

NETWORK OPTIMIZATION MODELS WITH FAIRNESS CONCERN FOR
DISASTER RELIEF OPERATIONS

by

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Submitted to the Institute for Graduate Studies in
Science and Engineering in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy

Graduate Program in Industrial Engineering
Boğaziçi University

2019

ACKNOWLEDGEMENTS

First of all, I would like to express my deepest gratitude to Prof. Ümit Bilge for her endless support, patience and guidance throughout my entire graduate study, and I feel myself lucky to have the opportunity to work with her. This work would not be completed without her critical interventions that prevented me from getting lost during this study.

Besides my supervisor, I am grateful to Prof. Z. Caner Taşkın and Prof. F. Sibel Salman for taking part in my thesis committee, and for their insightful comments and encouragements throughout this work. I also would like to thank Prof. Necati Aras and Assoc. Prof. Dilek Tüzün Aksu for being part of my thesis committee and for their comments, and Prof. İ. Kuban Altınel for welcoming me whenever I have questions.

I wish to thank all my friends, and the former and current members of BUFAIM team for their unignorable support and friendship. I want to thank Erinç and Umut for their guidance, and my colleagues Mert, Bahadır, Gökçe and Kübra for the great times we spent together in BUFAIM.

I do not think I will be able to find correct words to express my gratitude to my family. I would like to thank my brother for his support on any issue without hesitation, and being a friend to me. I thank my mother for her unlimited trust and encouragement, and my father for giving me the perspective whenever I feel doubtful about my decisions. Life would be much harder if I did not have their love and support, and I am indebted to my family for making me the person who I am today.

This work is supported by Boğaziçi University Research Fund Grant Number 12042. I also thank TUBITAK for their financial support during my doctoral studies under BİDEB-2211 programme.

ABSTRACT

NETWORK OPTIMIZATION MODELS WITH FAIRNESS CONCERN FOR DISASTER RELIEF OPERATIONS

Humanitarian logistics activities, which aim to alleviate the suffering of the population after a sudden and calamitous event, confront us with a large number of interrelated and challenging network optimization problems. This study focuses on the preparedness and response stages of the disaster life-cycle. Humanitarian network design decisions are of critical importance since they set the frame for all further post-disaster operations. Having an adequate number of strategically located storage and distribution centers for supplies is the key that enables effectiveness, efficiency and fairness when responding to a disaster. The preparedness model proposed in this study aims to find a robust relief network design that ensures the right mix of relief items can be supplied at the right time, and satisfies the demand for all given disaster scenarios. We propose a logic-based Benders decomposition approach to solve this problem to optimality. The numerical studies demonstrate that it is possible to obtain optimal or very good solutions to instances with realistic sizes for this NP-hard problem. After disaster occurrence, it is critical to have a relief distribution plan that is efficient and effective while being equitable among the beneficiaries. For this purpose, a rich vehicle routing model along with alternative linear objective functions is presented in the second stage of the study. These objectives provide a balance between timely and fair response plans. Two heuristic methods are presented for the response stage problem. Although solution quality is comparable to the solver in smaller sized problem instances, the heuristic methods provide robust solution methods since they are able to find solutions for larger cases where the solver fails. The assumptions and the parameters used in the models are justified by authorities of humanitarian organizations. The benefit of using these two complementary models consecutively to achieve a better response is also demonstrated.

