emission cost in the objective function, the emission model from Koç et al. is used [Koç et al., 2016]. In this section, this cost function will be explained. Same model is also successfully applied in several studies which are reviewed previously in Chapter 2 [Bektaş and Laporte, 2011, Demir et al., 2012, Demir et al., 2014, Franceschetti et al., 2013]. Parameters of the model are provided in Table 4.1.

A few assumptions are made to determine the values of the parameters described. Some of the parameters are environment-related and others are vehicle-specific. According to the data provided by the company, the vehicles owned by some of the food banks have capacities ranged from 1 ton up to 4 tons. Therefore, it is assumed that all of these vehicles are light duty vehicles as described in the emission model (light duty vehicle, type 1 [Koç et al., 2016]). The vehicle specific parameters are determined accordingly. It should also be noted that the currency is converted from GBP (pound sterling) to TRY (Turkish lira, 03/27/2020) for accurate cost translations.

The value of the speed parameter is determined according to several assumptions. Koç et al. consider different speed levels as their problem covers different speed zones. In our study, instead of several speed zones, only one speed level is required

Table 4.1: Parameters of the emission model [Koç et al., 2016]

Notations	Description	Typical values
ξ	Fuel-to-air mass ratio	1
g	Gravitational constant (m/s^2)	9.81
ρ	Air density (kg/m^3)	1.2041
C_R	Coefficient of rolling resistance	0.01
η	Efficiency parameter for diesel engines	0.45
f_C	Fuel and CO ₂ emissions cost (TRY/L)	11
κ	Efficiency parameter for diesel engines	44
ψ	Conversion factor (g/s to L/s)	737
n_T	Vehicle drive train efficiency	0.45
θ	Road angle	0
τ	Acceleration	0
w	Curb weight (kg)	3500
ν	Fixed speed level (km/h)	32
k_F	Engine friction factor ($kJ/rev/L$)	0.25
N	Engine speed (rev/s)	38.34
V	Engine displacement (L)	4.5
C_D	Coefficient of aerodynamics drag	0.6
A	Frontal surface area (m^2)	7

to handle the nature of the problem. In Turkey, General Directorate of Highways sets the maximum “in-city” road speed level as 50 km/h. However, it is not realistic to use this upper limit since there is a lot of circumstances in which the vehicles have to use lower speed levels, such as congestion, turns, traffic lights, pedestrian crossing, etc. In a report on the traffic services in UK by Kirby, it is asserted that 32 km/h speed limit provides invaluable benefits for the community and also for the environment [Kirby T, 2002]. The report concludes that this speed level improves the life quality and encourages healthier and more sustainable transport

modes such as walking and cycling. Further environmental benefits of using this speed level while driving at a steady pace include saving fuel and reducing pollution [Department for Transport, Government of the United Kingdom, 2013]. Since this speed level is safe, realistic and within the legal in-city road speed limits, it is used in the problem as the fixed speed level of the vehicles. Additionally, the maximum tour duration is set to 4 hours in a day. Pickup and delivery operations are assumed to be instantaneous, and hence their durations are not included in the model.

The parameters of the emission model are set in accordance with these assumptions. To calculate the fuel and emissions costs, there are several steps to follow for the estimation of fuel consumption resulting from vehicle usage. The fuel consumption rate FR (in L/s) of a vehicle can be calculated by Equation (4.1).

$$FR = \xi(k_F NV + P/\rho)/\kappa \quad (4.1)$$

In Equation (4.1), variable P is the second-by-second engine power output (in kW) of the vehicle, and it can be calculated by Equation (4.2).

$$P = P_{tract}/n_T + P_{acc} \quad (4.2)$$

In Equation (4.2), the engine power demand P_{acc} is associated with the running losses of the engine and the operation of vehicle accessories. It is assumed that $P_{acc} = 0$. The total tractive power requirement P_{tract} (in kW) can be calculated by Equation (4.3).

$$P_{tract} = (M\tau + Mg \sin \theta + 0.5C_D \rho A v^2 + MgC_R \cos \theta)v/1000 \quad (4.3)$$

In Equation (4.3), M is the total vehicle weight (in kg) and ν is the instantaneous vehicle speed (in m/s). The fuel consumption F (in L) over a distance d at constant speed ν can be calculated by Equation (4.4).

$$F = k_F NV \lambda d/\nu + P \lambda \gamma d \nu \quad (4.4)$$

In Equation (4.4), $\lambda = \xi \kappa \psi$ and $\gamma = 1/1000 n_T \eta$ are constants. F can be rewritten as in Equation (4.5).

$$F = \lambda(k_F NV d/\nu + M \gamma \alpha d + \beta \gamma d \nu^2) \quad (4.5)$$

In Equation (4.5), $\beta = 0.5C_D\rho A$ and $\alpha = \tau + g \sin \theta + gC_R \cos \theta$ are also constants. This equation is used to calculate the fuel and emission costs in the second part of the objective function (3.1). For a specific arc traveled, the length of the arc and the value of the decision variable l is included in the calculation. Note that M is the total vehicle weight, in other words, the summation of curb weight and the instantaneous load of the vehicle. Finally, the total fuel consumption is calculated and multiplied by fuel and CO₂ emissions cost f_C .

4.2 Data Preparation

Several data sets are devised from the yearly raw data provided by the company. As explained before, the donation system in Istanbul is considered for the logistics collaboration. Weekly donations data are considered for determining the period length in days. The data sets consist of donations, with their amounts, monetary value, type of the food donated, the donors who donated them, the day that they start to be available, and also the days left before their expiration within the donation horizon. The location information of the food banks and donors are known. For the distance calculation between these locations, Euclidean distances are used.

In the proposed system, the collection and distribution of the food donations for all members of the system, are conducted by the food banks with the vehicles. Furthermore, instead of FIFO approach for matching the donations, any food bank that is actively demanding in a week can profit from any of the donations while they are available. The number of food banks in Istanbul which is a member of Fazla Gıda is around 30. In line with the discussions made with the company, approximately any 5 to 10 of these food banks can be considered to demand actively in a weekly period. For each data set, three environments with 5, 10 and 15 food banks respectively, are developed to represent demands for the sake of creating realistic scenarios of the proposed system. Furthermore, the data sets are classified into three categories considering the number of donor nodes that each data set covers; small, medium and large. For small, medium and large data sets, different number of vehicles are determined to be able to handle different levels of total donations,

and also total number of nodes served. It should be noted that in general, the total amount of donations increases as the number of donors increases in a data set. These vehicles are assigned randomly according to the active food banks with vehicles in the specified data set. The depots of the vehicles are considered as their owners' locations.

The type of the donated food is classified into four specific food categories. These categories are *fruits and vegetables*, *dairy products*, *meat and poultry*, and *bakery, canned or packaged goods*. The data sets may include just one type or several types of food donated. Each active food bank is considered to have a non-zero demand in each category within a donation horizon. The demands are generated randomly, and the lowest possible demand is always set to represent the equal share among active food banks. The highest amount of demand depends on several parameters such as the number of food banks and the vehicles. To conclude, the total amount of demands is set to be greater than the total amount of donations to follow the real structure of the system.

A total of fifty data sets are derived from the yearly data based on the weeks to be used in the case studies. Since data itself is confidential, only detailed properties of the prepared data sets are provided in Appendix B. The size categorization of the data sets will be used in the following sections.

4.3 Computational Experiments

All computational experiments are performed on a workstation equipped with 2.4 GHz Intel Xeon PC with 2 processors and 12 GB RAM. The mathematical formulation is modeled with IBM CPLEX Optimization Studio (version 12.10) and the heuristic algorithm is implemented in Java programming language (version 8).

In the experiments, each small and medium-sized data set is executed with random 5, 10 and 15 food banks in separate runs. The vehicles and their owner food banks are also assigned according to the predetermined number of vehicles. For large-sized data sets, experiments with 10 and 15 food banks are executed. There are 18 small-sized, 18 medium-sized and 14 large-sized data sets in total. Therefore,

a total of 54 instances from small-sized, 54 from medium-sized and 28 from large-sized data sets are generated. In total, 136 instances are used for the computational experiments.

In Chapter 3, three case studies, that are developed to analyze the effect of logistics collaboration, are introduced. In the first case study, the solution approaches developed are tested on a system where collaboration exists as described in the original problem. In the second case, a food bank that does not have any vehicle, can rent a vehicle while the available vehicles continue to serve all of the food banks in the system with collaboration. In the third case, the operations are executed without logistics collaboration. The results of these cases are compared to find a strategy that all system components can profit while conducting donation operations.

4.3.1 Sensitivity Analysis on Vehicle Fixed Cost

Before the computational experiments, a sensitivity analysis is made on the cost of the vehicles to lead a more realistic study. In Chapter 3, the solution approach for the system with logistics collaboration was described. In this system, there are vehicles to be used mutually in conducting the donation operations for all of the food banks. In the first step of proposing a new system, it is assumed that the cost of using the vehicles which belong to some of the food banks can be left out for several reasons. However, it is also important to examine the solution approach with the consideration of such costs to improve the delivery of the study.

To conduct this analysis, the model introduced in Section 3.4.2 for Case Study 2 is used. In this model, a rental cost is used for each outsourced vehicle that is offered for the food banks without vehicles. However, a fixed cost for collaboration vehicle use is not identified. To examine the behaviour of the food rescue operations, a fixed cost for these vehicles is also specified in the model.

In the model, the value of the rental cost C_{rent} is taken from the study of Koç et al., since their emissions model is used [Koç et al., 2016]. They determine the vehicle fixed cost as £42 per one day usage. To set a price for the collaboration vehicle usage, a portion of the rental cost C_{rent} is added to the objective function of

the model of Case Study 2 as in Term (4.6). In Term (4.6), a is called as the *cost factor*.

$$- \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K} \setminus \mathcal{K}^{dummy}} C_{rent} \times a\% \times z_k^t \quad (4.6)$$

The sensitivity analysis on this model is performed as follows. From each type of generated instances, two instances are selected for the computational experiments. Therefore, a total of 16 instances are used for the analysis. Three different collaboration vehicle cost evaluations are used: 0%, 10% and 50% of the rental cost C_{rent} . The results of each specific instance are obtained by solving the specified model via CPLEX solver with one hour CPU time limitation and warm-up start procedure which uses the constructive heuristic algorithm introduced in Section 3.3. The detailed results are provided in Appendix C. Average results are summarized in Table 4.2.

Table 4.2: A summary of the average results for the sensitivity analysis

<i>Average Results</i>		Cost Factor		
<i>Criterion</i>		$a=50$	$a=10$	$a=0$
Gap		12.2%	9.2%	8.7%
Amount Rescued		93.3%	93.8%	94.4%
Avg. Demand Fill Rate		72.1%	73.6%	74.9%
Rental Vehicle Used		0.06	0.00	0.00

In Table 4.2, **Gap** shows the average relative percentage gap between the upper bound value (UB) and the incumbent value (IN). It is calculated as $100 \times (UB - IN)/UB$. The **Amount Rescued** criterion presents the average portion of picked donations (i.e. collected and distributed donations) with respect to the overall amount of donations. The **Avg. Demand Fill Rate** criterion gives the average fulfillment percentage of food banks' demands. Lastly, **Rental Vehicle Used** shows the times that an outsource vehicle is used by a food bank.

According to these results, it can be easily seen that rental vehicle usage is nearly zero, independent of the cost factor. It has occurred only once in one of the 16 instances. Even though the average relative percentage gap is not quite small in the results, solution quality in terms of gap, amount rescued, and average demand fill rate criteria are getting improved as the cost factor is decreased.

It is decided that not using a vehicle fixed cost for the vehicles that are used in the collaboration system is more advantageous and yet reasonable according to the results of the sensitivity analysis. Beside having better solution quality and rescuing more donations, there are also additional motivations behind not setting a vehicle cost for mutual usage. First, according to the data provided by the company, the total number of vehicles which are available by some of the food banks is 18. In the generated instances, the number of vehicles that are requested from the food banks can be 2, 4, and maximum 6 in total, changing accordingly to the data set size used (Appendix B). Therefore, it can be said that these requests are applicable since there is not an immoderate demand to use these vehicles for the operations. Another arrangement to make these vehicle requests reasonable is the tour duration/tour length limitations introduced in the assumptions of the new system. To represent a half-day of work, this duration is set to 4 hours. Furthermore, in the data preparation process, the food banks with the vehicles have determined and indicated the weekly availability of their vehicles. In other words, the number of days that a vehicle can be used during a donation horizon is determined by each food bank owning a vehicle. Additionally, a food bank with a vehicle can also be served by a vehicle that belongs to another food bank.

Due to these assumptions and arrangements made according to the regulations indicated by the vehicle owner food banks, it is concluded that not using a vehicle fixed cost is applicable for the setting of this study.

4.3.2 Case Study 1: Logistics Collaboration in the Donation Operations

Base Run

First, the mathematical model proposed in Subsection 3.3.1 is used to solve the problem with collaboration for all instances described. The results of each specific instance are obtained by solving the MILP via CPLEX solver with one hour CPU time limitation.

Table 4.3: A summary of average base run results

Data Sets	Food Banks $ \mathcal{F} $	Gap	Amount Rescued	Value Rescued	Avg. Demand Fill Rate	Cost/Gain
Small	5	3%	97%	98%	83%	12%
	10	9%	83%	96%	82%	15%
	15	22%	80%	85%	70%	19%
	Average	12%	87%	93%	78%	16%
Medium	5	22%	78%	81%	53%	7%
	10	40%	57%	63%	38%	9%
	15	56%	41%	47%	26%	9%
	Average	39%	59%	64%	39%	9%
Large	10	58%	36%	43%	21%	4%
	15	76%	19%	24%	12%	4%
	Average	67%	28%	33%	16%	4%

In total, 136 instances are used in the base run experiments. To be able to summarize the results in a convenient way, the average values of the critical performance criteria are given in Table 4.3. The detailed version of results and related explanations on several performance criteria are provided in Appendix D.

Table 4.3 is organized as follows. The **Data Sets** column identifies the size of the instances. The **Food Banks** column classifies the instances with the number of food banks included. The **Gap** column provides the average relative percentage gap between the upper bound value (UB) and the incumbent value (IN). It is calculated as $100 \times (UB - IN)/UB$. The **Amount Rescued** column presents the average

portion of picked donations (i.e. collected and distributed donations) with respect to the overall amount of donations. The **Value Rescued** column shows the average saving made from the collected donations compared to the total value of all donations within an instance. The **Avg. Demand Fill Rate** column gives the average fulfillment percentage of food banks' demands in the instances. While calculating the average demand fill rate in an instance, the average fulfillment in each food type is taken into account separately for one food bank. The last column **Cost/Gain** is calculated to compare the total gain and total cost in a solution and here, the average rates are listed. The **Average** rows summarize the average values of the columns specified overall. This format of the table is used for all of the summary tables in this section.

First of all, as the instance size grows, the relative percentage gap also grows on average since it becomes harder to solve the problem with the same time limitations. Also within the same size instances, the relative percentage gap increases as the number of food banks increases. Another observation is that in the instances which have greater rescued portion of the total donations, the relative percentage gap is relatively small. This indicates that saving more donations as much as possible is critical, especially for the larger instances due to larger total value of donations. It is also possible to assert that while saving the donations, picking the donations with higher monetary values is prioritized to maximize the objective. As expected, average demand fill rate is also decreasing as the rescued portion of donations gets smaller. It should be remembered that it is impossible to fulfill all of the demands as the total demand of food banks is always greater than the total amount of donations. One other interesting conclusion can be made regarding the total cost and total gain in the solutions. Even if the relative percentage gap is relatively large, the cost becomes less important when compared to the gain in the results of larger instances.

As can be seen from the summary of the base run results, it is imperative to improve the performance of the MILP model to be able to save more donations. To this end, a metaheuristic algorithm is developed and used to provide a starting solution to the MILP model.

Metaheuristic Algorithm: GRASP-ILS Implementation

A multi-start metaheuristic algorithm based on GRASP with an ILS implementation is developed. The heuristic algorithm developed uses greedy randomized functions, and it constructs solutions with the aim of maximizing the total amount of collected donations. There are several parameters required by the algorithm initially. Since the algorithm depends on randomization, chosen seed value affects the solutions created. Another parameter related to randomization is the threshold parameter α_t which is used for determining the candidate solution elements. The other input parameter is the maximum number of iterations to be made while determining the feasible insertions of the candidate food banks in Algorithm A.3. The last parameter is the starting day of using the vehicles.

First, several input parameter evaluations are set to create the initial solutions. 60 seed values, 11 threshold parameter values, 4 different limits on the maximum number of iterations, and 3 different starting days are determined as in Table 4.4. All possible combinations are used.

Table 4.4: Input parameters of the constructive heuristic algorithm in GRASP

Input Parameters	Set of Values
<i>seed</i>	0, 1, 2, ..., 59
α_t	0, 0.1, 0.2, ..., 1
<i>max_iterations</i>	30, 75, 120, 150
Starting day t'	1, 2, 3

In the metaheuristic implementation, once a solution is constructed, improvement process is followed by a local search first, then the ILS algorithm. The parameters of these algorithms are tuned according to the instances generated from medium and large-sized data sets with 10 food banks. It can be concluded that increasing the maximum number of iterations to perform the local search algorithms implemented increases the chance of finding better-quality solutions. However, the CPU time of the whole implementation is also considered as an important factor in

the parameter tuning process, since the solution found is intended to be fed to the model as a starting point in the warm-up procedure. Therefore, the parameters are set to find competitive solutions in terms of both solution quality and CPU time as follows. As introduced in Section 3.3.2, the local search phase of GRASP has the parameter *max_iterations_LS*, and the ILS has the parameters *max_it_pair* and *max_it_insert*. These parameters are set to 20, 10, and 15 respectively. As distinct from the number of iterations, the perturbation parameter of ILS is set with the trial-error method. This parameter is used to destroy the least-contributing routes. It is set as 20% since smaller values cause unchanged solutions in especially smaller instances, and larger values cause a large number of routes to be lost. To conclude, the metaheuristic algorithm is implemented as in Algorithm 4.1.

Algorithm 4.1 GRASP-ILS Implementation

```

1: Solution  $S \leftarrow null$  ▷ Current Solution
2: Solution  $S^* \leftarrow null$  ▷ Best Solution
3: for  $seed = 0, 1, 2, \dots, 59$  do
4:   for  $\alpha_t = 0, 0.1, 0.2, \dots, 1$  do
5:     for  $max\_iterations = 30, 75, 120, 150$  do
6:       for  $t' = 1, 2, 3$  do
7:          $S \leftarrow construct\_solution(seed, \alpha_t, max\_iterations, t')$ 
8:          $S.local\_search(max\_iterations\_LS=20);$ 
9:          $S.ILS(perturbation=20\%, max\_it\_pair=10, max\_it\_insert=15);$ 
10:        if  $S.objective > S^*.objective$  then
11:           $S^* \leftarrow S$ 
12:        end if
13:      end for
14:    end for
15:  end for
16: end for

```

Output: S^*

The results of the metaheuristic implementation are summarized in Table 4.5. The average relative percentage gap of base run, GRASP implementation, and GRASP-ILS implementation are provided for each instance group in the table. The

average CPU time of the whole GRASP-ILS implementation is also provided. To compare, the solution with the best objective function value is chosen and the upper bound from the base run is used to calculate the relative percentage gap for each instance. Moreover, if the objective function value of the best solution found by the metaheuristic is better than the objective found by the end of base run for a specific instance, it is reported in the last column of Table 4.5.

Table 4.5: A summary of average metaheuristic results

Data Sets	Food Banks $ \mathcal{F} $	Base Gap	GRASP (Best) Gap	GRASP-ILS (Best) Gap	CPU Time (sec)	Times Better Solution Observed
Small	5	3.3%	18.2%	10.9%	9.17	0 in 18
	10	9.0%	26.2%	15.8%	14.28	2 in 18
	15	22.4%	30.0%	20.0%	20.28	6 in 18
	Average	11.6%	24.8%	15.6%	14.57	15%
Medium	5	22.1%	15.3%	10.0%	46.33	11 in 18
	10	39.7%	22.6%	13.1%	62.83	15 in 18
	15	55.5%	25.7%	15.1%	80.94	17 in 18
	Average	39.1%	21.2%	12.7%	63.37	80%
Large	10	57.7%	18.5%	8.4%	148.64	14 in 14
	15	76.1%	19.5%	10.0%	190.43	14 in 14
	Average	66.9%	19.0%	9.2%	169.54	100%

As can be seen from the results, even only the GRASP implementation itself yields better-quality solutions on the average when the results are compared to the MILP model. ILS implementation provides a remarkable improvement on the initial solutions provided by the GRASP implementation. As the instance size gets larger, the algorithm responds better in terms of the relative percentage gap. Furthermore, in medium-sized and large-sized instances, the algorithm can directly find better solutions in a shorter time when compared to the MILP model. Especially for the large-sized instances, the relative percentage gap is improved significantly. Yet, the results can still be improved. Thus, the best solution found by the metaheuristic algorithm is provided as an initial starting solution for the MILP model. This procedure is also known as “warm-up start”.

Warm-up Start and Comparison of the Solution Procedures

The results obtained by the MILP model with warm-up start are provided in Appendix F in detail. A summary of these results, in terms of the critical performance criteria as described before, is given in Table 4.6.

Table 4.6: A summary of warm-up start results

Data Sets	Food Banks $ \mathcal{F} $	Gap	Amount Rescued	Value Rescued	Avg. Demand Fill Rate	Cost/Gain
Small	5	3%	97%	98%	83%	13%
	10	7%	97%	98%	86%	16%
	15	12%	95%	96%	82%	19%
	Average	7%	96%	97%	84%	16%
Medium	5	5%	98%	98%	69%	8%
	10	9%	97%	97%	71%	10%
	15	10%	96%	97%	71%	11%
	Average	8%	97%	98%	70%	10%
Large	10	6%	96%	98%	68%	7%
	15	8%	94%	97%	67%	8%
	Average	7%	95%	97%	67%	7%

The results in Table 4.6 show the improvements made when comparing the average relative percentage gap with the base run results. Interestingly, the warm-up start procedure becomes especially useful as the instance size gets larger in terms of the total amount of donors and donations. To see the comparison accurately, the final relative percentage gap of the solutions found by the specified procedures are calculated according to the tightest upper bound found for each instance. The final results comparing the performances of the different procedures in terms of the relative percentage gap can be found in Appendix G. The average relative percentage gap of the instances are also provided in Figure 4.1 with the instance size classification. It is obvious that the metaheuristic algorithm itself is a useful procedure in finding better solutions faster than the base MILP model. Furthermore, it can be asserted that a better starting solution yields a final solution with higher quality in

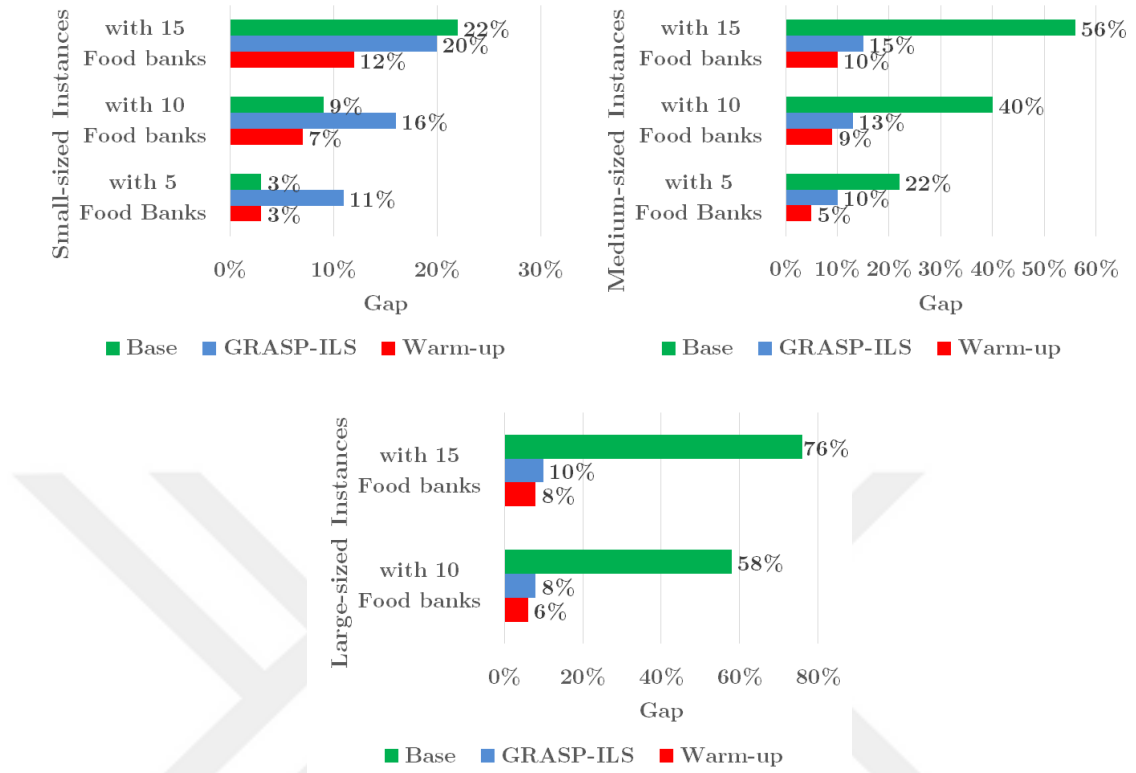


Figure 4.1: Comparison of the average relative percentage gap found by different solution procedures for (a) small, (b) medium, and (c) large-sized instances

almost every instance. However, the greatest improvement is seen in large-sized instances in terms of the solution quality, since the base MILP model cannot improve the solutions enough for these instances in limited time. Considering the mechanism of the algorithm implemented, it is easier to understand the results. When the instances are examined, it is seen that the donated amount of food within a donation usually increases as the instance size gets larger. Furthermore, the total value of the donations within a donation horizon also increases. Since the logistics cost becomes less important when compared to the total gain, the algorithm gives better-quality solutions while saving larger amount of donations as the instance sizes become larger. As the number of vehicles and their maximum number of days of service increase in the larger instances, it may also become easier to execute the operations even if the donation sizes grow in total. These points sum up why the

metaheuristic algorithm can make better improvements in terms of the objective function value.



Figure 4.2: Improvement of the warm-up start procedure in (a) percentage rescued amount, and (b) percentage rescued value

This study primarily aims to rescue the donated food as much as possible. According to the nature of the problem, the solution quality can also be interpreted by the donation amount which is rescued by the collaboration system. Therefore, the improvement on the rescued amount of donations made by the warm-up start

procedure is visualized in Figure 4.2. The increase in percentage rescued is quite noticeable. Furthermore, when the rescued portion is interpreted in terms of monetary value, results are even superior. It can be concluded that almost 96% of the donations can be rescued in terms of the monetary gain within a donation horizon, on average.

Solution Review

To have a better understanding of the outputs of the study, the donation operations in the two of the optimal solutions found by the collaboration model is visualized and analyzed.

First, the optimal solution of instance S_M1W1_5 is visualized as in Figure 4.3. In the solution visualisation, the routes and the donation operations are represented with nodes and arcs. It can be seen that in total, 3 distinct tours (i.e. routes) are executed on different days of the donation horizon. The information of remaining demands of each food bank in each food type, and the active donations (which are eligible to be collected on the specified day) of each donors can be seen in the solution.

As described in the introduction of the system with logistics collaboration, a vehicle starts a tour from the owner food bank depot. After several pickup and delivery operations of the donations, it returns to its depot. On the solution, unpaired collections and distributions can be seen, as well as split deliveries of the donations. For example, on the tour executed by Vehicle 1 on day 3, a collected donation is split between several food banks according to their demands. Different than the other tours, a mixed schedule of pickup and delivery operations is formed on the tour executed by Vehicle 2 on day 4. For this route, it should also be noticed that Food Bank 1 receives service from another vehicle than its own. In Table 4.7, the donations and their pickup information for the specified instance is summarized. As can be seen in the table, the donations can be collected only on the days that they are available. Furthermore, the donation can be collected with several visits on different days, or different vehicles.

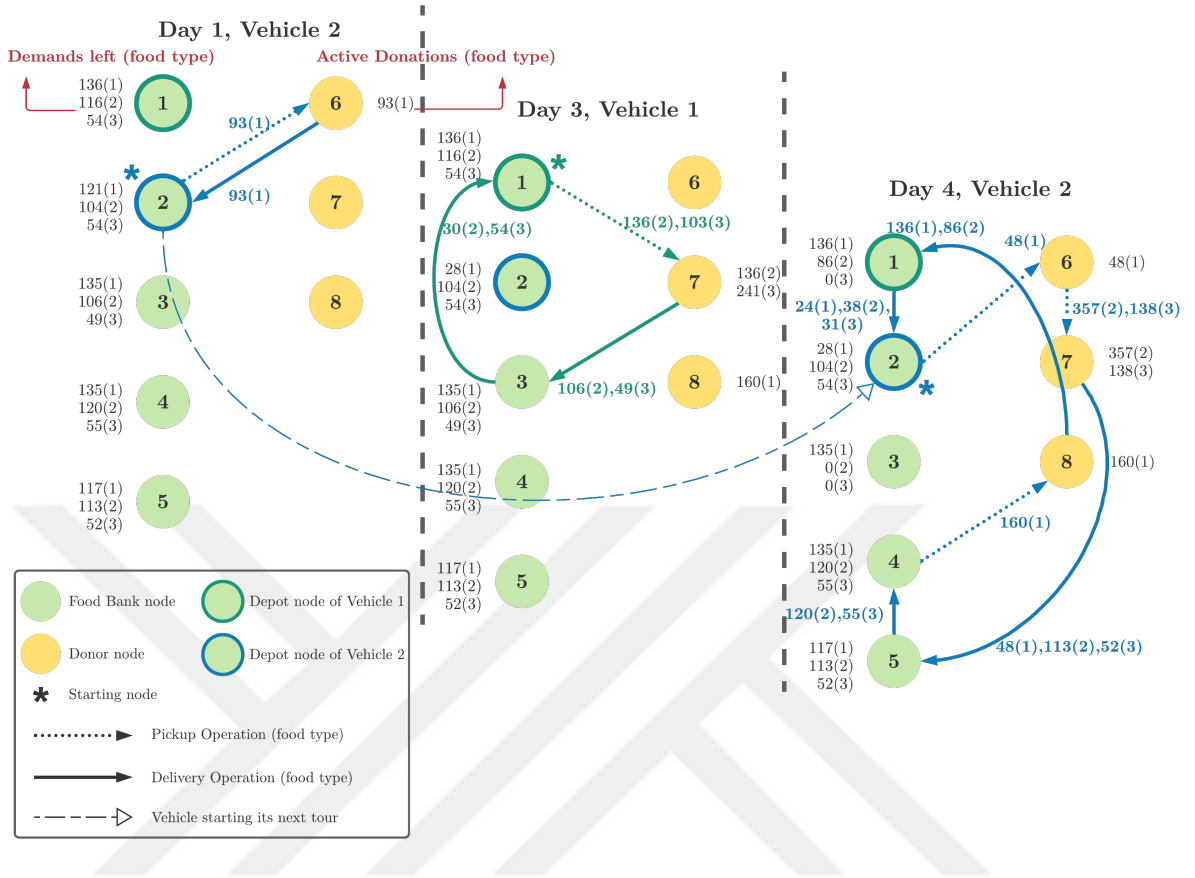


Figure 4.3: The optimal solution of instance S_M1W1_5

Table 4.7: Donation information of instance S_M1W1_5

Day	Donor	Food Type	Quantity (kg)	Days left (Perishability)	Days Available	Pickup Information
1	6	1	93	2	1,2	Day 1: 93
2	7	2	136	2	2,3	Day 3: 136
3	8	1	160	3	3,4,5	Day 4: 160
3	7	3	241	2	3,4	Day 3: 103, Day 4: 138
4	6	1	48	1	4	Day 4: 48
4	7	2	357	2	4,5	Day 4: 357
5	8	1	261	3	5	-

Finally, the demand fulfillment of each food bank at the end of the donation horizon is provided in Table 4.8. Since there is not any constraint on demand satisfaction, it can be seen that the demands can be fully or partially satisfied at the end of the donation horizon. According to this solution, 80% of the donations

are rescued and average demand fulfillment rate is 75%.

Table 4.8: Demand fulfillment of instance S_M1W1_5

Food Bank	Food Type	Demand	Fulfilled Amount	Fill Rate
1	1	136	136	100%
	2	116	116	100%
	3	54	54	100%
2	1	121	117	97%
	2	104	38	37%
	3	54	31	57%
3	1	135	0	0%
	2	106	106	100%
	3	49	49	100%
4	1	135	0	0%
	2	120	120	100%
	3	55	55	100%
5	1	117	48	41%
	2	113	113	100%
	3	52	52	100%

The second optimal solution visualization in Figure 4.4 belongs to instance S_M1W4_5. Similarly, information on donation information and demand fulfillment for this solution are provided in Table 4.9 and Table 4.10 respectively. According to this solution, 93% of the donations are rescued and average demand fulfillment rate is 73%.

Table 4.9: Donation information of instance S_M1W4_5

Day	Donor	Food Type	Quantity (kg)	Days left (Perishability)	Days Available	Pickup Information
1	6	1	155	2	1,2	Day 1: 155
1	7	1	58	2	1,2	-
2	7	1	198	2	2,3	Day 3: 198
2	8	3	11	2	2,3	Day 3: 8
3	9	1	10	2	3,4	Day 3: 10
3	7	1	159	2	3,4	Day 3: 159
4	7	1	60	2	4,5	Day 5: 60
5	8	2	85	1	5	Day 5: 79
5	7	1	240	2	5	Day 5: 234

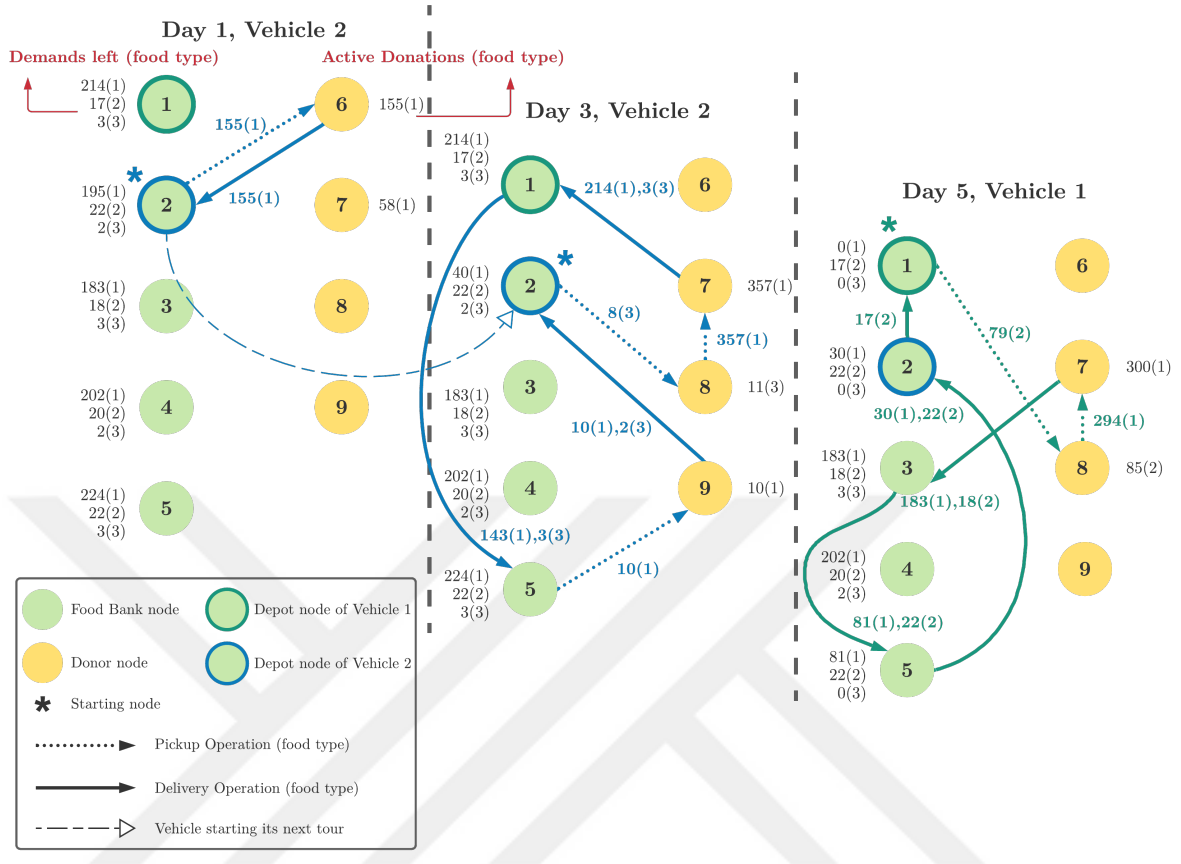


Figure 4.4: The optimal solution of instance S_M1W4_5

As explained for the first solution, the tours and donation operations are executed similarly in this solution. One of the remarkable operation that is seen in this solution is collecting two accumulated donations at once. It should be noted that on day 3, Donor 7 has two available donations in food type 1. These donations are collected with one visit on the available day that they share. Another observation on this solution is that Food Bank 4 is never visited. In the first solution, each food bank is served at least once in one of the food types. However, there is not an obligation on serving every food bank in the system. Thus, a food bank is not necessarily served within a donation horizon. As indicated before in the previous sections, the primary aim of this study is to maximize the donations rescued while setting a balance between the monetary gain and logistics costs. Equitable assignment of the donations is not included in this study.

Table 4.10: Demand fulfilment of instance S_M1W4_5

Food Bank	Food Type	Demand	Fulfilled Amount	Fill Rate
1	1	214	214	100%
	2	17	17	100%
	3	3	3	100%
2	1	195	195	100%
	2	22	22	100%
	3	2	2	100%
3	1	183	183	100%
	2	18	18	100%
	3	3	0	0%
4	1	202	0	0%
	2	20	0	0%
	3	2	0	0%
5	1	224	224	100%
	2	22	22	100%
	3	3	3	100%

4.3.3 Case Study 2: Donation Operations with Logistics Collaboration and Rental Vehicle Option

In this case study, every food bank without vehicles has an outsourcing option by renting vehicles. The MILP model in Subsection 3.4.2 is tested on the same instances with one hour time limitation and warm-up start. The initial solutions found by the GRASP implementation in Case 1 are used for this case in warm-up start procedure.

The value of the rental cost C_{rent} is taken from the study of Koç et al. [Koç et al., 2016]. Koç et al. use a vehicle fixed cost determined as £42 per day, whenever a vehicle is used. This value is also converted to TRY and used as the cost of renting one vehicle on a specific day in the study to be consistent with the other cost parameter f_C . This cost is also identified as a convenient price in the rental car sector of Turkey [Rentalcars.com, Online Services for Car Hire, 2020].

The results of the MILP model for this case are summarized in Table 4.11, which show that the vehicle rental option is never used in any of the instances. It should be noted that since the optimal solutions cannot be found within one hour time limit, the results do not necessarily indicate that renting vehicles will never be preferred

Table 4.11: A summary of average results for Case Study 2

Data Sets	Food Banks $ \mathcal{F} $	Gap	Amount Rescued	Value Rescued	Avg. Times Vehicle Rent Used
Small	5	4%	97%	98%	0 in 18
	10	9%	95%	97%	0 in 18
	15	15%	91%	93%	0 in 18
	Average	9%	96%	96%	0
Medium	5	7%	97%	98%	0 in 18
	10	11%	94%	95%	0 in 18
	15	13%	94%	96%	0 in 18
	Average	10%	95%	97%	0
Large	10	8%	93%	96%	0 in 14
	15	11%	92%	95%	0 in 14
	Average	10%	93%	96%	0

by the system. However, it can be concluded that just with the available vehicles, the system succeeds in rescuing a great portion of donations on average without using additional vehicles. To conclude, the results of this case indicate the efficiency of the logistics collaboration.

4.3.4 Case Study 3: Food Bank Operations Without Logistics Collaboration

The MILP model in Subsection 3.4.3 is used to conduct this case study where food banks act without collaboration for their logistics operations. A warm-up procedure is not used in this case study.

The real life shipment prices for door-to-door delivery service is used to create realistic scenarios for the generated instances. The prices of the leading cargo company of Turkey, which are available on the internet, are added to the data for the computational experiments of this case study. The shipment cost is added to the objective function as in (4.7) to include cost per kilogram of shipped donations. To create a linear function, several levels of the shipment amount and its price provided

are used from the tariff of the cargo company [Yurtiçi Kargo, 2020].

$$- \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} \sum_{\forall i \in \mathcal{F}} \sum_{\forall r \in \mathcal{R}} 2.9214 \times u_{kir}^t - \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} 8.7041 \times z_k^t \quad (4.7)$$

The linear function of delivery cost (4.8) is added to the objective function just as the shipment cost.

$$- \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} \sum_{\forall i \in \mathcal{F}} \sum_{\forall r \in \mathcal{R}} 1.1035 \times u_{kir}^t - \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} 4.8588 \times z_k^t \quad (4.8)$$

Finally, the case of extra cost is added to the objective function as in (4.9).

$$- \sum_{\forall t \in \mathcal{T}} \sum_{\forall k \in \mathcal{K}^{dummy}} 299.1 \times y_k^t \quad (4.9)$$

The same instances are used for this case study. The new formulation is tested on the instances again with one hour time limitation. The results are provided in Appendix H in detail. A summary of the results is given in Table 4.12, with the average results for each instance class. In the table, *Shipped Portion* column represents the portion of rescued donations delivered by the shipment service. The last column *Total Cost/Gain* is calculated to be able to compare the total gain and total cost (both logistics and shipment costs included) in a solution. The other columns are the same as in previous summary tables.