ÖZET

AFET YARDIMINDA ADİLLİK ÖNGÖREN AĞ ENİYİLEME MODELLERİ

Bir afet sonrasında etkilenen nüfusun acısını hafifletmeyi amaçlayan insani yardım lojistiği faaliyetleri birçok zor ve birbirleriyle ilintili ağ eniyileme problemleri ortaya çıkarır. Bu çalışmada, afete hazırlık ve müdahale aşamaları üzerinde çalışmalar yapılmıştır. Hazırlık aşamasındaki ağ tasarımı tüm afet sonrası aşamaların çerçevesini de belirlediği için kritik bir önemdedir. Yeterli sayıda ve stratejik olarak yerleri belirlenmiş depo ve dağıtım merkezleri verimli, etkin ve adil bir afet müdahalesini sağlar. Bu çalışmada önerilen hazırlık modeli, yardım malzemelerinin doğru zamanda tedarik edilmesini sağlayan, tüm afet senaryolarında talebi karşılayan ve müdahale sırasında daha iyi bir dağıtım sağlanmasına yardımcı olan gürbüz bir ağ tasarımı hedefler. Bu problem için mantık tabanlı Benders ayrıştırması kullanan bir kesin çözüm yöntemi önerilmiştir. Sayısal deneyler bu NP-zor problemin gerçekçi boyuttaki test örnekleri için kesin ya da çok iyi çözümlere ulaşılabildiğini göstermiştir. Afet sonrasında yardım dağıtım planı hazırlanmasında verimli ve etkin olunurken aynı zamanda etkilenen nüfus arasında adil olunması da önemlidir. Bu amaçla, müdahale aşaması için farklı doğrusal amaç fonksiyonları ile çalışan bir zengin araç rotalama modeli sunulmaktadır. Bu amaç fonksiyonları zamanında ve adil bir dağıtım arasında denge kurmayı amaçlarlar. Müdahale aşaması probleminin çözümü için iki metasezgisel yöntem önerilmiştir. Küçük boyutlu test örneklerinde çözüm kalitesi benzer olsa da, daha büyük problemlerde çözücü yazılımının olurlu bir çözüm bulamaması nedeniyle metasezgisel yöntemler daha gürbüz yöntemler olarak öne çıkmaktadır. Önerilen modellerin varsayım ve parametreleri afet yönetimi konusunda çalışan uzmanlar tarafından doğrulanmıştır. Ayrıca, birbirini tamamlayan bu iki modelin ardışık olarak kullanılmasıyla daha iyi bir müdahale planı elde edilebileceği gösterilmiştir.

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LIST OF SYMBOLS

A	Set of arcs
a_p	Parameter value that defines the slope of the linear constraint in p^{th} segment
B_{vnt}	Binary indicator of vehicle v that starts at node n at time t
b_p	Parameter value that defines the intercept of the linear constraint in p^{th} segment
c_{jt}	Fixed cost of PF at location j of size t
c_v	Capacity of vehicle v , in number of items
$coolCoe\!f$	Cooling coefficient
d_{ml}^s	Demand of point m for item l under scenario s
D_{ijt}	Difference between the satisfaction levels of TF i and TF j at time t
d_{it}	Demand generated at TF i at time t
D_t	The minimum satisfaction level among all TFs at time t
d_i	Total demand generated at TF i through the planning horizon
$destroyProb$	Destroy probability parameter
E_i	Amount of unsatisfied items for TF i at the end of the planning horizon
$F(S)$	Objective function value of solution S
F_{jil}^s	Amount of item l transported from PF j to TF i under scenario s
F_{it}	The disutility of TF i in time t
G_{vnt}	Binary variable indicating if vehicle v finishes its service at node n at time t
H_{jl}	Prepositioned inventory amount of item l at PF j
H_{jt}	Remaining amount of inventory at PF j at the beginning of time t
h_l	Acquisition, expected inventory holding and wastage costs cost of item l
I	Set of temporary facility (TF) locations
I'_{sm}	Set of equidistant TFs for a demand point $m \in M'_s$

I_m	Set of TFs that are close enough to serve demand point m
I_v	List of TFs that vehicle v is allowed to visit
$initTlim$	Initialization time limit for <i>SA-ALNS</i>
J	Set of permanent facility (PF) locations
J_i^k	Set of PFs that can serve TF i within SCW k
K	Set of service coverage windows
K_t^P	Capacity of a PF of size t
K_i^T	Capacity of the TF at location i
K'_{si}	Remaining capacity of TF i after assigning the demand points that have unique closest TF
K_v	Set of available visiting slots for vehicle v
L	Set of items
M	Set of demand points that are affected in any one of the scenarios
M_s	Set of demand points under disaster scenario s
M'_s	Set of demand points having alternative closest available TFs
$\widetilde{M}_{is}$	Set of demand points that must be assigned to available TF i due to closest assignment property under scenario s
N	Set of all nodes
P_{it}	The percentage of the satisfied cumulative demand in TF i at time t
$P_1(s)$	Set of TFs whose capacity is violated under scenario s
$P_2(s, i)$	Set of previously closed TF locations which are closer to at least one demand point assigned to TF i in scenario s
Q_{it}	Binary auxiliary variable indicating if the cumulative amount carried to TF i up to time t is larger than the cumulative demand requirement
$\widetilde{Q}_{mis}$	Set of TF points that demand point m can be assigned to under scenario s , but farther to m than TF i
R	The maximum disutility among TFs
r_{kl}	Proportion of demand for item l to be satisfied within service coverage window k
R_1	The maximum disutility among TFs

R_2	The minimum disutility among TFs
S	Set of scenarios
s_j	Amount of items initially held at PF j
$scoreG$	Score incrementation for encountering global best solution in <i>SA-ALNS</i>
$scoreI$	Score incrementation for encountering improving solution in <i>SA-ALNS</i>
$scoreSmooth$	Score smoothing parameter for <i>SA-ALNS</i>
$scoreW$	Score incrementation for encountering accepted worsening in <i>SA-ALNS</i>
T	Set of time segments
T^P	Set of PF sizes
T_{iter}	Temperature in iteration $iter$
$tilim$	Time limit for <i>SA-ALNS</i>
U_i	Approximated logarithm of the utility of TF i
u_l	Capacity consumption of item l
V	Set of vehicles
X_{im}^s	Binary variable indicating clustering decisions, i.e. if demand point m is assigned to TF i for scenario s
X_{vnk}	Binary variable indicating if node n is k^{th} in the sequence of vehicle v
$X_{vnm t}$	Binary variable indicating if vehicle v that traveled on arc (n, m) arrived to node m at time t
Y_i^s	Binary variable indicating if TF i is opened under scenario s
Y_{vjk}	Amount of items collected by vehicle v from PF j that is k^{th} in the sequence
$Y_{vnm t}$	Amount of items carried on vehicle v that traveled on arc (n, m) arrived to node m at time t
y_i	Utility of beneficiary i
Z_{jt}	Binary variable indicating if PF j of size t is opened
Z_{vik}	Amount of items satisfied by vehicle v at TF i that is k^{th} in the sequence
Z_{vit}	Amount of items satisfied at TF i by vehicle v at time t

α	Trade-off parameter to adjust the emphasis on fairness and effectiveness
β	Initial objective multiplier for temperature calculation
δ_{im}	Distance between TF i and demand point m
γ	Acceptance probability of a solution with β times worse objective in the first iteration
ϕ_j^r	Values of the extreme ray for ϕ_j variables
ϕ_j	Dual variables corresponding to inventory limit constraints in FDSP
τ_{nm}	Number of time segments it takes to travel on arc $(n, m) \in A$
$\tilde{\tau}_{nm}$	Shortest distance between nodes n and m
θ_{ik}^r	Values of the extreme ray for θ_{ik} variables
θ_{ik}	Dual variables corresponding to SCW constraints in FDSP

LIST OF ACRONYMS/ABBREVIATIONS

2SS	Two stage stochastic
AFAD	Republic of Turkey Disaster and Emergency Management Authority
AKOM	Disaster Coordination Center of İstanbul Metropolitan Municipality
ALNS	Adaptive large neighborhood search
CF	Cluster-first
CLFDIP	Clustering-location-flow distribution-inventory prepositioning problem
CSP	Clustering sub-problem
CVaR	Conditional-value-at-risk
CVRP	Capacitated vehicle routing problem
DFDSP	Dual of flow distribution sub-problem
FDSP	Flow distribution sub-problem
FEMA	Federal Emergency Management Agency
FSGH	Feasible sequence generation heuristic
HVRPM	Heterogeneous fleet vehicle routing problem with multiple use of vehicles
IFRC	International Federations of the Red Cross and Red Crescent Societies
JICA	Japan International Cooperation Agency
KOERI	Boğaziçi University Kandilli Observatory and Earthquake Research Institute
KP	Knapsack Problem
KPC	Knapsack Problem Complement
LBBD	Logic-based Benders decomposition
LIPMP	Location and inventory prepositioning master problem
LNS	Large neighborhood search
MDVRP	Multiple Depots vehicle routing problem
MIP	Mixed integer program

OVRP	Open vehicle routing problem
PF	Permanent facility
POF	Price of fairness
SA	Simulated annealing
SCW	Service coverage window
SDVRP	Split delivery vehicle routing problem
TF	Temporary facility
VRP	Vehicle routing problem
VRPRB	Vehicle routing problem with route balancing