As it can be seen from the results, the relative percentage gap is relatively small since the problem becomes more plain when collaboration is not allowed. The rescued portion of the donations gets smaller as the number of food banks increases within the data set results. A similar conclusion is also valid for the average demand fill rate. Furthermore, even if the rescued portion gets smaller, the shipped donations start to form a greater part of the rescued food. The reason behind these results is that as the number of food banks increases, the need to use shipment also increases since the available vehicles remain the same. The shipment usage also confirms this outcome, which can be found in the detailed results. Finally, as the shipment usage increases, the total cost causes greater proportional losses from the monetary gains. It is important to remember that the monetary value of a donation is saved if the donation is rescued. Therefore, managing the cost is highly impor-

Table 4.12: A summary of results for Case Study 3

Data Sets	Food Banks $ \mathcal{F} $	Gap	Amount Rescued	Shipped Portion	Avg. Demand Fill Rate	Total Cost / Gain
Small	5	2%	53%	14%	55%	20%
	10	2%	35%	34%	46%	31%
	15	2%	31%	49%	44%	39%
	Average	2%	40%	32%	48%	30%
Medium	5	9%	86%	4%	61%	9%
	10	7%	56%	24%	55%	19%
	15	7%	49%	41%	49%	27%
	Average	8%	64%	23%	55%	18%
Large	10	13%	71%	23%	56%	17%
	15	17%	59%	41%	52%	24%
	Average	15%	65%	32%	54%	21%

tant not to constrain the resources of the food banks, as the donations cannot be considered as their monetary income.

To evaluate the collaboration concept, the case study is also compared with the first case study. While the detailed comparison of the results is provided in Appendix I, the average results summary is provided in Table 4.13. From these results, it is clear that Case Study 1 provides better solutions with respect to the performance criteria. The portion of rescued donations and the portion of fulfilled demands are clearly larger in the solutions provided by the first case study. In this case study, it is concluded that total cost is increased because of the shipments and this causes greater losses from the saved monetary value. It is clear that collaboration provides a great advantage to save money by using the available resources all together.

To decide the best structure to follow in the new donation system, the proposed collaboration method is also compared with the shipment model of the third case study. The detailed results of this comparison is available in Appendix I, while the average results are provided in Table 4.14. This final comparison table shows how many times the collaboration method in Case Study 1 outperformed the shipment

Table 4.13: A summary of average results to compare Case Study 1 and Case Study 3

Criterion		Amount Rescued		Avg. Demand Fill Rate		Total Cost / Gain	
Data Sets	Food Banks $ \mathcal{F} $	Case -1-	Case -3-	Case -1-	Case -3-	Case -1-	Case -3-
Small	5	97%	53%	83%	55%	13%	20%
	10	97%	35%	86%	46%	16%	31%
	15	95%	31%	82%	44%	19%	39%
	Average	96%	40%	84%	48%	16%	30%
Medium	5	98%	86%	69%	61%	8%	9%
	10	97%	56%	71%	55%	10%	19%
	15	96%	49%	71%	49%	11%	27%
	Average	97%	64%	70%	55%	10%	18%
Large	10	96%	71%	68%	56%	7%	17%
	15	94%	59%	67%	52%	8%	24%
	Average	95%	65%	67%	54%	7%	21%

model developed in Case Study 3. To evaluate this, the upper bound found in the shipment model is compared to the best objective function value found in the collaboration model. If the upper bound found in the shipment model is worse than the collaboration model, then it is straightforward that the best solution of the shipment model cannot provide a better objective function value than the best solution of the collaboration model. In such a case, it can be said that the collaboration model outperforms the shipment model. As seen from the results, this outperforming condition is satisfied in most of the instances. The incomparable results are mostly observed in the medium-sized instances with 5 food banks. The reason behind this is probably the number of the vehicles. In medium-sized instances, there are 4 vehicles in the system in each instance. This makes it easier to rescue most of the donations by using only the available vehicles. However, in other instance classes, it is observed that the collaboration is more advantageous in terms of the

Table 4.14: Final comparison of Case Study 1 and Case Study 3

Data Sets	Food Banks $ \mathcal{F} $	Times Collaboration Outperforms	Difference in the Objective Value
Small	5	18 in 18	33%
	10	18 in 18	52%
	15	18 in 18	58%
	Average	100%	48%
Medium	5	5 in 18	7%
	10	18 in 18	30%
	15	18 in 18	41%
	Average	76%	26%
Large	10	14 in 14	24%
	15	14 in 14	37%
	Average	100%	30%

objective function value. The other performance indicator for this comparison is the average difference between the objective function values found in each case study. This percentage is calculated with a formula that is similar to the calculation of the relative percentage gap (see Appendix I for details). Since the difference is quite big on average in each instance class, it is asserted that the collaboration model provides high-quality results. Even if the outperforming condition is not observed, the difference between the objective function values clearly points out the outstanding performance of the system with logistics collaboration.

To conclude, over 136 instances, the system with logistics collaboration outperformed undoubtedly in 123. Especially when the number of food banks without vehicles increases, the collaboration model improves the donation system in terms of rescuing the donations in total and minimizing the logistics cost.

4.3.5 Comparison of The Proposed System and The Existing System: FIFO Analysis

The results of the case studies indicate that the system with logistics collaboration is quite useful in rescuing the donations and arranging the donation operations with fewer resources and costs. As it is introduced, the existing system uses the FIFO principle while assigning the donations to the food banks. To compare these systems, FIFO assignment procedure is also tested with the generated instances.

The computational experiments for evaluating the existing system are arranged as follows. Within an instance, each donation is directly matched with only one of the food banks in the instance, as if the food bank demands this donation first in the system. Starting from the earliest donation, a food bank is selected randomly among the other food banks that still have unfulfilled demand (non-zero) for the food type of the donation to be assigned. Therefore, it can be said that each donation has one certain owner in the existing system. However, once a donation assignment exceeds the demand of the food bank, it is assumed that food waste occurs because of the excessive amount of food. The food waste in the existing system and uncollected food donations in the proposed system comes up in the same situation. Therefore, if food waste occurs, the monetary gain of the amount wasted will be lost.

The described procedure is tested on each instance. The results of donation operations performed by the existing system are compared with the best solutions found in Case Study 1. A summary of the average results is given in Table 4.15.

In Table 4.15, several important decision criteria are used to compare the results of both systems: the amount of rescued donations, average demand fulfillment, and the number of food banks that are served at least once. In the end, the outputs of both systems are compared within each instance to determine the best strategy. It is trivial to see that in general, the system with logistics collaboration provides the opportunity to rescue more donations and satisfy more demands than the existing system. Furthermore, the average number of food banks that are served at least one time with the collaboration is also quite competitive. The last column *Collaboration Outperforms* compares the monetary gain of the existing system with the collabo-

Table 4.15: Summary of the average results of FIFO Analysis

Data Sets	Food Banks $ \mathcal{F} $	FIFO Amt. Rescued	FIFO Avg. Demand Fill Rate	FIFO Service	Collab. Amt. Rescued	Collab. Avg. Demand Fill Rate	Collab. Service	Collaboration Outperforms
Small	5	79%	51%	4.89	97%	83%	4.83	67%
	10	60%	38%	8.28	86%	97%	9.44	94%
	15	47%	30%	10.06	82%	95%	13.89	100%
	Average	62%	40%	-	88%	92%	-	87%
Medium	5	88%	53%	5.00	98%	69%	4.83	61%
	10	70%	42%	9.89	71%	97%	9.56	83%
	15	62%	34%	13.94	71%	96%	14.33	89%
	Average	73%	43%	-	80%	87%	-	78%
Large	10	72%	38%	10.00	68%	96%	9.79	93%
	15	64%	34%	14.71	67%	94%	14.43	100%
	Average	68%	36%	-	67%	95%	-	96%

ration system. It should be noted that in the existing system, only the rescue gain is examined, while the collaboration system produces the total monetary gain of the system including the logistics costs. Therefore, even if the logistics expenses are ignored in the existing system, food waste occurrences cannot be controlled since the demands are exceeded.

To conclude, in 86% of the instances, the proposed system with the logistics collaboration outperforms the existing system which uses FIFO principle in the assignments of the donations. The detailed results are provided in Appendix J.

Chapter 5

CONCLUSIONS

In this thesis study, a new system is being proposed to solve a real-life assignment and logistics problem observed in a charitable food donation system constructed and operated by an entrepreneur company. In the donation system, the donations are matched with the food banks including all non-profit agencies and these food banks are responsible for collecting their matched donations from the donors. There are two main goals targeted while proposing a new system. The first goal is to help non-profit food banks in the management of their scarce resources for the logistics operations of collecting the donations. In expectation to improve these operations in the system, a logistics collaboration among food banks is suggested in the proposed system. The second goal is rescuing as many donations as possible to prevent food waste caused by perishability and help needy people. To optimize the donation operations with the consideration of these objectives, a mathematical model representing the proposed system is developed with mixed integer linear programming (MILP) and tested on real-life based instances.

While optimizing the donation system, a logistics collaboration concept is proposed to promote sustainability in its all dimensions: social, environmental and economic. The logistics collaboration aims to use the available vehicles at hand belonging to some of the food banks in the system mutually. This collaboration concept is meant to help the food banks without vehicles, and further, to optimize the vehicle usage for less environmental damage. Socially, the logistics collaboration is expected to increase the solidarity and the companionship between the food banks. To realize the aforementioned promotion of sustainability environmentally and economically, beside minimizing the food waste, minimizing the fuel and emissions cost is also included in the objective of the model.

The mathematical model reflects three main operations of the system: pairing

the donations with the food banks, collecting and distributing the assigned donations, and constructing the routes and schedules of the vehicles. From the literature, the model is similar to the formulations for the Unpaired Pickup and Delivery Vehicle Routing Problem (U-PDVRP), since the donations are unpaired. The objective function of the proposed MILP model aims to maximize the total gain, while minimizing the fuel and emissions cost at the same time. The monetary values of the donated food are considered to be saved if and only if the donation is collected and distributed in the solution. While rescuing the donations, the least costly way to operate the logistics decisions is sought. As a case study with the collaboration concept, this exact solution method is tested on 136 instances first. Since the solutions found at the end of the base run are distant from being optimal, a problem-specific GRASP-ILS metaheuristic is developed to improve the solution quality. The solutions provided by the metaheuristic implementation are used in the warm-up start procedure that is applied to the MILP model. The warm-up start improved the solution quality clearly. In terms of the percentage gap, a 5% improvement in the small-sized, 31% in the medium-sized, and 60% in the large-sized instances are observed on average. The solutions found with the warm-up start procedure can save 95% of the donations on average in larger instances, while the base model only saves 28% on average. Furthermore, to test the yield of the collaboration concept tested in Case Study 1, two other case studies are developed and conducted on the same instances.

In Case Study 2, a daily vehicle rent option is additionally offered to the food banks without vehicles, at a regular price. The collaboration is still allowed, so available vehicles continued to collect and distribute the donations for all of the food banks in the system. However, the results of this case study showed that the food banks without vehicles do not opt to rent vehicles, since it has a price that causes losses in the objective function. This outcome points out that the available vehicles at hand are probably enough and useful for each component in the system.

In the last case study, Case Study 3, the collaboration is not allowed. Since using vehicle rent frequently is not a sustainable method, a model for using shipment is proposed. The food banks without vehicles can arrange shipments of the donations

by paying a reasonable price. The food banks having vehicles also continued to operate, but just for themselves. The results of this case study showed that as the amount shipped increased, the price being paid was also increased and this situation caused great losses from the monetary gain that the donations brought. Consequently, the model prevented over-use of shipments and the portion of the rescued donations in total decreased apparently. When Case Study 3 is compared to Case Study 1, it is seen that the collaboration model is much more advantageous in terms of total gains and total rescued donations. It is seen that around in 90% of the instances, the collaboration system outperformed the shipment model. Furthermore, in all of the instances, collaboration system rescued a greater portion of the donations than the shipment model. This result indicates that logistics collaboration is indeed useful for food banks to save money and resources, especially for the ones with no vehicles.

Another analysis made to evaluate the proposed system is the FIFO analysis. In this analysis, the donation rescue performance the existing system which uses the FIFO principle while assigning the donations is examined. According to the results, the proposed system outperforms the existing system in terms of the monetary gain in 86% of the instances.

To conclude, the results of this study showed that the proposed system operates efficiently with respect to saved donations by using logistics collaboration among food banks. The outcomes of this study are believed to provide invaluable help and benefits to encourage sustainability of the system in all dimensions.

Future Work

There can be several possible extensions of this work to be studied in the future. In this study, it is significant to rescue the donations as much as possible with the consideration of minimizing environmental and economic damage caused by the operations. Equitable distribution of food is not considered and this can be incorporated in the problem setting. Even if it is not possible to fulfill all of the demands completely in the current problem, a balanced and equitable sharing of the

donations can be studied to promote social sustainability of the system.

While developing the mathematical formulation for the problem, two main goals were combined in one objective function. One part maximizes total monetary savings from rescued donations, while the other part minimizes the total cost of logistics operations. These two parts can be used as two different objective functions, and the problem can be studied with a multi-objective perspective. In such a case, equity issue can also be added as another objective function.

To encourage sustainability, a collaboration concept was implemented in the study, which turned out to be very beneficial in terms of total savings. Any other concept compatible with the donation system can also be considered. For instance, Fazla Gıda may choose to operate their own vehicles for donation operations in the future. Other problems would occur in this case, such as optimizing the number of vehicles needed, vehicle operating costs, and organizing a depot or a facility.

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Appendix A

ALGORITHMS

The detailed pseudo-codes of the assignment functions in Section 3.3.2 are provided in this appendix.

Algorithm A.1 The pseudo-code of *greedy_randomized()*

Input: Seed e , Threshold parameter α_t , Node n , Set of candidate nodes $node_set$

```

1:  $r_{min} \leftarrow min\_distance(n, node\_set)$ ;
2:      $\triangleright$  find the node having the minimum distance to node  $n$  in the  $node\_set$ 
3:  $r_{max} \leftarrow max\_distance(n, node\_set)$ ;
4:      $\triangleright$  find the node having the maximum distance to node  $n$  in the  $node\_set$ 
5:  $r \leftarrow r_{min} + \alpha_t \times (r_{max} - r_{min})$ 
6:      $\triangleright$  determine the threshold value to restrict the candidates
7:  $candidates \leftarrow null$ 
8:      $\triangleright$  Restricted Candidate List (RCL) to determine the next component
9: for  $l = 1, \dots, |node\_set|$  do
10:    if  $distance(node\ n, node\ l) \leq r$  then
11:         $candidates.add(node\ l)$ ;
12:    end if
13: end for
14:  $selected\_node \leftarrow candidates.select(Seed\ e)$ 
15:      $\triangleright$  select one of the candidate nodes in RCL randomly

```

Output: $selected_node$

Algorithm A.2 The pseudo-code of *assign_donors()*

Input: Day t , Seed e , Threshold parameter α_t

```

1:  $active\_donors \leftarrow find\_active\_donors(t)$ ;
2:            $\triangleright$  find active donors: donors who have available donations for the specified day
3:  $available\_vehicles \leftarrow find\_available\_vehicles()$ ;
4:            $\triangleright$  find available vehicles: vehicles which have available days left
5: while  $active\_donors \neq \emptyset$  &  $available\_vehicles \neq \emptyset$  do
6:   for vehicle  $k = 1, \dots, |\mathcal{K}|$  do
7:     if vehicle  $k$  is available then
8:        $donor\_node \leftarrow greedy\_randomized(e, \alpha_t, k.owner\_node, active\_donors)$ ;
9:        $\triangleright$  a random node is chosen among restricted donor candidate list
10:       $route_{tk}.add(donor\_node)$ ;
11:       $\triangleright$  add the chosen donor to the end of the route
12:    end if
13:  end for
14: end while
15: for vehicle  $k = 1, \dots, |\mathcal{K}|$  do
16:   if  $route_{tk}$  violates total route length constraint then
17:      $route_{tk}.make\_feasible(donor\_node)$ ;
18:      $\triangleright$  excludes donors with lower donation values from the route until the route length becomes
        feasible
19:   end if
20: end for
21: for vehicle  $k = 1, \dots, |\mathcal{K}|$  do
22:   if  $route_{tk} \neq \emptyset$  then
23:      $k \leftarrow active$ ;
24:      $\triangleright$  if a vehicle has at least one donor assigned, then it is set as active
25:   end if
26: end for

```

Output: $\cup_{k=1}^{|\mathcal{K}|} route_{tk}$

Algorithm A.3 The pseudo-code of *assign_food_banks()*

Input: Day t , Seed e , Threshold parameter α_t , $max_iterations$

```

1:  $active\_food\_banks \leftarrow find\_active\_food\_banks(t)$ ;
2:  $\triangleright$  find active food banks: food banks who have non-zero demand in total and do not have any
   active vehicle for the specified day
3:  $counter \leftarrow 0$ ;
4: while  $active\_donors \neq \emptyset$  &  $counter < max\_iterations$  do
5:    $k \leftarrow$  random vehicle among  $|\mathcal{K}|$  vehicles;
6:   if vehicle  $k$  is active then
7:      $fb\_node \leftarrow greedy\_randomized(e, \alpha_t, k.owner\_node, active\_food\_banks)$ 
8:      $\triangleright$  a random node is chosen among restricted food bank candidate list
9:     if  $route_{tk}.insert\_fb(fb\_node, random\_order)$  is feasible then
10:       $\triangleright$  a random order on the route (after the donors) is chosen for insertion
11:       $route_{tk}.insert\_fb(fb\_node, random\_order)$ ;
12:       $\triangleright$  insertion is made if the route is feasible
13:       $active\_food\_banks.remove(fb\_node)$ ;
14:       $\triangleright$  inserted food bank node is excluded from the candidates
15:     end if
16:   end if
17:    $counter \leftarrow counter + 1$ ;
18: end while

```

Output: $\cup_{k=1}^{|\mathcal{K}|} route_{tk}$

Algorithm A.4 The pseudo-code of *insert_pair()*

Input: Pair p , Route $route$

```

1:  $fb\_node \leftarrow p.food\_bank\_node$ 
2:  $donor\_node \leftarrow p.donor\_node$ 
3:                                      $\triangleright$  the donor and food bank nodes of the pair  $p$  are approached
4:  $new\_route \leftarrow route$ 
5: if  $fb\_node$  is not on  $route$  then
6:    $new\_route.insert(fb\_node, random\_fb);$ 
7:    $\triangleright$  the food bank node of pair  $p$  is added to  $new\_route$ , it is inserted right before a randomly
   chosen food bank node in the route order if it is not already on the route
8: end if
9: if  $donor\_node$  is not on  $route$  then
10:   $new\_route.insert(donor\_node, random\_donor);$ 
11:   $\triangleright$  the donor node of pair  $p$  is added to  $new\_route$ , it is inserted right before a randomly
   chosen donor node in the route order if it is not already on the route
12: end if
13: if  $new\_route.length > max\_route\_length$  then
14:   $new\_route \leftarrow route$ 
15:                                      $\triangleright$  if the route length of  $new\_route$  is infeasible, use  $route$ 
16: else
17:   $amount \leftarrow \min(p.donation\_left, p.fb\_demand\_left, new\_route.vehicle\_cap\_left)$ 
18:   $\triangleright$  the feasible amount to be collected and distributed with the insertion of pair  $p$  is calculated
   according to the remaining amounts of the related donation, demand, and the vehicle capacity
19:   $new\_route.collect\_deliver(fb\_node, donor\_node, amount)$ 
20:                                      $\triangleright$  the donations operations in  $new\_route$  is presented
21: end if

```

Output: new_route

Appendix B

PROPERTIES OF THE DATA SETS

Several properties of the data sets are provided in this appendix. The data sets are driven from the real-life data and the instances to be used in the experiments are generated based on the given data sets.