1. INTRODUCTION

The International Federation of the Red Cross and Red Crescent Societies (IFRC) defines a disaster as “a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community’s or society’s ability to cope using its own resources.” As pointed out by Altay and Green (2006), the daily response resources of ambulance, police or fire departments are inadequate and a humanitarian relief logistics network needs to be designed and operated for effective response in such calamitous events. Humanitarian logistics is defined as the activities of planning, implementing and controlling the storage and flow of goods and information between the origin and consumption point, with the goal of satisfying the needs of beneficiaries (Thomas and Mizushima, 2005).

Activities for managing humanitarian relief chains are generally classified based on the following disaster life-cycle stages: mitigation, preparedness, response, and recovery (Green, 2002; Waugh, 2000; Godschalk, 1991; Waugh and Hy, 1990). The definitions of these stages and some typical activities associated with them are given below (Altay and Green, 2006):

- *Mitigation*: The activities that are performed in order to prevent the outbreak of a disaster or to reduce the impact that would occur. Constructing barriers to avert disaster forces, policies to impose insurance to lessen the financial impacts, defining active preventive measures to control onsetting situations and controlling rebuilding after events can be given as examples of mitigation activities.
- *Preparedness*: The actions that prepare the community to react when a disaster occurs. Emergency planning, public education, building warehouses and prepositioning emergency supplies, constructing operation centers and recruiting emergency service personnel are some of the preparedness activities.
- *Response*: The utilization of the resources and the emergency plans to protect lives, properties, the environment, and the socio-economical integrity of the com-

munity. Activating emergency operations centers and plans, distributing relief items, evacuating the affected people, providing shelters and providing medical care are some examples of the activities in the response stage.

- *Recovery*: The activities performed after the immediate effects of the disaster are eased, and aim to restore the normal state of the community in the long run. Cleaning up debris, rebuilding infrastructure, providing financial assistance to individuals are some activities performed in the recovery stage.

In this study, we focus on the preparedness and response stages of the disaster life-cycle. At first, we propose a mathematical model to design a humanitarian logistic network that will be used to distribute relief items to those in need. Then in the second part of the study, a model and alternative objective functions are offered to distribute the goods when a disaster occurs. Then finally the importance of relating the pre- and post-disaster decisions is discussed. The following sections provide more detail on the motivation of the dissertation, and the structure of the manuscript.

1.1. Motivation

There are several fundamental differences between business supply chains and humanitarian relief chains (Van Wassenhove, 2006; Holguín-Veras *et al.*, 2007). The unpredictable and sudden occurrence of demand, and the high importance of timely and sufficient delivery of emergency supplies are unique characteristics that bring additional complexity to humanitarian relief chains (Kovács and Spens, 2007; Balcik and Beamon, 2008). Holguín-Veras *et al.* (2012) point out that most of the models offered for humanitarian logistics are extensions of those built for business supply chains and therefore do not fully account for the particular challenges in humanitarian operations. They underline that operational costs are of secondary importance for humanitarian logistics and that the main concern is on the social welfare associated with victims' access to critical commodities.

It should be noted that while maximizing the overall social benefit, ensuring fairness among those in need is also crucial. Tomasini and Van Wassenhove (2009) state

that, apart from operational costs, delivery time and quality are common indicators of efficiency and effectiveness. However, these quantitative metrics alone fail to provide a complete picture of the humanitarian problem, so ways to quantify qualitative (e.g. socio-political) indicators are required. In other words, effectiveness, efficiency and equity should all be pursued by humanitarian logistics models. Effectiveness ensures that needs are met in a sufficient and timely manner; efficiency avoids the wasting of scarce resources and ensures that aid can be supplied to a greater number; and equity stipulates that all beneficiaries receive comparable service (Savas, 1978; Beamon and Balcik, 2008; Berenguer, 2016).

The ad hoc nature of a typical disaster—as opposed to the repetitive and continuous nature of commercial logistics functions—renders planning based on expected behavior inadequate and, in most cases, not viable. Therefore, looking for robust decisions that perform well across a range of scenarios is more appropriate for disaster relief operations (Noyan, 2012). In addition to this, as underlined by Battarra *et al.* (2018) in a recent study, there is no unified approach to obtain scenarios and corresponding probabilities for rare disasters. They point out that even if the same historical data is used, different probabilities can be generated and results can be very sensitive to slight changes in scenario probabilities. Furthermore, the probabilities associated with scenarios, which are usually very small, may lead to instability in mathematical models.