Table B.1: The properties of small-sized data sets

Name	$ \mathcal{T} $ <i>days</i>	$ \mathcal{R} $ <i>food types</i>	$ \mathcal{G} $ <i>donors</i>	# Donations
S_M1W1	5	3	3	7
S_M1W2	5	3	6	12
S_M1W3	6	3	5	15
S_M1W4	5	3	4	9
S_M2W1	6	2	4	10
S_M2W2	6	3	4	12
S_M2W3	5	3	3	11
S_M2W4	6	3	3	9
S_M3W1	6	2	4	10
S_M3W3	7	3	8	22
S_M3W4	6	3	8	15
S_M3W5	6	2	8	20
S_M4W1	7	1	9	23
S_M5W1	4	2	5	9
S_M5W2	6	1	7	13
S_M5W3	5	1	7	16
S_M6W1	7	2	9	17
S_M6W3	7	3	8	22
$ \mathcal{K} = \mathbf{2}$ (<i>vehicles</i>) for all instances.				

Table B.2: The properties of medium-sized data sets

Name	$ \mathcal{T} $ <i>days</i>	$ \mathcal{R} $ <i>food types</i>	$ \mathcal{G} $ <i>donors</i>	# Donations
M_M3W2	7	3	10	26
M_M4W2	6	2	12	29
M_M4W3	7	2	13	26
M_M4W4	7	1	13	25
M_M5W4	6	3	14	27
M_M5W5	7	2	14	26
M_M6W2	6	3	12	17
M_M6W4	7	3	16	36
M_M7W1	7	3	16	32
M_M7W2	7	3	15	34
M_M7W3	6	3	15	32
M_M7W4	7	3	16	33
M_M8W2	7	3	19	45
M_M8W4	7	3	17	32
M_M9W3	7	3	19	47
M_M10W1	7	3	18	44
M_M10W3	7	2	16	39
M_M12W3	6	3	15	32
$ \mathcal{K} = 4$ (<i>vehicles</i>) for all instances.				

Table B.3: The properties of large-sized data sets

Name	$ \mathcal{T} $ <i>days</i>	$ \mathcal{R} $ <i>food types</i>	$ \mathcal{G} $ <i>donors</i>	# Donations
L_M8W1	7	3	21	49
L_M8W3	7	4	21	42
L_M9W1	7	2	21	48
L_M9W2	7	3	24	51
L_M9W4	7	3	20	52
L_M10W2	7	3	20	44
L_M10W4	6	2	21	42
L_M10W5	7	4	26	55
L_M11W1	7	3	20	45
L_M11W2	7	3	22	50
L_M11W3	7	3	24	49
L_M11W4	6	4	27	58
L_M12W1	6	4	22	41
L_M12W2	7	3	21	41
$ \mathcal{K} = \mathbf{6}$ (<i>vehicles</i>) for all instances.				

Appendix C

SENSITIVITY ANALYSIS

The instances are described with their size and the number of food banks in their names. The first letter of the instance name stands for the size of the data set used. "S" stands for small-sized, "M" stands for medium-sized and "L" stands for large-sized data set. The second part identifies the data set (available in Appendix B), and the number at the end shows the number of the food banks included in the instance. For example, the name "M_M4W4_10" indicates that this instance is generated from the medium-sized data set and it covers 10 food banks in total.

In Table C.1, the *Instance* column identifies the instance. The *Gap* column provides the relative percentage gap between the upper bound value (UB) and the incumbent value (IN). It is calculated as $100 \times (UB - IN) / UB$. The *Amount Rescued* column presents the portion of picked donations (i.e. collected and distributed donations) among the overall amount of donations. The *Avg. Demand Fill Rate* column gives the average fulfillment percentage of food banks. While calculating the average demand fill rate, the average fulfillment in each food type is taken into account separately for one food bank. The *Rental Vehicle Used* column gives the total times that an outsource vehicle is used. The average of each column is provided in the last column.

Appendix D

CASE STUDY 1: BASE RUN RESULTS

To mention briefly, a table of results for Case Study 1 is organized as follows. The *Instance* column identifies the instance. The *Gap* column provides the relative percentage gap between the upper bound value (UB) and the incumbent value (IN). It is calculated as $100 \times (UB - IN)/UB$. The total amount of donations in any type made within the instance is given in the *Total Donated* column. The *Amount Rescued* column presents the portion of picked donations (i.e. collected and distributed donations) among the overall amount of donations. The *Rescue Gain* column gives the monetary value of the donations saved. The *Value Rescued* column shows the saving made from the collected donations compared to the total value of all donations in the instance. As explained before, even if the type and amount of two donations are the same, these donations have different values most of the time since their contents differ. That is why *Amount Rescued* and *Value Rescued* percentages are different than each other in a solution. The *Total Demand* column presents the total amount of food in any type demanded by the food banks. It should be noted that the amount of total demand is greater than the total amount of donations. The *Avg. Demand Fill Rate* column gives the average fulfillment percentage of food banks. While calculating the average demand fill rate, the average fulfillment in each food type is taken into account separately for one food bank. The *Cost* column shows the total fuel and emission cost, and the *Total Distance* gives the total distance traversed in the solution. The last column *Cost/Gain* is calculated to be able to compare the total gain and total cost in a solution. The rows in the second part summarizes the minimum, maximum and average values of the columns specified. Percentage values are rounded to the nearest integer. The same format is also valid for other tables of results.

Table D.1: Base Run Results: Small-sized instances with 5 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost / Gain
S_M1W1_5	0%	1296	80%	4282.00	96%	1467	75%	440.65	170.5	10%
S_M1W2_5	5%	1220	100%	4650.00	100%	1419	85%	620.43	240.1	13%
S_M1W3_5	4%	1972	100%	9325.00	100%	2269	85%	966.96	375	10%
S_M1W4_5	0%	976	93%	2827.43	92%	1130	73%	586.16	227.7	21%
S_M2W1_5	4%	1488	100%	5924.00	100%	1730	83%	847.05	327.3	14%
S_M2W2_5	5%	1609	98%	6990.07	99%	1851	85%	634.19	245	9%
S_M2W3_5	0%	1147	100%	9600.00	100%	1313	86%	433.46	167.6	5%
S_M2W4_5	4%	1235	93%	4207.19	93%	1453	80%	405.87	155.8	10%
S_M3W1_5	6%	1314	99%	4704.31	98%	1531	83%	570.15	219.9	12%
S_M3W3_5	2%	1302	100%	9672.00	100%	1447	90%	710.53	275	7%
S_M3W4_5	2%	933	100%	4222.00	100%	1057	86%	504.03	194.7	12%
S_M3W5_5	4%	1354	100%	5791.00	100%	1535	88%	813.67	315.7	14%
S_M4W1_5	7%	1463	100%	6124.00	100%	1601	91%	840.84	326.4	14%
S_M5W1_5	0%	622	92%	2087.45	93%	722	78%	326.82	127	16%
S_M5W2_5	0%	994	97%	2537.00	97%	1150	84%	483.03	187.6	19%
S_M5W3_5	0%	1514	100%	6091.00	100%	1719	88%	609.47	235.1	10%
S_M6W1_5	12%	1778	92%	4863.93	94%	2140	69%	905.07	350.9	19%
S_M6W3_5	5%	3472	100%	13965.00	100%	3986	85%	1365.77	527.6	10%
Average	3%		97%		98%		83%			12%
<i>Min</i>	0%		80%		92%		69%			5%
<i>Max</i>	12%		100%		100%		91%			21%

Table D.2: Base Run Results: Small-sized instances with 10 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
S_M1W1_10	5%	1296	73%	4165.00	94%	1415	74%	424.68	163.6	10%
S_M1W2_10	9%	1220	72%	4607.13	99%	1355	86%	870.05	337.9	19%
S_M1W3_10	6%	1972	86%	9317.29	100%	2163	90%	1120.17	434.2	12%
S_M1W4_10	5%	976	76%	3074.00	100%	1095	79%	803.44	312.4	26%
S_M2W1_10	12%	1488	99%	5751.71	97%	1635	80%	948.57	367.3	16%
S_M2W2_10	8%	1609	65%	6956.85	99%	1746	89%	805.90	311.8	12%
S_M2W3_10	3%	1147	86%	9520.62	99%	1245	90%	664.92	257.7	7%
S_M2W4_10	10%	1235	66%	4071.99	90%	1379	80%	410.13	158.4	10%
S_M3W1_10	3%	1314	77%	4740.57	99%	1447	90%	501.31	192.5	11%
S_M3W3_10	23%	1302	91%	8207.72	85%	1407	77%	1227.15	478.2	15%
S_M3W4_10	5%	933	55%	4188.05	99%	1026	86%	692.79	268.9	17%
S_M3W5_10	5%	1354	92%	5783.60	100%	1476	91%	895.12	347.2	15%
S_M4W1_10	6%	1463	99%	6050.19	99%	1579	90%	784.38	304.5	13%
S_M5W1_10	11%	622	96%	2190.43	98%	695	78%	555.82	216.1	25%
S_M5W2_10	9%	994	97%	2537.00	97%	1077	89%	617.76	238.9	24%
S_M5W3_10	2%	1514	100%	6020.29	99%	1645	90%	565.88	219	9%
S_M6W1_10	16%	1778	92%	4774.09	92%	1973	67%	1055.13	409.2	22%
S_M6W3_10	24%	3472	74%	11081.82	79%	3761	49%	930.91	358.2	8%
Average	9%		83%		96%		82%			15%
<i>Min</i>	2%		55%		79%		49%			7%
<i>Max</i>	24%		100%		100%		91%			26%

Table D.3: Base Run Results: Small-sized instances with 15 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
S_M1W1_15	8%	1296	80%	4265.83	96%	1381	79%	752.84	292.3	18%
S_M1W2_15	16%	1220	90%	4259.17	92%	1316	71%	915.75	356.1	22%
S_M1W3_15	42%	1972	43%	6097.05	65%	2112	60%	1107.61	431.6	18%
S_M1W4_15	13%	976	94%	2952.76	96%	1070	78%	877.95	341.2	30%
S_M2W1_15	14%	1488	97%	5737.37	97%	1599	77%	1152.06	447.6	20%
S_M2W2_15	25%	1609	82%	6240.02	89%	1718	80%	1331.09	518.3	21%
S_M2W3_15	5%	1147	97%	9518.06	99%	1238	90%	824.82	319.2	9%
S_M2W4_15	19%	1235	87%	4019.89	89%	1341	79%	797.21	309.8	20%
S_M3W1_15	8%	1314	99%	4696.66	98%	1411	90%	673.58	258.8	14%
S_M3W3_15	77%	1302	18%	2562.28	26%	1387	20%	506.94	198.2	20%
S_M3W4_15	26%	933	77%	3344.27	79%	1011	69%	620.22	240.7	19%
S_M3W5_15	17%	1354	97%	5541.91	96%	1450	70%	1288.28	501.9	23%
S_M4W1_15	11%	1463	100%	6124.00	100%	1545	95%	1150.18	447	19%
S_M5W1_15	13%	622	85%	2002.00	89%	681	70%	444.52	172.6	22%
S_M5W2_15	18%	994	91%	2485.96	95%	1055	86%	755.59	293.9	30%
S_M5W3_15	4%	1514	100%	6091.00	100%	1617	93%	733.55	283.7	12%
S_M6W1_15	35%	1778	64%	3686.88	71%	1916	33%	814.43	317.3	22%
S_M6W3_15	53%	3472	47%	6828.85	49%	3692	20%	560.54	216.5	8%
Average	22%		80%		85%		70%			19%
<i>Min</i>	4%		18%		26%		20%			8%
<i>Max</i>	77%		100%		100%		95%			30%

Table D.4: Base Run Results: Medium-sized instances with 5 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
M_M3W2_5	4%	1617	100%	10513.19	100%	2015	80%	710.83	274.8	7%
M_M4W2_5	4%	1511	100%	6540.33	100%	1950	69%	697.98	270	11%
M_M4W3_5	5%	1657	100%	6976.67	99%	2120	60%	958.92	371.8	14%
M_M4W4_5	6%	1771	100%	8519.00	100%	1945	92%	846.80	327.5	10%
M_M5W4_5	14%	2055	91%	9820.29	91%	2740	50%	1059.43	409.7	11%
M_M5W5_5	6%	1975	99%	8275.41	99%	2324	71%	1063.37	412.4	13%
M_M6W2_5	13%	1162	92%	5146.00	92%	1527	49%	763.16	297	15%
M_M6W4_5	11%	3873	91%	18248.57	92%	5045	50%	1149.01	445.5	6%
M_M7W1_5	8%	4418	98%	23447.09	95%	5855	51%	1068.80	407.7	5%
M_M7W2_5	76%	5045	38%	7366.69	27%	6213	19%	1027.71	398	14%
M_M7W3_5	31%	3736	71%	15024.30	70%	4391	54%	727.39	280.5	5%
M_M7W4_5	34%	6204	56%	28870.90	66%	7383	51%	474.05	181.7	2%
M_M8W2_5	56%	7095	56%	17398.54	46%	8855	35%	980.06	376.3	6%
M_M8W4_5	29%	7008	71%	26944.58	72%	8922	28%	811.93	308.5	3%
M_M9W3_5	30%	7239	51%	39058.80	71%	9345	35%	1030.57	397.5	3%
M_M10W1_5	16%	5280	76%	37187.36	86%	6454	59%	1360.31	524.4	4%
M_M10W3_5	39%	11453	33%	39073.82	61%	13715	34%	1143.83	441.5	3%
M_M12W3_5	15%	4837	87%	18839.28	87%	5946	68%	1102.38	419.6	6%
Average	22%		78%		81%		53%			7%
<i>Min</i>	4%		33%		27%		19%			2%
<i>Max</i>	76%		100%		100%		92%			15%

Table D.5: Base Run Results: Medium-sized instances with 10 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
M_M3W2_10	43%	1617	58%	6500.21	62%	1879	50%	703.96	274	11%
M_M4W2_10	13%	1511	92%	6199.77	94%	1838	68%	907.70	351.7	15%
M_M4W3_10	14%	1657	93%	6602.00	94%	1920	72%	1139.03	442.3	17%
M_M4W4_10	8%	1771	98%	8374.83	98%	1917	90%	929.68	359.9	11%
M_M5W4_10	36%	2055	64%	7250.50	67%	2453	42%	736.75	282.4	10%
M_M5W5_10	46%	1975	35%	4804.80	57%	2297	15%	556.83	217	12%
M_M6W2_10	37%	1162	67%	4098.83	73%	1359	37%	997.43	389.5	24%
M_M6W4_10	29%	3873	66%	14534.67	73%	4477	33%	899.51	347.3	6%
M_M7W1_10	22%	4418	81%	19798.91	80%	5100	34%	1010.66	391	5%
M_M7W2_10	89%	5045	13%	3786.89	14%	5849	9%	717.75	280.2	19%
M_M7W3_10	26%	3736	64%	16456.05	77%	4305	48%	1120.91	434.2	7%
M_M7W4_10	63%	6204	34%	16697.85	38%	7046	27%	650.20	251.5	4%
M_M8W2_10	80%	7095	18%	7891.17	21%	8211	15%	578.63	225.6	7%
M_M8W4_10	27%	7008	69%	28404.36	76%	8033	35%	1401.37	538.5	5%
M_M9W3_10	37%	7239	51%	35421.04	64%	8576	41%	1382.64	533.6	4%
M_M10W1_10	27%	5280	67%	31952.95	74%	6083	30%	1091.80	421.4	3%
M_M10W3_10	57%	11453	23%	26710.30	41%	13054	10%	346.16	133.2	1%
M_M12W3_10	61%	4837	40%	8520.02	39%	5443	34%	301.73	113.6	4%
Average	40%		57%		63%		38%			9%
<i>Min</i>	8%		13%		14%		9%			1%
<i>Max</i>	89%		98%		98%		90%			24%

Table D.6: Base Run Results: Medium-sized instances with 15 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
M_M3W2_15	25%	1617	77%	8674.71	82%	1805	71%	1080.33	420.4	12%
M_M4W2_15	75%	1511	9%	1587.80	24%	1733	4%	61.45	24	4%
M_M4W3_15	72%	1657	52%	2357.00	34%	1855	18%	602.65	233.9	26%
M_M4W4_15	9%	1771	100%	8481.00	100%	1909	92%	1089.51	422.6	13%
M_M5W4_15	43%	2055	64%	6680.49	62%	2332	33%	900.53	350	13%
M_M5W5_15	49%	1975	45%	4699.61	56%	2230	21%	770.28	300.3	16%
M_M6W2_15	50%	1162	60%	3298.32	59%	1316	30%	785.19	306.1	24%
M_M6W4_15	63%	3873	29%	7483.69	38%	4336	16%	488.16	190.5	7%
M_M7W1_15	32%	4418	70%	17411.54	70%	4922	29%	888.77	343	5%
M_M7W2_15	54%	5045	41%	13427.27	49%	5608	33%	1068.66	414.1	8%
M_M7W3_15	45%	3736	42%	12075.96	56%	4197	22%	733.49	284.3	6%
M_M7W4_15	65%	6204	31%	15945.46	36%	6867	30%	791.76	307.7	5%
M_M8W2_15	84%	7095	13%	6480.00	17%	7871	8%	467.16	182.3	7%
M_M8W4_15	64%	7008	15%	13254.80	35%	7853	7%	187.09	72.8	1%
M_M9W3_15	67%	7239	19%	18868.69	34%	8146	21%	737.32	287.1	4%
M_M10W1_15	73%	5280	16%	12211.05	28%	5861	12%	588.91	229.4	5%
M_M10W3_15	67%	11453	15%	20739.47	32%	12751	11%	334.33	129.3	2%
M_M12W3_15	62%	4837	40%	8254.81	38%	5280	13%	356.44	136.1	4%
Average	56%		41%		47%		26%			9%
<i>Min</i>	9%		9%		17%		4%			1%
<i>Max</i>	84%		100%		100%		92%			26%

Table D.7: Base Run Results: Large-sized instances with 10 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
L_M8W1_10	55%	4844	41%	18013.37	46%	5789	28%	771.32	299	4%
L_M8W3_10	58%	10870	36%	20314.99	42%	13038	18%	539.33	205.9	3%
L_M9W1_10	81%	15352	5%	11467.00	20%	18898	7%	216.36	84.4	2%
L_M9W2_10	68%	7022	24%	15676.36	32%	8103	27%	491.16	189.2	3%
L_M9W4_10	36%	10629	40%	53616.90	62%	13232	17%	917.52	350.6	2%
L_M10W2_10	62%	15501	27%	29092.61	36%	19420	16%	894.71	343.3	3%
L_M10W4_10	37%	6417	45%	28218.68	64%	8155	22%	1120.17	435.5	4%
L_M10W5_10	72%	7856	25%	19102.90	29%	8969	15%	682.53	265.8	4%
L_M11W1_10	39%	5429	60%	21250.24	62%	6635	24%	715.18	275	3%
L_M11W2_10	59%	6460	37%	19493.02	41%	7934	14%	384.68	148.7	2%
L_M11W3_10	59%	7946	40%	21296.42	42%	9390	24%	741.49	283.1	3%
L_M11W4_10	75%	7169	27%	17483.00	25%	8676	14%	496.73	193.2	3%
L_M12W1_10	55%	4864	49%	13598.75	46%	5775	17%	622.63	239.6	5%
L_M12W2_10	50%	5135	55%	12877.34	54%	6132	43%	1336.09	515	10%
Average	58%		36%		43%		21%			4%
<i>Min</i>	36%		5%		20%		7%			2%
<i>Max</i>	81%		60%		64%		43%			10%

Table D.8: Base Run Results: Large-sized instances with 15 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
L_M8W1_15	77%	4844	24%	9134.04	23%	5593	16%	288.50	111.9	3%
L_M8W3_15	79%	10870	24%	9966.21	21%	12490	6%	238.53	92.2	2%
L_M9W1_15	89%	15352	2%	6701.05	11%	17572	4%	190.64	74.5	3%
L_M9W2_15	91%	7022	9%	4646.55	9%	7918	7%	152.62	59.5	3%
L_M9W4_15	80%	10629	10%	16687.57	19%	12308	5%	276.72	106.4	2%
L_M10W2_15	47%	15501	33%	40895.48	51%	18164	20%	1604.17	620.1	4%
L_M10W4_15	48%	6417	33%	23128.81	53%	7535	14%	593.18	229.6	3%
L_M10W5_15	72%	7856	21%	18606.15	28%	8798	15%	685.95	266.7	4%
L_M11W1_15	64%	5429	27%	12890.19	37%	6248	18%	765.37	297.4	6%
L_M11W2_15	64%	6460	32%	17606.48	37%	7508	14%	536.95	208.8	3%
L_M11W3_15	98%	7946	2%	1205.68	2%	9239	3%	95.24	37.2	8%
L_M11W4_15	88%	7169	10%	8376.20	12%	8350	7%	189.12	73.8	2%
L_M12W1_15	85%	4864	14%	4719.96	16%	5494	8%	290.72	113.4	6%
L_M12W2_15	83%	5135	19%	4379.25	18%	5948	29%	484.21	188.3	11%
Average	76%		19%		24%		12%			4%
<i>Min</i>	47%		2%		2%		3%			2%
<i>Max</i>	98%		33%		53%		29%			11%

Appendix E

CASE STUDY 1: METAHEURISTIC RESULTS

The tables in this appendix are organized as follows. The *Instance* column identifies the instance (with size and number of food banks covered). The *GRASP (Best)* and *GRASP-ILS (Best)* columns present the best objective function values among the solutions found by the GRASP and GRASP-ILS implementation during the trials for a specific instance. The *Total CPU Time* shows the duration that the best solution found with the GRASP-ILS implementation in seconds. The *Base Run Objective*, *Base Run Upper Bound*, and *Base Run Gap* columns provide the value of objective function of the best solution found, the upper bound of the instance, and the relative percentage gap respectively. Lastly, the *GRASP Gap* and *GRASP-ILS Gap* columns show the relative percentage gap where the upper bound found in the base run, and the best objective function value provided by the heuristic algorithm specified are used in the calculation.

Table E.1: Metaheuristic Results: Small-sized instances

Instance	GRASP (Best)	GRASP-ILS (Best)	Total CPU Time (sec)	Base Run Objective	Base Run Upper Bound	Base Run Gap	GRASP Gap	GRASP-ILS Gap
S_M1W1_5	3592.85	3599.23	5	3841.35	3841.72	0.0%	6.5%	6.3%
S_M1W2_5	1442.38	3441.64	10	4029.57	4228.60	4.7%	65.9%	18.6%
S_M1W3_5	7856.21	7856.21	9	8358.04	8695.41	3.9%	9.7%	9.7%
S_M1W4_5	1673.77	2055.24	6	2241.26	2241.47	0.0%	25.3%	8.3%
S_M2W1_5	4346.91	4508.04	9	5076.95	5296.95	4.2%	17.9%	14.9%
S_M2W2_5	5816.05	6068.13	8	6355.87	6662.90	4.6%	12.7%	8.9%
S_M2W3_5	8635.35	8635.35	7	9166.54	9167.45	0.0%	5.8%	5.8%
S_M2W4_5	3569.00	3569.00	6	3801.32	3977.85	4.4%	10.3%	10.3%
S_M3W1_5	3263.83	3673.25	9	4134.16	4390.77	5.8%	25.7%	16.3%
S_M3W3_5	8453.23	8670.34	10	8961.47	9131.11	1.9%	7.4%	5.0%
S_M3W4_5	3418.04	3494.25	9	3717.97	3775.49	1.5%	9.5%	7.4%
S_M3W5_5	3865.46	4475.66	13	4977.33	5177.92	3.9%	25.3%	13.6%
S_M4W1_5	4270.07	4975.08	15	5283.16	5705.54	7.4%	25.2%	12.8%
S_M5W1_5	1616.18	1616.18	6	1760.63	1760.79	0.0%	8.2%	8.2%
S_M5W2_5	1462.09	1737.82	8	2053.97	2054.07	0.0%	28.8%	15.4%
S_M5W3_5	5256.47	5256.47	7	5481.53	5482.08	0.0%	4.1%	4.1%
S_M6W1_5	3123.60	3484.89	16	3958.86	4485.16	11.7%	30.4%	22.3%
S_M6W3_5	12013.85	12154.02	12	12599.23	13308.16	5.3%	9.7%	8.7%
S_M1W1_10	3452.41	3452.41	9	3740.32	3920.32	4.6%	11.9%	11.9%
S_M1W2_10	2368.77	3075.01	15	3737.08	4119.40	9.3%	42.5%	25.4%
S_M1W3_10	5657.32	7020.11	15	8197.12	8687.04	5.6%	34.9%	19.2%
S_M1W4_10	1461.99	2036.74	10	2270.56	2390.47	5.0%	38.8%	14.8%
S_M2W1_10	3692.55	4204.68	16	4803.14	5433.88	11.6%	32.0%	22.6%
S_M2W2_10	5840.79	6020.81	13	6150.95	6666.27	7.7%	12.4%	9.7%
S_M2W3_10	8304.03	8332.18	12	8855.70	9136.37	3.1%	9.1%	8.8%
S_M2W4_10	3112.30	3382.84	9	3661.87	4082.74	10.3%	23.8%	17.1%
S_M3W1_10	3417.33	3609.91	15	4239.26	4385.71	3.3%	22.1%	17.7%
S_M3W3_10	6360.61	8377.03	18	6980.57	9095.56	23.3%	30.1%	7.9%
S_M3W4_10	2969.42	3266.74	13	3495.26	3679.08	5.0%	19.3%	11.2%
S_M3W5_10	3523.23	4269.80	21	4888.48	5134.86	4.8%	31.4%	16.8%
S_M4W1_10	3826.31	4852.64	21	5265.81	5610.75	6.1%	31.8%	13.5%
S_M5W1_10	1394.96	1394.96	10	1634.61	1830.14	10.7%	23.8%	23.8%
S_M5W2_10	973.64	1699.31	12	1919.24	2118.09	9.4%	54.0%	19.8%
S_M5W3_10	5165.07	5165.07	10	5454.41	5568.79	2.1%	7.2%	7.2%
S_M6W1_10	3010.96	3363.76	23	3718.97	4432.20	16.1%	32.1%	24.1%
S_M6W3_10	11599.92	11656.16	15	10150.91	13420.19	24.4%	13.6%	13.1%
S_M1W1_15	3194.22	3194.22	14	3512.99	3800.62	7.6%	16.0%	16.0%
S_M1W2_15	1000.73	2787.19	23	3343.42	3992.61	16.3%	74.9%	30.2%
S_M1W3_15	3627.25	6067.63	22	4989.44	8588.79	41.9%	57.8%	29.4%
S_M1W4_15	1507.68	1681.09	13	2074.81	2376.12	12.7%	36.5%	29.3%
S_M2W1_15	3217.74	4019.15	18	4585.31	5338.28	14.1%	39.7%	24.7%
S_M2W2_15	5772.28	5818.44	20	4908.93	6549.93	25.1%	11.9%	11.2%
S_M2W3_15	7367.30	8009.89	17	8693.24	9129.28	4.8%	19.3%	12.3%
S_M2W4_15	3006.18	3182.16	14	3222.67	4002.08	19.5%	24.9%	20.5%
S_M3W1_15	3343.55	3451.48	20	4023.09	4371.15	8.0%	23.5%	21.0%
S_M3W3_15	5626.47	8067.85	29	2055.34	8966.81	77.1%	37.3%	10.0%
S_M3W4_15	2801.74	3101.61	19	2724.04	3670.30	25.8%	23.7%	15.5%
S_M3W5_15	4018.24	4156.86	27	4253.63	5139.35	17.2%	21.8%	19.1%
S_M4W1_15	3948.02	4635.41	31	4973.82	5566.25	10.6%	29.1%	16.7%
S_M5W1_15	1218.23	1218.23	14	1557.48	1782.74	12.6%	31.7%	31.7%
S_M5W2_15	1404.53	1579.58	15	1730.37	2104.69	17.8%	33.3%	24.9%
S_M5W3_15	5100.64	5100.64	14	5357.45	5595.07	4.2%	8.8%	8.8%
S_M6W1_15	2764.51	3219.05	31	2872.45	4409.54	34.9%	37.3%	27.0%
S_M6W3_15	11654.73	11705.20	24	6268.31	13344.77	53.0%	12.7%	12.3%

Table E.2: Metaheuristic Results: Medium-sized instances

Instance	GRASP (Best)	GRASP-ILS (Best)	Total CPU Time (sec)	Base Run Objective	Base Run Upper Bound	Base Run Gap	GRASP Gap	GRASP-ILS Gap
M_M3W2_5	9174.14	9393.92	39	9802.36	10195.14	3.9%	10.0%	7.9%
M_M4W2_5	5054.53	5229.92	27	5842.35	6117.61	4.5%	17.4%	14.5%
M_M4W3_5	4457.42	5142.86	49	6017.75	6367.47	5.5%	30.0%	19.2%
M_M4W4_5	6629.41	6959.16	46	7672.20	8145.14	5.8%	18.6%	14.6%
M_M5W4_5	7842.81	8620.60	37	8760.85	10236.43	14.4%	23.4%	15.8%
M_M5W5_5	5795.65	6488.78	47	7212.05	7682.55	6.1%	24.6%	15.5%
M_M6W2_5	3762.52	3914.40	28	4382.84	5032.97	12.9%	25.2%	22.2%
M_M6W4_5	17214.76	17695.25	44	17099.55	19196.12	10.9%	10.3%	7.8%
M_M7W1_5	20771.81	22546.40	50	22378.28	24207.82	7.6%	14.2%	6.9%
M_M7W2_5	24891.11	24968.81	46	6338.98	26836.57	76.4%	7.2%	7.0%
M_M7W3_5	19390.95	19390.95	41	14296.91	20793.19	31.2%	6.7%	6.7%
M_M7W4_5	33341.67	40738.70	55	28396.86	43233.39	34.3%	22.9%	5.8%
M_M8W2_5	34064.81	35175.54	59	16418.48	37358.00	56.1%	8.8%	5.8%
M_M8W4_5	30535.50	35012.71	54	26132.65	36862.83	29.1%	17.2%	5.0%
M_M9W3_5	51544.74	51981.87	71	38028.23	54377.51	30.1%	5.2%	4.4%
M_M10W1_5	39647.65	40171.45	56	35827.05	42482.81	15.7%	6.7%	5.4%
M_M10W3_5	49708.70	56825.08	45	37930.00	61926.61	38.8%	19.7%	8.2%
M_M12W3_5	19308.41	19308.41	40	17736.90	20879.90	15.1%	7.5%	7.5%
M_M3W2_10	6748.08	8698.61	55	5796.26	10198.41	43.2%	33.8%	14.7%
M_M4W2_10	4670.50	4926.56	35	5292.07	6075.31	12.9%	23.1%	18.9%
M_M4W3_10	3706.43	5002.52	65	5462.97	6346.30	13.9%	41.6%	21.2%
M_M4W4_10	4800.65	6578.82	56	7445.15	8132.19	8.4%	41.0%	19.1%
M_M5W4_10	7772.14	8100.92	49	6523.75	10188.28	36.0%	23.7%	20.5%
M_M5W5_10	4926.64	6175.56	64	4247.97	7824.38	45.7%	37.0%	21.1%
M_M6W2_10	3118.43	3601.22	39	3101.40	4946.83	37.3%	37.0%	27.2%
M_M6W4_10	13951.75	17359.10	60	13635.16	19102.33	28.6%	27.0%	9.1%
M_M7W1_10	20216.63	22024.85	65	18788.25	24105.61	22.1%	16.1%	8.6%
M_M7W2_10	23197.01	23965.06	77	3069.14	26811.44	88.6%	13.5%	10.6%
M_M7W3_10	18561.54	18776.65	60	15335.13	20751.40	26.1%	10.6%	9.5%
M_M7W4_10	35336.96	38768.87	77	16047.66	43193.24	62.8%	18.2%	10.2%
M_M8W2_10	30475.62	34877.46	90	7312.55	37349.27	80.4%	18.4%	6.6%
M_M8W4_10	30407.61	34484.31	65	27002.99	36835.93	26.7%	17.5%	6.4%
M_M9W3_10	50425.14	51184.88	90	34038.39	54329.14	37.3%	7.2%	5.8%
M_M10W1_10	38425.44	39102.34	76	30861.15	42432.28	27.3%	9.4%	7.8%
M_M10W3_10	48685.15	56037.39	58	26364.14	62004.24	57.5%	21.5%	9.6%
M_M12W3_10	18877.53	18939.00	50	8218.29	20899.13	60.7%	9.7%	9.4%
M_M3W2_15	6496.15	8425.37	75	7594.38	10123.22	25.0%	35.8%	16.8%
M_M4W2_15	4123.60	4703.30	53	1526.35	6089.73	74.9%	32.3%	22.8%
M_M4W3_15	3496.69	4695.80	88	1754.35	6362.38	72.4%	45.0%	26.2%
M_M4W4_15	4853.96	6477.21	72	7391.49	8084.92	8.6%	40.0%	19.9%
M_M5W4_15	7165.75	7992.10	62	5779.96	10229.56	43.5%	30.0%	21.9%
M_M5W5_15	5065.07	6087.54	83	3929.33	7747.34	49.3%	34.6%	21.4%
M_M6W2_15	3391.45	3462.61	51	2513.13	5063.01	50.4%	33.0%	31.6%
M_M6W4_15	16481.87	16964.12	80	6995.53	19128.04	63.4%	13.8%	11.3%
M_M7W1_15	20309.52	21708.52	85	16522.76	24129.09	31.5%	15.8%	10.0%
M_M7W2_15	13521.15	23733.18	81	12358.62	26733.11	53.8%	49.4%	11.2%
M_M7W3_15	15413.96	18479.04	79	11342.48	20716.13	45.2%	25.6%	10.8%
M_M7W4_15	33683.26	36390.58	89	15153.70	43124.65	64.9%	21.9%	15.6%
M_M8W2_15	30478.16	34651.45	112	6012.84	37316.79	83.9%	18.3%	7.1%
M_M8W4_15	31579.34	34287.29	89	13067.71	36796.10	64.5%	14.2%	6.8%
M_M9W3_15	50742.28	50749.08	120	18131.37	54321.70	66.6%	6.6%	6.6%
M_M10W1_15	38147.22	38656.90	103	11622.14	42381.30	72.6%	10.0%	8.8%
M_M10W3_15	48580.61	56450.95	73	20405.14	62031.74	67.1%	21.7%	9.0%
M_M12W3_15	18055.98	18113.88	62	7898.37	20920.47	62.2%	13.7%	13.4%

Table E.3: Metaheuristic Results: Large-sized instances

Instance	GRASP (Best)	GRASP-ILS (Best)	Total CPU Time (sec)	Base Run Objective	Base Run Upper Bound	Base Run Gap	GRASP Gap	GRASP-ILS Gap
L_M8W1_10	31960.93	35903.08	158	17242.05	38384.05	55.1%	16.7%	6.5%
L_M8W3_10	32970.04	40463.06	133	19775.66	47402.17	58.3%	30.4%	14.6%
L_M9W1_10	32363.86	53950.92	177	11250.64	57704.64	80.5%	43.9%	6.5%
L_M9W2_10	42604.39	44213.39	194	15185.20	48170.82	68.5%	11.6%	8.2%
L_M9W4_10	78876.49	79119.23	103	52699.38	82491.16	36.1%	4.4%	4.1%
L_M10W2_10	66115.59	68472.10	158	28197.91	74401.48	62.1%	11.1%	8.0%
L_M10W4_10	40372.01	40684.89	124	27098.50	43311.37	37.4%	6.8%	6.1%
L_M10W5_10	56203.82	60431.35	169	18420.38	65076.79	71.7%	13.6%	7.1%
L_M11W1_10	27062.28	30082.39	149	20535.07	33675.24	39.0%	19.6%	10.7%
L_M11W2_10	42594.74	44244.21	132	19108.34	47029.98	59.4%	9.4%	5.9%
L_M11W3_10	34332.34	47105.29	135	20554.93	50366.77	59.2%	31.8%	6.5%
L_M11W4_10	57552.50	63566.16	178	16986.27	69272.84	75.5%	16.9%	8.2%
L_M12W1_10	21996.24	26064.12	140	12976.12	29115.46	55.4%	24.5%	10.5%
L_M12W2_10	18640.81	19390.75	131	11541.25	22890.74	49.6%	18.6%	15.3%
L_M8W1_15	33119.77	35343.63	201	8845.53	38484.45	77.0%	13.9%	8.2%
L_M8W3_15	33392.82	42490.54	179	9727.68	47423.79	79.5%	29.6%	10.4%
L_M9W1_15	35543.40	50276.13	237	6510.41	57693.70	88.7%	38.4%	12.9%
L_M9W2_15	37734.34	43557.57	241	4493.93	48164.83	90.7%	21.7%	9.6%
L_M9W4_15	78205.97	78205.97	137	16410.86	82478.09	80.1%	5.2%	5.2%
L_M10W2_15	56543.51	67371.63	199	39291.31	74370.12	47.2%	24.0%	9.4%
L_M10W4_15	39251.28	40372.33	160	22535.63	43252.64	47.9%	9.3%	6.7%
L_M10W5_15	54977.53	59212.52	205	17920.21	65014.54	72.4%	15.4%	8.9%
L_M11W1_15	28372.24	29778.57	190	12124.82	33715.11	64.0%	15.8%	11.7%
L_M11W2_15	42364.92	44065.46	165	17069.53	47096.80	63.8%	10.0%	6.4%
L_M11W3_15	37322.54	43522.09	170	1110.44	50334.07	97.8%	25.9%	13.5%
L_M11W4_15	56669.04	62594.27	215	8187.08	69294.79	88.2%	18.2%	9.7%
L_M12W1_15	21352.88	25978.77	193	4429.25	29156.05	84.8%	26.8%	10.9%
L_M12W2_15	18512.27	19223.82	174	3895.04	22894.37	83.0%	19.1%	16.0%

Appendix F

CASE STUDY 1: WARM-UP START RESULTS

The following tables of results are given in the same format with the base run results in Appendix D. It should be noted that the tightest upper bound from both base run and warm-up start run is used to calculate the gap value for the warm-up start results of each instance.