In this study, we target the strategic humanitarian network design and operational relief distribution problems by proposing new mathematical models that address the issues stated above. Network design decisions are of critical importance in humanitarian relief logistics because they set the frame for all further post-disaster operations. Therefore, although we study the preparedness and response stage models in different frameworks, the same mindset to provide a fair and effective relief is pursued. The key that enables effective, efficient and fair response to a disaster situation, is having an adequate number of strategically located storage and distribution centers for critical supplies (food, water, and medicine, among others). Therefore the preparedness model determines locations and inventory levels for these facilities in a way that facilitates the right mix of relief items to be supplied to all beneficiaries at the right time, under

a given set of disaster scenarios. Then the response stage problem is modeled in a level of realistic detail for distributing the items in a timely and fair fashion. To be applicable in practice, the assumptions of the models are validated with the help of humanitarian organizations, and the model parameters are chosen such that they are easily predictable by these authorities.

1.2. Organization

The rest of the manuscript starts with a literature review. Section 2.1 and Section 2.2 summarize the related literature in the preparedness and response stages, each of which are followed by a discussion. Section 2.3 concludes the chapter by briefly outlining the fairness issue and main approaches to handle fairness.

Chapter 3 is dedicated to our studies related with the preparedness stage of disaster relief. The model properties are given, the mathematical model itself is introduced, and the problem complexity is discussed. For this hard problem, an exact solution method is proposed and the details are explained. Finally, experimental results that compare the performance of the proposed solution method to off-the-shelf solvers, and further numerical analyses complete the chapter. The contents related to the preparedness stage are published recently in the *European Journal of Operational Research* (Erbeyoğlu and Bilge, 2019).

The studies on the response stage are provided in Chapter 4. As before, Chapter 4 starts with a discussion on the properties of the problem, and states the mathematical model. Selection of a suitable objective function for the model is one of the main issues of our study. A set of new objective functions are proposed as well as adapting some objective functions from the literature. We then compare the performances of these objective functions on a set of small problems, and select three of them to continue with the studies. Two matheuristic methods are provided as solution methods and numerical studies to conclude the chapter.

Since the decisions in the preparedness and response stages are interdependent, Chapter 5 is devoted to assess the benefits of considering them together while building the models and solution methods. Thus, further numerical experimentations are provided in Chapter 5. Finally the last chapter, Chapter 6, concludes the study and points out some possible future research directions.

2. LITERATURE REVIEW

The number of studies published in the area of humanitarian logistics has an increasing trend and there are many studies that approach the problem from different aspects. Among the studies reviewing the relevant literature, Altay and Green (2006) classify the studies mainly based on disaster life-cycle stages. Later, Galindo and Batta (2013a) evaluate the progress in the area as a continuation of the review of Altay and Green (2006). Caunhye *et al.* (2012) review optimization models in humanitarian logistics, where studies are mainly categorized as facility location and relief distribution models. More recently, Anaya-Arenas *et al.* (2014) and Habib *et al.* (2016) discuss the model characteristics in depth in their surveys. Their systematic reviews give details on model characteristics such as objective functions, decisions, uncertainties and solution methods. Özdamar and Ertem (2015) focus on the response and recovery phases of the disaster life-cycle. Balcik *et al.* (2016) present a survey on inventory planning in humanitarian logistics models. Hoyos *et al.* (2015) focus on stochastic modes, and Gutjahr and Nolz (2016) review the literature on multi-objective optimization in humanitarian logistics models. Ertem *et al.* (2017) survey the intermodal freight transportation in disaster relief, and Trivedi and Singh (2018) provide a review focusing on facility location decisions. In the following sections, we summarize some of the studies in preparedness and response stages, and provide a discussion that motivates our work.

2.1. Preparedness Stage¹

The optimization models related to humanitarian relief network design may include several decision components. The location decision component (L) indicates the decisions related with opening facilities on the humanitarian supply network. Allocation (A) represents matching of these facilities to other facilities/demand nodes for supplying relief items. When a facility/demand node can be served by more than one facility, the allocation decisions are replaced by flow distribution (FD) decisions, which consider amount of transported items explicitly. Inventory prepositioning (IP) decisions

¹This section appears in Erbeyoğlu and Bilge (2019) as a part of its content.

consider the amount of items stocked in facilities before the disaster occurrence. The clustering (C) decision component deals with grouping the individual demand points (e.g. buildings) to obtain aggregated demand nodes of the supply network. Table 2.1 gives a broad summary for the preparedness stage models reviewed in this study in terms of their main decision components, optimization types, objective function components, uncertainty type, demand satisfaction approaches, and equity aspects. The abbreviations used in the table are explained under the table.

Table 2.1 organizes the reviewed studies first by their main decision components, then by their optimization approaches where relevant, and then by their year of publication within a group. Our discussion herein generally keeps to this order as well. The studies that focus on location of facilities and direct assignment of demand points to opened facilities (L/A), use mostly deterministic MIP models that derive from p-median, p-center or covering problems (Drezner *et al.*, 2006; Jia *et al.*, 2007; Ukkusuri and Yushimito, 2008; Horner and Widener, 2011). More recently, Salman and Yücel (2015) study emergency facility location problem where the network arcs are subject to failures. Mostajabdaveh *et al.* (2019) provide another location model where ex-ante and ex-post equity decisions (inequity in the expected outcome and expected inequity of the possible outcomes) are combined with efficiency in their objective function.

In most of the studies, the demand points are assumed to be already clustered and given as an input to the problem, thus reducing the number of echelons considered in the problem. Among the papers that consider clustering as a distinct echelon, Görmez *et al.* (2011) and Chang *et al.* (2007) decompose the problem in two separate stages. They provide a model to cluster the demand points first; then, another model to solve the actual problem. Horner and Downs (2010), Li *et al.* (2011), Kılıcı *et al.* (2015), Chapman and Mitchell (2018), Üster and Dalal (2017), Dalal and Üster (2017), Noham and Tzur (2018), and Kınay *et al.* (2018) integrate the clustering decisions in their models. Kılıcı *et al.* (2015), Chapman and Mitchell (2018) and Kınay *et al.* (2018) consider only C/L decisions. Unlike other studies Kılıcı *et al.* (2015), and Kınay *et al.* (2018), which is a stochastic extension of the former, consider dissimilar candidate locations for shelter areas. The inventory prepositioning decisions are considered only

Table 2.1. Overview of studies on disaster logistic network design.

	Decisions	Optimization Type	Objectives	Uncertainty	Demand Satisfaction	Equity Aspect
Drezner <i>et al.</i> (2006)	L/A	Det/MINLP	(MO) Cov/D/E	-	Uncapacitated facilities	Variance in distance
Jia <i>et al.</i> (2007)	L/A	Det/MIP	Cov and D	-	Uncapacitated facilities	-
Ukkusuri and Yushimito (2008)	L/A	Det/MIP	R	AF	Uncapacitated facilities	-
Horner and Widener (2011)	L/A	Det/MIP	Cost	-	No shortage	Closest assignment
Salman and Yücel (2015)	L/A	Stoc/MIP	Cov	AF	Uncapacitated facilities	Distance limit
Mostajabdaveh <i>et al.</i> (2019)	L/A	Stoc/MIP	D/E	Sc	Chance constraint	Gini's mean absolute difference on distances
Chang <i>et al.</i> (2007)	C and L/FD/IP	Stoc/MIP and 2SS/MIP	D and Cost	Sc	Penalty cost	-
Horner and Downs (2010)	C/L/FD	Det/MIP	Cost	-	No shortage	-
Görmez <i>et al.</i> (2011)	C and L/A	Det/MIP	D and (MO) D/NF	-	No shortage	-
Li <i>et al.</i> (2011)	C/L/FD/IP	2SS/MIP	Cost	Sc	Penalty cost	-
Kılıcı <i>et al.</i> (2015)	C/L	Det/MIP	P	-	No shortage	Shelter utilization difference limit, distance limit, closest assignment
Chapman and Mitchell (2018)	C/L	Det/MINLP	Cost	-	No shortage	Non-linear walking cost, CVaR of walking costs
Üster and Dalal (2017)	C/L/FD	Det/MIP	(MO) D/Cost	-	No shortage	Minmax distance
Dalal and Üster (2017)	C/L/FD	2SS/Rob/MIP	(MO) D/Cost	Sc	Penalty cost	Minmax distance

Table 2.1. Overview of studies on disaster logistic network design. (cont.)