Table F.1: Warm-up Start Results: Small-sized instances with 5 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost / Gain
S_M1W1_5	0%	1296	80%	4282.00	96%	1467	75%	440.65	170.5	10%
S_M1W2_5	9%	1220	100%	4650.00	100%	1419	85%	803.74	312.8	17%
S_M1W3_5	4%	1972	100%	9325.00	100%	2269	84%	954.44	370.7	10%
S_M1W4_5	0%	976	93%	2827.43	92%	1130	73%	586.16	227.7	21%
S_M2W1_5	4%	1488	100%	5924.00	100%	1730	83%	843.03	326.3	14%
S_M2W2_5	4%	1609	98%	6990.07	99%	1851	84%	623.60	240.8	9%
S_M2W3_5	0%	1147	100%	9600.00	100%	1313	86%	433.46	167.6	5%
S_M2W4_5	4%	1235	93%	4207.19	93%	1453	80%	410.72	158.7	10%
S_M3W1_5	7%	1314	99%	4704.31	98%	1531	83%	598.72	231.9	13%
S_M3W3_5	3%	1302	100%	9672.00	100%	1447	90%	821.54	319.1	8%
S_M3W4_5	1%	933	100%	4222.00	100%	1057	86%	501.25	193.8	12%
S_M3W5_5	5%	1354	100%	5791.00	100%	1535	88%	850.58	329.4	15%
S_M4W1_5	6%	1463	100%	6124.00	100%	1601	92%	742.03	288.3	12%
S_M5W1_5	0%	622	92%	2087.45	93%	722	78%	326.82	127	16%
S_M5W2_5	0%	994	97%	2537.00	97%	1150	84%	483.03	187.6	19%
S_M5W3_5	0%	1514	100%	6091.00	100%	1719	88%	609.47	235.1	10%
S_M6W1_5	10%	1778	92%	4863.93	94%	2140	69%	837.49	324.2	17%
S_M6W3_5	5%	3472	100%	13965.00	100%	3986	84%	1265.03	486.9	9%
Average	3%		97%		98%		83%			13%
<i>Min</i>	0%		80%		92%		69%			5%
<i>Max</i>	10%		100%		100%		92%			21%

Table F.2: Warm-up Start Results: Small-sized instances with 10 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
S_M1W1_10	5%	1296	96%	4323.00	97%	1415	88%	603.9627	233	14%
S_M1W2_10	6%	1220	99%	4639.22	100%	1355	86%	768.7285	298.8	17%
S_M1W3_10	6%	1972	100%	9317.29	100%	2163	89%	1163.685	451.8	12%
S_M1W4_10	5%	976	100%	3074.00	100%	1095	79%	803.8985	312.6	26%
S_M2W1_10	11%	1488	97%	5774.46	97%	1635	80%	932.0495	361.8	16%
S_M2W2_10	6%	1609	100%	7039.00	100%	1746	90%	790.8509	305	11%
S_M2W3_10	3%	1147	97%	9520.62	99%	1245	90%	665.4831	257.9	7%
S_M2W4_10	13%	1235	89%	4087.47	90%	1379	80%	552.2545	213.9	14%
S_M3W1_10	4%	1314	99%	4740.57	99%	1447	90%	507.9091	195.5	11%
S_M3W3_10	6%	1302	100%	9654.00	100%	1407	93%	1140.428	443.6	12%
S_M3W4_10	6%	933	97%	4183.43	99%	1026	86%	731.7602	284	17%
S_M3W5_10	5%	1354	100%	5783.60	100%	1476	91%	902.6185	350.1	16%
S_M4W1_10	6%	1463	100%	6124.00	100%	1579	93%	871.3592	338	14%
S_M5W1_10	11%	622	99%	2190.43	98%	695	79%	565.7142	220.1	26%
S_M5W2_10	9%	994	97%	2537.00	97%	1077	89%	607.3111	235.9	24%
S_M5W3_10	3%	1514	98%	6020.29	99%	1645	90%	626.19	242.4	10%
S_M6W1_10	14%	1778	92%	4860.32	94%	1973	73%	1041.1	403.3	21%
S_M6W3_10	13%	3472	93%	13201.69	94%	3761	79%	1499.307	578.6	11%
Average	7%		97%		98%		86%			16%
<i>Min</i>	3%		89%		90%		73%			7%
<i>Max</i>	14%		100%		100%		93%			26%

Table F.3: Warm-up Start Results: Small-sized instances with 15 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
S_M1W1_15	6%	1296	79%	4237.00	95%	1381	78%	650.58	252.1	15%
S_M1W2_15	10%	1220	99%	4581.39	99%	1316	81%	1002.41	389.2	22%
S_M1W3_15	16%	1972	89%	8686.31	93%	2112	85%	1482.09	576.3	17%
S_M1W4_15	13%	976	93%	2798.65	91%	1070	71%	719.22	279.5	26%
S_M2W1_15	16%	1488	98%	5772.34	97%	1599	80%	1261.68	490.7	22%
S_M2W2_15	8%	1609	99%	7012.79	100%	1718	91%	976.93	377.6	14%
S_M2W3_15	5%	1147	97%	9518.06	99%	1238	91%	846.29	328.2	9%
S_M2W4_15	17%	1235	93%	4151.69	92%	1341	81%	814.60	314.9	20%
S_M3W1_15	16%	1314	100%	4763.34	100%	1411	92%	1104.40	428.3	23%
S_M3W3_15	8%	1302	98%	9535.25	99%	1387	89%	1292.36	502.5	14%
S_M3W4_15	11%	933	90%	3979.15	94%	1011	83%	700.65	271.4	18%
S_M3W5_15	12%	1354	92%	5359.90	93%	1450	77%	831.84	322.8	16%
S_M4W1_15	9%	1463	100%	6124.00	100%	1545	95%	1036.19	402	17%
S_M5W1_15	10%	622	100%	2197.00	98%	681	79%	591.61	229.4	27%
S_M5W2_15	14%	994	97%	2537.00	97%	1055	92%	728.32	283.1	29%
S_M5W3_15	5%	1514	100%	6091.00	100%	1617	93%	767.78	297.2	13%
S_M6W1_15	21%	1778	86%	4551.71	88%	1916	51%	1082.73	420.6	24%
S_M6W3_15	12%	3472	96%	13402.36	96%	3692	76%	1613.25	621.9	12%
Average	12%		95%		96%		82%			19%
<i>Min</i>	5%		79%		88%		51%			9%
<i>Max</i>	21%		100%		100%		95%			29%

Table F.4: Warm-up Start Results: Medium-sized instances with 5 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
M_M3W2_5	3%	1617	100%	10566.00	100%	2015	80%	723.14	281.3	7%
M_M4W2_5	4%	1511	99%	6513.33	99%	1950	67%	671.53	260.4	10%
M_M4W3_5	7%	1657	98%	6835.00	97%	2120	39%	943.22	366.4	14%
M_M4W4_5	5%	1771	100%	8500.73	100%	1945	90%	741.55	286.4	9%
M_M5W4_5	5%	2055	100%	10754.86	100%	2740	72%	1061.55	411	10%
M_M5W5_5	7%	1975	96%	8117.00	97%	2324	78%	919.39	356.1	11%
M_M6W2_5	14%	1162	95%	5360.74	96%	1527	62%	991.44	386.3	18%
M_M6W4_5	6%	3873	94%	19146.57	96%	5045	51%	1168.39	453.5	6%
M_M7W1_5	4%	4418	99%	24563.83	99%	5855	65%	1397.87	538.3	6%
M_M7W2_5	3%	5045	99%	27289.39	99%	6213	77%	1284.70	490.5	5%
M_M7W3_5	4%	3736	99%	21183.00	99%	4391	83%	1228.89	473.9	6%
M_M7W4_5	4%	6204	98%	43171.68	98%	7383	83%	1728.79	663	4%
M_M8W2_5	4%	7095	100%	37900.00	99%	8855	78%	1980.26	758.6	5%
M_M8W4_5	4%	7008	100%	37436.00	100%	8922	53%	1924.04	738.6	5%
M_M9W3_5	3%	7239	96%	54471.00	99%	9345	52%	1773.02	680.1	3%
M_M10W1_5	5%	5280	99%	43020.00	99%	6454	74%	2456.38	950.2	6%
M_M10W3_5	6%	11453	87%	60961.87	94%	13715	61%	2538.38	969.2	4%
M_M12W3_5	5%	4837	98%	21353.00	99%	5946	79%	1465.81	564.3	7%
Average	5%		98%		98%		69%			8%
<i>Min</i>	3%		87%		94%		39%			3%
<i>Max</i>	14%		100%		100%		90%			18%

Table F.5: Warm-up Start Results: Medium-sized instances with 10 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
M_M3W2_10	8%	1617	99%	10487	99%	1879	85%	1078.78	418.7	10%
M_M4W2_10	10%	1511	100%	6453.66667	98%	1838	63%	981.50	381.9	15%
M_M4W3_10	12%	1657	97%	6785	97%	1920	83%	1221.25	475.3	18%
M_M4W4_10	9%	1771	100%	8481	100%	1917	92%	1099.78	427.9	13%
M_M5W4_10	11%	2055	98%	10480.9135	97%	2453	71%	1426.42	553.8	14%
M_M5W5_10	14%	1975	93%	7938.76471	95%	2297	46%	1244.87	483.8	16%
M_M6W2_10	21%	1162	91%	4989.73296	89%	1359	45%	1082.03	421.3	22%
M_M6W4_10	8%	3873	98%	19644.4648	99%	4477	77%	2096.69	809.6	11%
M_M7W1_10	6%	4418	98%	24050.5355	97%	5100	63%	1365.29	520.4	6%
M_M7W2_10	9%	5045	98%	26941.973	98%	5849	85%	2408.52	928.4	9%
M_M7W3_10	5%	3736	98%	21184.8019	99%	4305	77%	1372.24	523.6	6%
M_M7W4_10	9%	6204	96%	42076.3529	96%	7046	83%	2572.67	987.7	6%
M_M8W2_10	3%	7095	100%	38105.0691	100%	8211	86%	2070.59	791.8	5%
M_M8W4_10	5%	7008	100%	37449.8	100%	8033	61%	2327.53	890.5	6%
M_M9W3_10	5%	7239	96%	54027	98%	8576	56%	2327.73	897.2	4%
M_M10W1_10	7%	5280	97%	42005	97%	6083	82%	2472.45	957.2	6%
M_M10W3_10	5%	11453	89%	61149.4336	95%	13054	54%	2513.00	958	4%
M_M12W3_10	8%	4837	97%	21080.4097	97%	5443	77%	1878.99	721.6	9%
Average	9%		97%		97%		71%			10%
<i>Min</i>	3%		89%		89%		45%			4%
<i>Max</i>	21%		100%		100%		92%			22%

Table F.6: Warm-up Start Results: Medium-sized instances with 15 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
M_M3W2_15	7%	1617	100%	10520.15	100%	1805	87%	1170.86	454.2	11%
M_M4W2_15	15%	1511	97%	6359.00	97%	1733	56%	1184.45	460.1	19%
M_M4W3_15	14%	1657	96%	6753.28	96%	1855	86%	1284.98	499.8	19%
M_M4W4_15	10%	1771	98%	8410.43	99%	1909	91%	1132.24	439.8	13%
M_M5W4_15	14%	2055	95%	10283.93	96%	2332	59%	1523.71	592.2	15%
M_M5W5_15	17%	1975	98%	8207.09	98%	2230	61%	1794.27	698.3	22%
M_M6W2_15	27%	1162	88%	5092.78	91%	1316	44%	1391.79	542.4	27%
M_M6W4_15	7%	3873	94%	19146.02	96%	4336	58%	1463.03	561.5	8%
M_M7W1_15	7%	4418	98%	24409.79	99%	4922	67%	2016.24	778.2	8%
M_M7W2_15	9%	5045	98%	26888.28	98%	5608	78%	2457.50	948.4	9%
M_M7W3_15	7%	3736	97%	21181.09	99%	4197	81%	1822.20	700.9	9%
M_M7W4_15	11%	6204	91%	41111.80	94%	6867	80%	2512.46	970.1	6%
M_M8W2_15	6%	7095	99%	37782.00	99%	7871	87%	2583.96	996.2	7%
M_M8W4_15	5%	7008	100%	37436.00	100%	7853	59%	2623.85	1003.7	7%
M_M9W3_15	6%	7239	97%	54127.35	98%	8146	58%	3002.50	1158.4	6%
M_M10W1_15	8%	5280	98%	41985.92	97%	5861	85%	2871.57	1110.3	7%
M_M10W3_15	7%	11453	87%	60592.69	94%	12751	56%	2622.91	1001.5	4%
M_M12W3_15	9%	4837	98%	21112.92	97%	5280	77%	2153.21	831.4	10%
Average	10%		96%		97%		71%			11%
<i>Min</i>	5%		87%		91%		44%			4%
<i>Max</i>	27%		100%		100%		91%			27%

Table F.7: Warm-up Start Results: Large-sized instances with 10 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
L_M8W1_10	5%	4844	100%	39246.00	100%	5789	84%	2699.55	1046.2	7%
L_M8W3_10	8%	10870	95%	46995.94	97%	13038	79%	3479.83	1339.2	7%
L_M9W1_10	5%	15352	100%	58386.00	100%	18898	78%	3484.89	1337.9	6%
L_M9W2_10	6%	7022	99%	48783.53	99%	8103	83%	3338.52	1291.2	7%
L_M9W4_10	3%	10629	86%	82552.76	95%	13232	70%	2817.34	1079.8	3%
L_M10W2_10	6%	15501	77%	74235.72	92%	19420	56%	3947.18	1519.8	5%
L_M10W4_10	3%	6417	100%	43903.82	100%	8155	40%	1969.45	755.9	4%
L_M10W5_10	6%	7856	98%	64842.87	98%	8969	71%	3544.92	1368.4	5%
L_M11W1_10	7%	5429	98%	34026.28	98%	6635	54%	2750.08	1067.4	8%
L_M11W2_10	4%	6460	98%	47371.20	99%	7934	50%	2407.48	930.9	5%
L_M11W3_10	6%	7946	99%	50460.00	99%	9390	72%	3212.14	1230.7	6%
L_M11W4_10	7%	7169	96%	68227.19	97%	8676	78%	3847.27	1486	6%
L_M12W1_10	7%	4864	98%	29452.00	99%	5775	69%	2402.04	927.9	8%
L_M12W2_10	13%	5135	96%	22970.69	97%	6132	70%	2980.07	1154.7	13%
Average	6%		96%		98%		68%			7%
<i>Min</i>	3%		77%		92%		40%			3%
<i>Max</i>	13%		100%		100%		84%			13%

Table F.8: Warm-up Start Results: Large-sized instances with 15 food banks

Instance	Gap	Total Donated (kg)	Amount Rescued	Rescue Gain (TRY)	Value Rescued	Total Demand (kg)	Avg. Demand Fill Rate	Cost (TRY)	Total Distance (km)	Cost/Gain
L_M8W1_15	6%	4844	98%	39028.00	99%	5593	86%	3043.97	1181.1	8%
L_M8W3_15	7%	10870	97%	47060.25	97%	12490	67%	3043.87	1160	6%
L_M9W1_15	11%	15352	89%	55063.22	94%	17572	79%	3573.17	1365.2	6%
L_M9W2_15	8%	7022	99%	48687.10	99%	7918	85%	4512.48	1748.8	9%
L_M9W4_15	5%	10629	84%	81719.71	94%	12308	66%	2965.00	1135.4	4%
L_M10W2_15	9%	15501	74%	72572.93	90%	18164	52%	4764.92	1838.3	7%
L_M10W4_15	5%	6417	100%	43872.92	100%	7535	42%	2750.13	1061.6	6%
L_M10W5_15	9%	7856	95%	63261.39	96%	8798	61%	3798.30	1465.9	6%
L_M11W1_15	9%	5429	98%	34077.00	99%	6248	57%	3339.13	1296.1	10%
L_M11W2_15	5%	6460	98%	47270.56	99%	7508	44%	2792.13	1079	6%
L_M11W3_15	13%	7946	93%	46985.43	92%	9239	63%	3248.58	1250.4	7%
L_M11W4_15	7%	7169	97%	68136.92	97%	8350	82%	3963.12	1530.4	6%
L_M12W1_15	8%	4864	99%	29700.00	100%	5494	70%	3019.99	1169.1	10%
L_M12W2_15	13%	5135	98%	23057.70	97%	5948	77%	3262.02	1263.5	14%
Average	8%		94%		97%		67%			8%
<i>Min</i>	5%		74%		90%		42%			4%
<i>Max</i>	13%		100%		100%		86%			14%

Appendix G

CASE STUDY 1: COMPARISON OF THE SOLUTION PROCEDURES

The results found by the base run, GRASP-ILS implementation and warm-up start procedures are provided on bar charts for each instance in terms of relative percentage gap. When calculating the relative percentage gap, the tightest upper bound found is used for each instance.



Figure G.1: Comparison of the percentage gap found by different solution procedures for small-sized instances with (a) 5, (b) 10, (c) 15 food banks



Figure G.2: Comparison of the percentage gap found by different solution procedures for medium-sized instances with (a) 5, (b) 10, (c) 15 food banks



Figure G.3: Comparison of the percentage gap found by different solution procedures for large-sized instances with (a) 10, (b) 15 food banks

Appendix H

CASE STUDY 3: RUN RESULTS

To mention briefly, the table of results for Case Study 3 is organized as follows. The *Instance* column identifies the instance. The *Gap* column provides the relative percentage gap. The *Amount Rescued* column presents the portion of picked donations (i.e. collected and distributed donations) among the overall amount of donations. The *Rescue Gain* column gives the monetary value of the donations saved in the solution. The *Logistics Cost* column shows the total fuel and emission cost of the available vehicles in the system. The *Avg. Demand Fill Rate* column gives the average fulfillment percentage of food banks. While calculating the average demand fill rate, the average fulfillment in each food type is taken into account separately for one food bank. The *Times Shipment Used* column shows how many times the shipment service is used in the solution. The *Shipped Portion* column represents the portion of rescued donations delivered by the shipment service. The *Total Shipment Cost* column gives the total shipment, delivery and extra weight costs for employed services. The *Shipments > 100 kgs* column shows how many times a shipment weights more than 100 kilograms. Each time this case is faced, extra weight cost occurs. The last column *Total Cost/Gain* is calculated to be able to compare the total gain and total cost (both logistics and shipment costs included) in a solution. The rows in the second part summarizes the minimum, maximum and average values of the columns specified.

Table H.1: Case Study 3 Run Results: Small-sized instances with 5 food banks

Instance	Gap	Amount Rescued	Rescue Gain (TRY)	Logistics Cost	Avg. Demand Fill Rate	Times Shipment Used	Shipped Portion	Total Shipment Cost	Shipments >100 kgs	Total Cost / Gain
S_M1W1_5	0%	64%	3589.90	277.97	55%	4	33%	1153.05	0	40%
S_M1W2_5	3%	54%	3867.36	471.32	43%	3	13%	390.86	0	22%
S_M1W3_5	0%	56%	7572.54	428.12	69%	4	20%	962.67	0	18%
S_M1W4_5	0%	46%	2287.58	200.69	59%	6	15%	355.07	0	24%
S_M2W1_5	0%	48%	3745.79	655.87	40%	0	0%	0.00	0	18%
S_M2W2_5	0%	60%	5473.25	524.69	69%	3	21%	861.77	0	25%
S_M2W3_5	0%	71%	8682.26	343.53	71%	4	34%	1157.07	0	17%
S_M2W4_5	0%	54%	3213.99	346.89	69%	3	15%	435.13	0	24%
S_M3W1_5	0%	57%	3164.93	377.25	62%	3	18%	584.05	0	30%
S_M3W3_5	4%	60%	8233.85	451.95	73%	6	25%	866.23	0	16%
S_M3W4_5	7%	54%	3160.82	376.37	68%	3	14%	334.51	0	22%
S_M3W5_5	7%	52%	3968.83	403.87	64%	3	5%	181.56	0	15%
S_M4W1_5	3%	50%	4141.81	267.78	44%	2	9%	284.72	0	13%
S_M5W1_5	0%	47%	1410.77	220.06	59%	4	6%	130.72	0	25%
S_M5W2_5	4%	49%	1647.69	201.47	42%	1	4%	98.09	0	18%
S_M5W3_5	0%	47%	4198.80	313.01	40%	0	0%	0.00	0	7%
S_M6W1_5	10%	41%	2817.60	315.42	20%	0	0%	0.00	0	11%
S_M6W3_5	6%	51%	8487.26	476.46	51%	4	15%	1104.75	0	19%
Average	2%	53%			55%		14%			20%
<i>Min</i>	0%	41%			20%		0%			7%
<i>Max</i>	10%	71%			73%		34%			40%

Table H.2: Case Study 3 Run Results: Small-sized instances with 10 food banks

Instance	Gap	Amount Rescued	Rescue Gain (TRY)	Logistics Cost	Avg. Demand Fill Rate	Times Shipment Used	Shipped Portion	Total Shipment Cost	Shipments >100 kgs	Total Cost / Gain
S_M1W1_10	0%	52%	3043.79	277.33	44%	8	58%	1666.14	0	64%
S_M1W2_10	0%	32%	3380.12	250.25	36%	8	36%	663.94	0	27%
S_M1W3_10	0%	35%	6694.43	390.42	66%	12	39%	1270.41	0	25%
S_M1W4_10	0%	29%	1872.94	56.38	37%	9	32%	488.33	0	29%
S_M2W1_10	0%	20%	2382.20	300.85	10%	0	0%	0.00	0	13%
S_M2W2_10	0%	40%	4485.59	379.51	63%	7	46%	1290.34	0	37%
S_M2W3_10	0%	63%	8431.00	311.97	71%	9	65%	2005.72	0	27%
S_M2W4_10	0%	33%	2538.30	207.79	63%	8	38%	736.39	0	37%
S_M3W1_10	1%	37%	2389.79	260.70	55%	9	46%	1023.64	0	54%
S_M3W3_10	3%	51%	7791.77	236.98	72%	15	58%	1753.03	0	26%
S_M3W4_10	6%	34%	2562.32	290.59	64%	7	35%	533.65	0	32%
S_M3W5_10	8%	33%	3134.49	335.78	58%	8	31%	663.94	0	32%
S_M4W1_10	0%	40%	3731.45	123.23	38%	3	47%	1151.56	0	34%
S_M5W1_10	0%	25%	962.84	110.58	45%	8	17%	217.18	0	34%
S_M5W2_10	0%	24%	1128.03	171.68	22%	1	9%	98.09	0	24%
S_M5W3_10	0%	31%	3342.05	193.98	28%	2	28%	550.36	0	22%
S_M6W1_10	8%	22%	1935.42	196.52	11%	1	13%	222.86	0	22%
S_M6W3_10	6%	25%	5092.69	364.25	45%	9	19%	794.22	0	23%
Average	2%	35%			46%		34%			31%
<i>Min</i>	0%	20%			10%		0%			13%
<i>Max</i>	8%	63%			72%		65%			64%

Table H.3: Case Study 3 Run Results: Small-sized instances with 15 food banks

Instance	Gap	Amount Rescued	Rescue Gain (TRY)	Logistics Cost	Avg. Demand Fill Rate	Times Shipment Used	Shipped Portion	Total Shipment Cost	Shipments >100 kgs	Total Cost / Gain
S_M1W1_15	0%	47%	2837.07	277.09	40%	12	70%	1861.26	0	75%
S_M1W2_15	0%	25%	3156.86	187.22	34%	13	47%	751.88	0	30%
S_M1W3_15	0%	32%	6507.48	294.34	65%	18	56%	1645.60	0	30%
S_M1W4_15	0%	23%	1799.33	56.32	35%	14	43%	580.30	0	35%
S_M2W1_15	0%	23%	2485.00	139.84	11%	2	41%	590.61	0	29%
S_M2W2_15	0%	35%	4255.74	329.56	62%	12	60%	1519.15	0	43%
S_M2W3_15	0%	67%	8593.93	275.16	73%	15	78%	2626.43	0	34%
S_M2W4_15	0%	27%	2309.10	207.49	62%	13	50%	832.38	0	45%
S_M3W1_15	0%	30%	2002.21	56.34	50%	13	61%	1150.34	0	60%
S_M3W3_15	2%	46%	7545.31	104.27	70%	23	73%	2050.70	0	29%
S_M3W4_15	7%	27%	2343.86	275.69	61%	11	47%	632.18	0	39%
S_M3W5_15	8%	36%	3289.19	264.99	55%	11	60%	1328.49	0	48%
S_M4W1_15	0%	37%	3574.84	115.35	35%	4	62%	1398.57	0	42%
S_M5W1_15	0%	18%	832.93	110.50	40%	10	24%	244.30	0	43%
S_M5W2_15	0%	21%	1069.82	151.58	20%	2	31%	288.74	0	41%
S_M5W3_15	0%	26%	3103.52	142.26	24%	2	45%	735.51	0	28%
S_M6W1_15	4%	13%	1428.71	208.60	7%	0	0%	0.00	0	15%
S_M6W3_15	7%	19%	4215.60	363.11	43%	15	28%	919.88	0	30%
Average	2%	31%			44%		49%			39%
<i>Min</i>	0%	13%			7%		0%			15%
<i>Max</i>	8%	67%			73%		78%			75%

Table H.4: Case Study 3 Run Results: Medium-sized instances with 5 food banks

Instance	Gap	Amount Rescued	Rescue Gain (TRY)	Logistics Cost	Avg. Demand Fill Rate	Times Shipment Used	Shipped Portion	Total Shipment Cost	Shipments >100 kgs	Total Cost / Gain
M_M3W2_5	6%	82%	9804.27	594.90	73%	2	9%	494.01	0	11%
M_M4W2_5	10%	80%	5806.46	608.57	65%	2	1%	55.30	0	11%
M_M4W3_5	11%	77%	6155.18	880.15	50%	1	1%	45.76	0	15%
M_M4W4_5	5%	89%	7896.55	609.85	80%	1	1%	49.79	0	8%
M_M5W4_5	8%	97%	10516.33	835.37	58%	1	0%	33.69	0	8%
M_M5W5_5	9%	73%	7240.90	773.94	40%	0	0%	0.00	0	11%
M_M6W2_5	18%	94%	5259.33	860.83	56%	1	2%	102.11	0	18%
M_M6W4_5	8%	92%	19008.00	881.40	53%	2	3%	437.67	0	7%
M_M7W1_5	5%	99%	24480.65	1137.99	59%	1	1%	158.46	0	5%
M_M7W2_5	6%	99%	27290.95	1673.95	68%	2	1%	276.67	0	7%
M_M7W3_5	6%	92%	20590.59	1016.58	71%	2	1%	155.92	0	6%
M_M7W4_5	35%	62%	32450.36	711.51	53%	4	25%	4257.50	1	15%
M_M8W2_5	4%	89%	36557.16	1368.56	77%	2	2%	457.79	0	5%
M_M8W4_5	3%	92%	35988.28	1343.52	57%	2	1%	176.05	0	4%
M_M9W3_5	19%	66%	45399.98	829.65	36%	8	17%	3316.35	0	9%
M_M10W1_5	4%	93%	42018.01	1668.10	77%	2	3%	614.76	0	5%
M_M10W3_5	2%	80%	59322.45	1602.50	58%	1	1%	375.80	0	3%
M_M12W3_5	5%	97%	21401.00	1207.01	76%	2	3%	618.79	0	9%
Average	9%	86%			61%		4%			9%
<i>Min</i>	2%	62%			36%		0%			3%
<i>Max</i>	35%	99%			80%		25%			18%

Table H.5: Case Study 3 Run Results: Medium-sized instances with 10 food banks

Instance	Gap	Amount Rescued	Rescue Gain (TRY)	Logistics Cost	Avg. Demand Fill Rate	Times Shipment Used	Shipped Portion	Total Shipment Cost	Shipments >100 kgs	Total Cost / Gain
M_M3W2_10	8%	57%	8512.17	591.93	69%	6	38%	1502.17	0	25%
M_M4W2_10	5%	44%	4458.41	309.68	53%	6	18%	552.29	0	19%
M_M4W3_10	10%	40%	4498.53	506.60	44%	3	12%	362.68	0	19%
M_M4W4_10	3%	54%	5749.13	311.25	50%	2	21%	832.11	0	20%
M_M5W4_10	8%	68%	8579.03	431.67	52%	8	32%	1915.68	0	27%
M_M5W5_10	9%	34%	5443.87	597.04	25%	0	0%	0.00	0	11%
M_M6W2_10	15%	66%	4610.91	371.07	55%	6	33%	1107.73	0	32%
M_M6W4_10	7%	56%	14435.73	803.86	44%	8	19%	1766.76	0	18%
M_M7W1_10	5%	53%	18507.13	664.40	58%	6	8%	809.88	0	8%
M_M7W2_10	9%	61%	21165.98	1265.51	55%	8	24%	3046.68	0	20%
M_M7W3_10	5%	53%	16426.00	873.27	61%	6	16%	1365.32	0	14%
M_M7W4_10	18%	58%	34337.01	893.52	56%	17	47%	7408.22	1	24%
M_M8W2_10	7%	50%	29995.47	1313.46	57%	10	12%	1814.01	0	10%
M_M8W4_10	5%	52%	28612.31	1070.95	56%	8	11%	1790.91	0	10%
M_M9W3_10	4%	61%	46262.77	802.22	46%	20	42%	7850.14	0	19%
M_M10W1_10	3%	67%	36864.31	970.41	74%	15	34%	5073.57	0	16%
M_M10W3_10	2%	50%	48555.40	1071.73	55%	7	9%	2063.12	0	6%
M_M12W3_10	5%	88%	19564.47	583.80	72%	21	49%	8624.41	0	47%
Average	7%	56%			55%		24%			19%
<i>Min</i>	2%	34%			25%		0%			6%
<i>Max</i>	18%	88%			74%		49%			47%

Table H.6: Case Study 3 Run Results: Medium-sized instances with 15 food banks

Instance	Gap	Amount Rescued	Rescue Gain (TRY)	Logistics Cost	Avg. Demand Fill Rate	Times Shipment Used	Shipped Portion	Total Shipment Cost	Shipments >100 kgs	Total Cost / Gain
M_M3W2_15	6%	50%	8132.95	412.23	68%	10	55%	1914.63	0	29%
M_M4W2_15	2%	38%	4111.64	180.24	43%	9	39%	1031.69	0	29%
M_M4W3_15	6%	34%	4185.84	337.25	35%	4	33%	794.83	0	27%
M_M4W4_15	1%	55%	5844.00	232.63	52%	5	49%	1975.62	0	38%
M_M5W4_15	8%	52%	7320.47	351.68	50%	12	44%	2074.58	0	33%
M_M5W5_15	8%	22%	4627.06	403.58	13%	0	0%	0.00	0	9%
M_M6W2_15	12%	58%	4343.04	260.61	46%	8	52%	1521.24	0	41%
M_M6W4_15	7%	52%	13771.21	716.12	44%	16	45%	3807.22	0	33%
M_M7W1_15	3%	39%	16239.62	410.32	56%	10	22%	1673.14	0	13%
M_M7W2_15	8%	53%	19746.66	990.07	53%	15	45%	5065.52	0	31%
M_M7W3_15	6%	58%	16933.57	691.80	60%	14	51%	4589.10	0	31%
M_M7W4_15	24%	45%	28268.90	858.16	43%	18	53%	6209.03	0	25%
M_M8W2_15	5%	35%	27218.91	1176.61	48%	11	16%	1763.18	0	11%
M_M8W4_15	3%	36%	25266.85	657.53	47%	11	18%	1916.12	0	10%
M_M9W3_15	13%	43%	37749.84	827.90	29%	20	48%	6328.73	0	19%
M_M10W1_15	2%	74%	38254.05	526.02	78%	29	62%	10049.06	0	28%
M_M10W3_15	1%	45%	46395.47	540.97	53%	19	35%	7550.81	0	17%
M_M12W3_15	5%	94%	20894.22	386.42	69%	33	70%	13262.86	0	65%
Average	7%	49%			49%		41%			27%
<i>Min</i>	1%	22%			13%		0%			9%
<i>Max</i>	24%	94%			78%		70%			65%

Table H.7: Case Study 3 Run Results: Large-sized instances with 10 food banks

Instance	Gap	Amount Rescued	Rescue Gain (TRY)	Logistics Cost	Avg. Demand Fill Rate	Times Shipment Used	Shipped Portion	Total Shipment Cost	Shipments >100 kgs	Total Cost / Gain
L_M8W1_10	6%	74%	35156.46	1478.14	68%	8	21%	3147.30	0	13%
L_M8W3_10	19%	45%	34336.15	968.75	55%	14	14%	2975.11	0	11%
L_M9W1_10	10%	56%	44648.58	1662.39	58%	7	4%	1620.38	0	7%
L_M9W2_10	34%	48%	30204.18	865.25	51%	14	29%	4130.26	0	17%
L_M9W4_10	3%	63%	76153.60	1232.97	63%	21	29%	7928.11	0	12%
L_M10W2_10	16%	56%	65139.48	2005.68	50%	15	23%	9196.07	4	17%
L_M10W4_10	3%	81%	41604.83	1425.36	31%	3	4%	962.39	0	6%
L_M10W5_10	11%	75%	56121.82	1422.72	48%	21	46%	12049.35	3	24%
L_M11W1_10	8%	83%	31881.57	1611.83	59%	8	13%	2535.52	0	13%
L_M11W2_10	5%	79%	43697.45	1641.76	50%	6	9%	1981.13	0	8%
L_M11W3_10	18%	63%	38690.55	1859.52	52%	13	20%	4124.74	0	15%
L_M11W4_10	18%	90%	62581.93	956.30	65%	16	39%	10957.95	2	19%
L_M12W1_10	12%	91%	28036.07	1621.51	66%	14	28%	5261.25	0	25%
L_M12W2_10	23%	92%	22467.79	2029.69	64%	21	44%	8721.01	0	48%
Average	13%	71%			56%		23%			17%
<i>Min</i>	3%	45%			31%		4%			6%
<i>Max</i>	34%	92%			68%		46%			48%

Table H.8: Case Study 3 Run Results: Large-sized instances with 15 food banks

Instance	Gap	Amount Rescued	Rescue Gain (TRY)	Logistics Cost	Avg. Demand Fill Rate	Times Shipment Used	Shipped Portion	Total Shipment Cost	Shipments >100 kgs	Total Cost / Gain
L_M8W1_15	5%	79%	36049.78	817.6991	77%	21	53%	8455.368	0	26%
L_M8W3_15	22%	32%	29364.65	1302.907	45%	14	17%	2540.422	0	13%
L_M9W1_15	15%	31%	36695.35	1323.898	54%	11	6%	1304.338	0	7%
L_M9W2_15	45%	34%	22293.67	935.2086	42%	14	34%	3413.826	0	20%
L_M9W4_15	2%	60%	75107.01	979.4524	62%	33	48%	12759.74	0	18%
L_M10W2_15	17%	44%	62811.61	1283.543	52%	30	47%	14244.24	3	25%
L_M10W4_15	2%	69%	38696.88	873.0718	29%	13	29%	5279.891	0	16%
L_M10W5_15	32%	44%	38811.11	801.3485	40%	24	59%	8644.978	0	24%
L_M11W1_15	10%	79%	30829.42	1112.463	58%	23	44%	7830.46	0	29%
L_M11W2_15	3%	74%	42672.5	1017.089	47%	20	39%	7705.248	0	20%
L_M11W3_15	24%	51%	35804.31	867.5781	52%	26	55%	9424.76	0	29%
L_M11W4_15	27%	70%	50337.55	1344.682	55%	25	44%	9226.052	0	21%
L_M12W1_15	19%	82%	25563.02	1699.901	59%	24	50%	8411.534	0	40%
L_M12W2_15	20%	74%	18438.97	1162.442	51%	25	54%	8594.142	0	53%
Average	17%	59%			52%		41%			24%
<i>Min</i>	2%	31%			29%		6%			7%
<i>Max</i>	45%	82%			77%		59%			53%

Appendix I

COMPARISON OF CASE STUDY 1 AND CASE STUDY 3

The tables of comparison are organized as follows. The *Instance* column identifies the instance (with size and number of food banks covered). The *Case-3 Objective* column provides the best objective function value found, while the *Case-3 Upper Bound* gives the upper bound found for the instance. The *Case-1 Objective* column provides the best objective function value found for the same instance in Case Study 1 (with the warm-up start procedure). The *Objective Comparison* column compares the objective function values observed from both of the studies via using their difference. To compare these objective values, a formula similar to relative percentage gap calculation is used: $(Obj_{Case1} - Obj_{Case3})/Obj_{Case1}$. The *Case-1 Obj. > Case-3 UB* column compares the best objective value found in Case Study 1 and the upper bound (*UB*) value found in Case Study 3. If this inequality holds for an instance, it means that Case Study 1 provides a more profitable solution than Case Study 3. It is trivial to see that if the upper bound found in Case Study 3 is worse than the best solution objective of Case Study 1 for an instance, then it is impossible to see better results from Case Study 3 in terms of the monetary gain being maximized. The *Case-3 Amount Rescued* and *Case-1 Amount Rescued* columns represent the amount of rescued donations in Case Study 1 and Case Study 3 respectively. The last column compares the percentages rescued in these case studies separately. The *Average* row below shows the average values and observations of the specified columns.

Table I.1: The results of small-sized instances: Comparison of Case Study 1 and Case Study 3

Instance	Case-3	Case-3	Case-1	Objective Comparison	Case-1 Obj. >	Case-3	Case-1	Case-1 Rescued >
	Objective	Upper Bound	Objective		Case-3 UB	Amount Rescued	Amount Rescued	Case-3 Rescued
S_M1W1_5	2158.882	2159.039	3841.347	44%	True	64%	80%	True
S_M1W2_5	3005.18	3102.578	3846.263	22%	True	54%	100%	True
S_M1W3_5	6181.749	6182.367	8370.557	26%	True	56%	100%	True
S_M1W4_5	1731.821	1731.969	2241.264	23%	True	46%	93%	True
S_M2W1_5	3089.922	3090.165	5080.972	39%	True	48%	100%	True
S_M2W2_5	4086.788	4087.187	6366.465	36%	True	60%	98%	True
S_M2W3_5	7181.651	7182.308	9166.541	22%	True	71%	100%	True
S_M2W4_5	2431.972	2432.076	3796.47	36%	True	54%	93%	True
S_M3W1_5	2203.63	2203.849	4105.585	46%	True	57%	99%	True
S_M3W3_5	6915.67	7200.327	8850.462	22%	True	60%	100%	True
S_M3W4_5	2449.945	2642.722	3720.749	34%	True	54%	100%	True
S_M3W5_5	3383.396	3638.89	4940.419	32%	True	52%	100%	True
S_M4W1_5	3589.307	3700.133	5381.967	33%	True	50%	100%	True
S_M5W1_5	1059.983	1059.983	1760.625	40%	True	47%	92%	True
S_M5W2_5	1348.139	1405.593	2053.973	34%	True	49%	97%	True
S_M5W3_5	3885.785	3886.164	5481.53	29%	True	47%	100%	True
S_M6W1_5	2502.182	2783.301	4026.439	38%	True	41%	92%	True
S_M6W3_5	6906.056	7325.063	12699.97	46%	True	51%	100%	True
S_M1W1_10	1100.329	1100.438	3719.037	70%	True	52%	96%	True
S_M1W2_10	2465.932	2466.119	3870.488	36%	True	32%	99%	True
S_M1W3_10	5033.605	5052.272	8153.61	38%	True	35%	100%	True
S_M1W4_10	1328.229	1328.33	2270.101	41%	True	29%	100%	True
S_M2W1_10	2081.35	2081.525	4842.411	57%	True	20%	97%	True
S_M2W2_10	2815.743	2815.815	6248.149	55%	True	40%	100%	True
S_M2W3_10	6113.312	6113.87	8855.138	31%	True	63%	97%	True
S_M2W4_10	1594.125	1594.249	3535.211	55%	True	33%	89%	True
S_M3W1_10	1105.441	1118.293	4232.66	74%	True	37%	99%	True
S_M3W3_10	5801.76	5989.087	8513.572	32%	True	51%	100%	True
S_M3W4_10	1738.074	1840.49	3451.666	50%	True	34%	97%	True
S_M3W5_10	2134.778	2326.267	4880.978	56%	True	33%	100%	True
S_M4W1_10	2456.665	2459.919	5252.641	53%	True	40%	100%	True
S_M5W1_10	635.0846	635.0846	1624.713	61%	True	25%	99%	True
S_M5W2_10	858.2635	858.3185	1929.689	56%	True	24%	97%	True
S_M5W3_10	2597.711	2597.971	5394.096	52%	True	31%	98%	True
S_M6W1_10	1516.04	1656.757	3819.217	60%	True	22%	92%	True
S_M6W3_10	3934.212	4206.472	11702.39	66%	True	25%	93%	True
S_M1W1_15	698.7139	698.7424	3586.419	81%	True	47%	79%	True
S_M1W2_15	2217.755	2226.386	3578.986	38%	True	25%	99%	True
S_M1W3_15	4567.545	4576.225	7204.22	37%	True	32%	89%	True
S_M1W4_15	1162.722	1162.722	2079.426	44%	True	23%	93%	True
S_M2W1_15	1754.546	1754.648	4510.654	61%	True	23%	98%	True
S_M2W2_15	2407.028	2409.652	6035.857	60%	True	35%	99%	True
S_M2W3_15	5692.338	5709.211	8671.772	34%	True	67%	97%	True
S_M2W4_15	1269.24	1269.28	3337.089	62%	True	27%	93%	True
S_M3W1_15	795.5319	797.0121	3658.934	78%	True	30%	100%	True
S_M3W3_15	5390.345	5525.131	8242.892	35%	True	46%	98%	True
S_M3W4_15	1435.992	1536.863	3278.503	56%	True	27%	90%	True
S_M3W5_15	1695.714	1839.77	4528.063	63%	True	36%	92%	True
S_M4W1_15	2060.926	2069.877	5087.815	59%	True	37%	100%	True
S_M5W1_15	478.1283	478.1283	1605.391	70%	True	18%	100%	True
S_M5W2_15	629.4984	629.5602	1808.683	65%	True	21%	97%	True
S_M5W3_15	2225.75	2225.973	5323.22	58%	True	26%	100%	True
S_M6W1_15	1220.109	1276.888	3468.975	65%	True	13%	86%	True
S_M6W3_15	2932.613	3162.423	11789.11	75%	True	19%	96%	True
Average				48%	100%			100%

Table I.2: The results of medium-sized instances: Comparison of Case Study 1 and Case Study 3

Instance	Case-3	Case-3	Case-1	Objective Comparison	Case-1 Obj.	Case-3	Case-1	Case-1 Rescued
	Objective	Upper Bound	Objective		> Case-3 UB	Amount Rescued	Amount Rescued	> Case-3 Rescued
M_M3W2_5	8715.354	9224.658	9842.859	11%	True	82%	100%	True
M_M4W2_5	5142.588	5684.926	5841.799	12%	True	80%	99%	True
M_M4W3_5	5229.274	5902.635	5891.776	11%	False	77%	98%	True
M_M4W4_5	7236.908	7645.737	7759.18	7%	True	89%	100%	True
M_M5W4_5	9647.279	10519.66	9693.31	0%	False	97%	100%	True
M_M5W5_5	6466.957	7144.2	7197.607	10%	True	73%	96%	True
M_M6W2_5	4296.392	5244.476	4369.296	2%	False	94%	95%	True
M_M6W4_5	17688.93	19193.71	17978.17	2%	False	92%	94%	True
M_M7W1_5	23184.2	24511.63	23165.97	0%	False	99%	99%	True
M_M7W2_5	25340.34	27099.87	26004.7	3%	False	99%	99%	True
M_M7W3_5	19418.09	20708.7	19954.11	3%	False	92%	99%	True
M_M7W4_5	27481.35	42252.98	41442.89	34%	False	62%	98%	True
M_M8W2_5	34730.81	36179.68	35919.74	3%	False	89%	100%	True
M_M8W4_5	34468.72	35612.78	35511.96	3%	False	92%	100%	True
M_M9W3_5	41253.99	51078.24	52697.98	22%	True	66%	96%	True
M_M10W1_5	39735.16	41177.53	40563.62	2%	False	93%	99%	True
M_M10W3_5	57344.15	58663.19	58423.5	2%	False	80%	87%	True
M_M12W3_5	19575.2	20571.68	19887.19	2%	False	97%	98%	True
M_M3W2_10	6418.066	6988.23	9408.223	32%	True	57%	99%	True
M_M4W2_10	3596.442	3774.401	5472.17	34%	True	44%	100%	True
M_M4W3_10	3629.249	4051.265	5563.749	35%	True	40%	97%	True
M_M4W4_10	4605.766	4745.965	7381.224	38%	True	54%	100%	True
M_M5W4_10	6231.677	6782.337	9054.495	31%	True	68%	98%	True
M_M5W5_10	4846.831	5304.857	6693.892	28%	True	34%	93%	True
M_M6W2_10	3132.116	3677.826	3907.699	20%	True	66%	91%	True
M_M6W4_10	11865.11	12691.05	17547.78	32%	True	56%	98%	True
M_M7W1_10	17032.85	17837.06	22685.24	25%	True	53%	98%	True
M_M7W2_10	16853.8	18445.28	24533.45	31%	True	61%	98%	True
M_M7W3_10	14187.41	14895.39	19812.56	28%	True	53%	98%	True
M_M7W4_10	26035.27	31834.89	39503.69	34%	True	58%	96%	True
M_M8W2_10	26868	28771.12	36034.48	25%	True	50%	100%	True
M_M8W4_10	25750.45	26967.46	35122.27	27%	True	52%	100%	True
M_M9W3_10	37610.4	39179.87	51699.27	27%	True	61%	96%	True
M_M10W1_10	30820.33	31701.82	39532.55	22%	True	67%	97%	True
M_M10W3_10	45420.56	46343.47	58636.43	23%	True	50%	89%	True
M_M12W3_10	10356.26	10879.2	19201.42	46%	True	88%	97%	True
M_M3W2_15	5806.089	6158.404	9349.292	38%	True	50%	100%	True
M_M4W2_15	2899.714	2966.122	5174.555	44%	True	38%	97%	True
M_M4W3_15	3053.758	3259.346	5468.297	44%	True	34%	96%	True
M_M4W4_15	3635.754	3678.584	7278.192	50%	True	55%	98%	True
M_M5W4_15	4894.199	5343.189	8760.218	44%	True	52%	95%	True
M_M5W5_15	4223.475	4574.144	6412.822	34%	True	22%	98%	True
M_M6W2_15	2561.188	2919.457	3700.99	31%	True	58%	88%	True
M_M6W4_15	9247.87	9979.32	17682.99	48%	True	52%	94%	True
M_M7W1_15	14156.16	14579.17	22393.54	37%	True	39%	98%	True
M_M7W2_15	13691.06	14950.58	24430.78	44%	True	53%	98%	True
M_M7W3_15	11652.67	12459.52	19358.9	40%	True	58%	97%	True
M_M7W4_15	21201.7	27851.25	38599.34	45%	True	45%	91%	True
M_M8W2_15	24279.13	25452.23	35198.04	31%	True	35%	99%	True
M_M8W4_15	22693.19	23447.06	34812.15	35%	True	36%	100%	True
M_M9W3_15	30593.2	35199.46	51124.84	40%	True	43%	97%	True
M_M10W1_15	27678.97	28310.25	39114.35	29%	True	74%	98%	True
M_M10W3_15	38303.68	38796.15	57969.78	34%	True	45%	87%	True
M_M12W3_15	7244.94	7648.93	18959.71	62%	True	94%	98%	True
Average				26%	76%			100%

Table I.3: The results of large-sized instances: Comparison of Case Study 1 and Case Study 3

Instance	Case-3 Objective	Case-3 Upper Bound	Case-1 Objective	Objective Comparison	Case-1 Obj. > Case-3 UB	Case-3 Amount Rescued	Case-1 Amount Rescued	Case-1 Rescued > Case-3 Rescued
L_M8W1_10	30531.02	32512.98	36546.45	16%	True	74%	100%	True
L_M8W3_10	30392.3	37321.01	43516.11	30%	True	45%	95%	True
L_M9W1_10	41365.81	45930.65	54901.11	25%	True	56%	100%	True
L_M9W2_10	25208.67	38406.21	45445.01	45%	True	48%	99%	True
L_M9W4_10	66992.52	69352.26	79735.42	16%	True	63%	86%	True
L_M10W2_10	53937.72	64266.73	70288.54	23%	True	56%	77%	True
L_M10W4_10	39217.08	40536.79	41934.36	6%	True	81%	100%	True
L_M10W5_10	42649.74	48152.38	61297.94	30%	True	75%	98%	True
L_M11W1_10	27734.22	30010.67	31276.19	11%	True	83%	98%	True
L_M11W2_10	40074.56	41999.35	44963.72	11%	True	79%	98%	True
L_M11W3_10	32706.28	39899.72	47247.86	31%	True	63%	99%	True
L_M11W4_10	50667.67	62041.51	64379.92	21%	True	90%	96%	True
L_M12W1_10	21153.3	24170.99	27049.96	22%	True	91%	98%	True
L_M12W2_10	11717.09	15303.29	19990.63	41%	True	92%	96%	True
L_M8W1_15	26776.71	28105.01	35984.03	26%	True	79%	98%	True
L_M8W3_15	25521.32	32523.61	44016.38	42%	True	32%	97%	True
L_M9W1_15	34067.12	40114.04	51490.05	34%	True	31%	89%	True
L_M9W2_15	17944.63	32544.32	44174.61	59%	True	34%	99%	True
L_M9W4_15	61367.81	62736.12	78754.71	22%	True	60%	84%	True
L_M10W2_15	47283.83	56820.15	67808.01	30%	True	44%	74%	True
L_M10W4_15	32543.92	33286.47	41122.8	21%	True	69%	100%	True
L_M10W5_15	29364.78	43164.55	59463.09	51%	True	44%	95%	True
L_M11W1_15	21886.49	24197.11	30737.87	29%	True	79%	98%	True
L_M11W2_15	33950.16	35142	44478.43	24%	True	74%	98%	True
L_M11W3_15	25511.97	33437.62	43736.86	42%	True	51%	93%	True
L_M11W4_15	39766.82	54265.43	64173.8	38%	True	70%	97%	True
L_M12W1_15	15451.58	19000.51	26680.01	42%	True	82%	99%	True
L_M12W2_15	8682.387	10875.4	19795.68	56%	True	74%	98%	True
Average				30%	100%			100%

Appendix J

FIFO ANALYSIS

A table of results is organized as follows. *Instance* column specifies the instance. The *FIFO Rescue Gain* column provides the monetary gain saved by the rescued donations with the existing system (the system which use FIFO principle in the assignment of the donations). The *FIFO Amount Rescued* and *FIFO Avg. Demand Fill Rate* columns show the percentage of the rescued donations and average demand fulfillment in the existing system. The *FIFO Service* column gives the total number of food banks that is served at least once in the existing system. The *Collaboration Monetary Gain* column simply provides the best objective function value observed for this instance in Case Study 1 (warm-up). In the following columns, similar to FIFO columns, the same outputs of the collaboration system are provided. In the last column, the monetary gain from the collaboration system and the rescue gain from the existing system are compared. If the collaboration system yields more monetary gain for an instance, then the outcome is shown with "True" otherwise with "False".

Table J.1: FIFO Analysis: Small-sized instances

Instance	FIFO Rescue Gain (TRY)	FIFO Amount Rescued	FIFO Avg. Demand Fill Rate	FIFO Service	Collab. Monetary Gain (TRY)	Collab. Amount Rescued	Collab. Avg. Demand Fill Rate	Collab. Service	Collab. Out- performs
S_M1W1_5	2088.90	38%	48%	5	3841.35	80%	75%	5	True
S_M1W2_5	2158.90	39%	79%	5	3846.26	100%	85%	5	True
S_M1W3_5	6081.84	52%	77%	5	8370.56	100%	84%	5	True
S_M1W4_5	2236.11	38%	79%	5	2241.26	93%	73%	4	True
S_M2W1_5	5061.16	48%	84%	5	5080.97	100%	83%	5	True
S_M2W2_5	4058.39	42%	70%	5	6366.47	98%	84%	5	True
S_M2W3_5	4870.62	53%	67%	5	9166.54	100%	86%	5	True
S_M2W4_5	2482.36	36%	70%	4	3796.47	93%	80%	4	True
S_M3W1_5	3224.15	52%	69%	4	4105.58	99%	83%	5	True
S_M3W3_5	5338.47	50%	81%	5	8850.46	100%	90%	5	True
S_M3W4_5	2731.79	41%	82%	5	3720.75	100%	86%	5	True
S_M3W5_5	5077.54	51%	88%	5	4940.42	100%	88%	5	False
S_M4W1_5	5549.47	82%	89%	5	5381.97	100%	92%	5	False
S_M5W1_5	1615.84	50%	84%	5	1760.63	92%	78%	4	True
S_M5W2_5	2522.08	82%	96%	5	2053.97	97%	84%	5	False
S_M5W3_5	5746.99	81%	92%	5	5481.53	100%	88%	5	False
S_M6W1_5	4117.52	45%	78%	5	4026.44	92%	69%	5	False
S_M6W3_5	12843.07	49%	95%	5	12699.97	100%	84%	5	False
S_M1W1_10	1125.87	22%	28%	6	3719.04	88%	96%	9	True
S_M1W2_10	1723.29	30%	66%	9	3870.49	86%	99%	9	True
S_M1W3_10	4022.05	34%	58%	7	8153.61	89%	100%	10	True
S_M1W4_10	1662.02	24%	54%	8	2270.10	79%	100%	9	True
S_M2W1_10	4261.53	37%	65%	9	4842.41	80%	97%	9	True
S_M2W2_10	3294.24	30%	54%	8	6248.15	90%	100%	10	True
S_M2W3_10	3519.34	36%	44%	7	8855.14	90%	97%	10	True
S_M2W4_10	1929.97	26%	56%	7	3535.21	80%	89%	10	True
S_M3W1_10	2337.15	37%	54%	8	4232.66	90%	99%	9	True
S_M3W3_10	3514.08	32%	57%	10	8513.57	93%	100%	10	True
S_M3W4_10	2053.12	29%	63%	9	3451.67	86%	97%	9	True
S_M3W5_10	4054.52	36%	66%	8	4880.98	91%	100%	10	True
S_M4W1_10	5002.69	69%	74%	10	5252.64	93%	100%	10	True
S_M5W1_10	1130.85	35%	59%	7	1624.71	79%	99%	9	True
S_M5W2_10	2161.27	73%	78%	9	1929.69	89%	97%	9	False
S_M5W3_10	3730.92	64%	69%	8	5394.10	90%	98%	9	True
S_M6W1_10	3738.97	39%	69%	10	3819.22	73%	92%	9	True
S_M6W3_10	8244.94	31%	59%	9	11702.39	79%	93%	10	True
S_M1W1_15	735.77	16%	19%	7	3586.42	78%	79%	14	True
S_M1W2_15	1294.23	22%	48%	10	3578.99	81%	99%	14	True
S_M1W3_15	3378.80	27%	49%	11	7204.22	85%	89%	13	True
S_M1W4_15	1386.67	18%	40%	9	2079.43	71%	93%	13	True
S_M2W1_15	3542.21	28%	50%	8	4510.65	80%	98%	14	True
S_M2W2_15	2703.02	24%	45%	10	6035.86	91%	99%	14	True
S_M2W3_15	2266.98	24%	30%	8	8671.77	91%	97%	15	True
S_M2W4_15	1416.89	19%	42%	7	3337.09	81%	93%	13	True
S_M3W1_15	1622.20	26%	36%	7	3658.93	92%	100%	14	True
S_M3W3_15	3044.25	28%	52%	14	8242.89	89%	98%	14	True
S_M3W4_15	1574.68	22%	48%	11	3278.50	83%	90%	13	True
S_M3W5_15	3667.94	32%	59%	14	4528.06	77%	92%	13	True
S_M4W1_15	4856.58	67%	72%	14	5087.81	95%	100%	15	True
S_M5W1_15	851.74	27%	42%	7	1605.39	79%	100%	14	True
S_M5W2_15	1555.48	54%	57%	10	1808.68	92%	97%	14	True
S_M5W3_15	4332.05	56%	61%	10	5323.22	93%	100%	14	True
S_M6W1_15	3106.96	31%	54%	12	3468.98	51%	86%	14	True
S_M6W3_15	6982.54	25%	48%	12	11789.11	76%	96%	15	True

Table J.2: FIFO Analysis: Medium-sized instances

Instance	FIFO Rescue Gain (TRY)	FIFO Amount Rescued	FIFO Avg. Demand Fill Rate	FIFO Service	Collab. Monetary Gain (TRY)	Collab. Amount Rescued	Collab. Avg. Demand Fill Rate	Collab. Service	Collab. Out- performs
M_M3W2_5	7976.61	55%	81%	5	9842.86	100%	80%	5	True
M_M4W2_5	6371.14	58%	99%	5	5841.80	99%	67%	5	False
M_M4W3_5	6156.91	44%	85%	5	5891.78	98%	39%	4	False
M_M4W4_5	8254.96	90%	97%	5	7759.18	100%	90%	5	False
M_M5W4_5	10147.39	54%	96%	5	9693.31	100%	72%	5	False
M_M5W5_5	7831.53	57%	91%	5	7197.61	96%	78%	4	False
M_M6W2_5	4368.42	35%	81%	5	4369.30	95%	62%	4	True
M_M6W4_5	17517.00	41%	84%	5	17978.17	94%	51%	5	True
M_M7W1_5	19885.45	46%	78%	5	23165.97	99%	65%	5	True
M_M7W2_5	20501.02	53%	81%	5	26004.70	99%	77%	5	True
M_M7W3_5	18071.69	53%	87%	5	19954.11	99%	83%	5	True
M_M7W4_5	30223.92	49%	73%	5	41442.89	98%	83%	5	True
M_M8W2_5	31546.91	48%	81%	5	35919.74	100%	78%	5	True
M_M8W4_5	32839.33	48%	93%	5	35511.96	100%	53%	5	True
M_M9W3_5	54060.37	58%	97%	5	52697.98	96%	52%	5	False
M_M10W1_5	40500.97	50%	95%	5	40563.62	99%	74%	5	True
M_M10W3_5	60616.67	64%	89%	5	58423.50	87%	61%	5	False
M_M12W3_5	19295.00	49%	90%	5	19887.19	98%	79%	5	True
M_M3W2_10	5961.73	40%	70%	10	9408.22	85%	99%	9	True
M_M4W2_10	5948.67	46%	87%	10	5472.17	63%	100%	9	False
M_M4W3_10	5984.66	72%	84%	9	5563.75	83%	97%	9	False
M_M4W4_10	7219.54	75%	81%	10	7381.22	92%	100%	10	True
M_M5W4_10	7822.64	38%	74%	10	9054.50	71%	98%	10	True
M_M5W5_10	7003.32	43%	73%	10	6693.89	46%	93%	9	False
M_M6W2_10	3716.93	26%	61%	9	3907.70	45%	91%	9	True
M_M6W4_10	13010.27	30%	63%	10	17547.78	77%	98%	10	True
M_M7W1_10	16955.16	36%	65%	10	22685.24	63%	98%	10	True
M_M7W2_10	13249.29	34%	49%	10	24533.45	85%	98%	10	True
M_M7W3_10	14982.43	40%	63%	10	19812.56	77%	98%	9	True
M_M7W4_10	22770.06	36%	52%	10	39503.69	83%	96%	10	True
M_M8W2_10	28320.16	38%	65%	10	36034.48	86%	100%	9	True
M_M8W4_10	28829.54	36%	66%	10	35122.27	61%	100%	10	True
M_M9W3_10	46538.97	43%	83%	10	51699.27	56%	96%	10	True
M_M10W1_10	37544.86	42%	84%	10	39532.55	82%	97%	10	True
M_M10W3_10	54515.71	47%	73%	10	58636.43	54%	89%	9	True
M_M12W3_10	14935.23	35%	69%	10	19201.42	77%	97%	10	True
M_M3W2_15	4795.46	30%	53%	14	9349.29	87%	100%	15	True
M_M4W2_15	5377.63	40%	75%	14	5174.55	56%	97%	13	False
M_M4W3_15	5253.73	41%	71%	12	5468.30	86%	96%	13	True
M_M4W4_15	6150.03	66%	72%	14	7278.19	91%	98%	14	True
M_M5W4_15	6763.69	31%	63%	15	8760.22	59%	95%	14	True
M_M5W5_15	6762.57	38%	68%	15	6412.82	61%	98%	15	False
M_M6W2_15	3533.47	23%	59%	11	3700.99	44%	88%	14	True
M_M6W4_15	12604.07	26%	57%	15	17682.99	58%	94%	15	True
M_M7W1_15	14730.03	28%	54%	14	22393.54	67%	98%	15	True
M_M7W2_15	11708.38	27%	44%	14	24430.78	78%	98%	15	True
M_M7W3_15	13896.49	33%	56%	14	19358.90	81%	97%	15	True
M_M7W4_15	19686.61	30%	44%	14	38599.34	80%	91%	15	True
M_M8W2_15	25044.26	31%	52%	15	35198.04	87%	99%	15	True
M_M8W4_15	24749.49	27%	48%	12	34812.15	59%	100%	14	True
M_M9W3_15	47477.35	41%	81%	15	51124.84	58%	97%	14	True
M_M10W1_15	36243.50	35%	77%	15	39114.35	85%	98%	15	True
M_M10W3_15	52102.98	41%	69%	14	57969.78	56%	87%	12	True
M_M12W3_15	14784.18	31%	70%	14	18959.71	77%	98%	15	True

Table J.3: FIFO Analysis: Large-sized instances

Instance	FIFO Rescue Gain (TRY)	FIFO Amount Rescued	FIFO Avg. Demand Fill Rate	FIFO Service	Collab. Monetary Gain (TRY)	Collab. Amount Rescued	Collab. Avg. Demand Fill Rate	Collab. Service	Collab. Out- performs
L_M8W1_10	30673.55	39%	72%	10	36546.45	84%	100%	10	True
L_M8W3_10	31342.78	33%	52%	10	43516.11	79%	95%	10	True
L_M9W1_10	40036.41	32%	44%	10	54901.11	78%	100%	10	True
L_M9W2_10	34056.82	50%	70%	10	45445.01	83%	99%	10	True
L_M9W4_10	77285.71	43%	77%	10	79735.42	70%	86%	8	True
L_M10W2_10	52160.97	20%	43%	10	70288.54	56%	77%	10	True
L_M10W4_10	43300.92	44%	99%	10	41934.36	40%	100%	9	False
L_M10W5_10	52526.66	39%	79%	10	61297.94	71%	98%	10	True
L_M11W1_10	29978.05	42%	90%	10	31276.19	54%	98%	10	True
L_M11W2_10	42514.35	40%	89%	10	44963.72	50%	98%	10	True
L_M11W3_10	38340.56	40%	76%	10	47247.86	72%	99%	10	True
L_M11W4_10	44700.45	38%	72%	10	64379.92	78%	96%	10	True
L_M12W1_10	20914.88	33%	77%	10	27049.96	69%	98%	10	True
L_M12W2_10	17356.37	42%	72%	10	19990.63	70%	96%	10	True
L_M8W1_15	26089.29	36%	62%	14	35984.03	86%	98%	15	True
L_M8W3_15	29216.41	26%	44%	15	44016.38	67%	97%	14	True
L_M9W1_15	38621.76	31%	39%	15	51490.05	79%	89%	14	True
L_M9W2_15	32020.55	44%	65%	14	44174.61	85%	99%	15	True
L_M9W4_15	71875.32	37%	65%	15	78754.71	66%	84%	13	True
L_M10W2_15	49895.08	18%	37%	15	67808.01	52%	74%	14	True
L_M10W4_15	38486.79	39%	82%	14	41122.80	42%	100%	14	True
L_M10W5_15	46998.41	30%	68%	15	59463.09	61%	95%	14	True
L_M11W1_15	29668.07	38%	88%	15	30737.87	57%	98%	15	True
L_M11W2_15	41376.97	35%	83%	15	44478.43	44%	98%	15	True
L_M11W3_15	35322.38	37%	64%	15	43736.86	63%	93%	15	True
L_M11W4_15	42432.62	35%	71%	15	64173.80	82%	97%	15	True
L_M12W1_15	17704.95	28%	65%	15	26680.01	70%	99%	15	True
L_M12W2_15	15961.30	35%	67%	14	19795.68	77%	98%	14	True