	Decisions	Optimization Type	Objectives	Uncertainty	Demand Satisfaction	Equity Aspect
Noham and Tzur (2018)	C/L/A	Stoc/MINLP	AoRT	Sc	Limited by equality constraint	Closest assignment, satisfaction difference limit
Kinay <i>et al.</i> (2018)	C/L	Stoc/MIP	P	Cont	Chance constraint	Closest assignment
Balcik and Beamon (2008)	L/FD/IP	Stoc/MIP	Cov	Sc	Maximize coverage	-
Duran <i>et al.</i> (2011)	L/FD/IP	Stoc/MIP	T	Sc	No shortage	-
Galindo and Batta (2013b)	L/FD/IP	Stoc/MIP	Cost	DP	No shortage on expected demand	-
Barzinpour and Esmaili (2014)	L/FD/IP	Det/MIP	(MO) Cov/Cost	-	Penalty cost	-
Renkli and Duran (2015)	L/FD/IP	Stoc/MIP	D	AF	No shortage	Distance limit
Paul and MacDonald (2016)	L/IP	Stoc/MINLP	Cost	Cont	Penalty cost of fatalities	-
Mete and Zabinsky (2010)	L/FD/IP	2SS/MIP	Cost	Sc	Penalty cost	-
Rawls and Turnquist (2010)	L/FD/IP	2SS/MIP	Cost	Sc	Penalty cost	-
Rawls and Turnquist (2011)	L/FD/IP	2SS/MIP	Cost	Sc	Penalty cost	-
Rawls and Turnquist (2012)	L/FD/IP	2SS/MIP	Cost	Sc	Penalty cost	-
Döyen <i>et al.</i> (2012)	L/FD/IP	2SS/MIP	Cost	Sc	Penalty cost	Distance limit
Hong <i>et al.</i> (2015)	L/FD/IP	2SS/MIP	Cost	Sc	Chance constraint	Same reliability level for all regions
Pradhananga <i>et al.</i> (2016)	L/FD/IP	2SS/MIP	Cost	Sc	Non-linear penalty cost	Exponentially increasing deprivation cost
Tofghi <i>et al.</i> (2016)	L/FD/IP	2SS/MIP	(MO) Cost/T	Sc	Penalty cost	Minmax weighted travel time
Mohammadi <i>et al.</i> (2016)	L/FD/IP	2SS/MIP	(MO) Cov/Cost/E	Sc	Maximize coverage	Minmax satisfaction difference

Table 2.1. Overview of studies on disaster logistic network design. (cont.)

	Decisions	Optimization Type	Objectives	Uncertainty	Demand Satisfaction	Equity Aspect
Noyan (2012)	L/FD/IP	2SS/Rob/MIP	Cost	Sc	Penalty cost	-
Bozorgi-Amiri <i>et al.</i> (2012)	L/FD/IP	2SS/Rob/MIP	Cost	Sc	Penalty cost	-
Bozorgi-Amiri <i>et al.</i> (2013)	L/FD/IP	2SS/Rob/MIP	(MO) Cost/S	Sc	Penalty cost	Maxmin satisfaction
Rezaei-Malek <i>et al.</i> (2016)	L/FD/IP	2SS/Rob/MIP	(MO) T/Cost	Sc	Penalty cost	Demand point penalty difference limit
Elçi and Noyan (2018)	L/FD/IP	2SS/Rob/MIP	Cost	Sc	No shortage, or penalty cost and chance constraint	Distance limit
Arnette and Zobel (2019)	IP	Det/MIP	Risk	-	Risk minimization	Coverage limit or minmax risk
<i>This study</i>	C/L/FD/IP	Rob/MIP	Cost	Sc	No shortage	Distance limit, closest assignment, service coverage windows

L:Location, A:Allocation, C:Clustering, FD:Flow Distribution, IP:Inventory Prepositioning, Det:Deterministic, Stoc:Stochastic, Rob:Robust

2SS:Two stage stochastic, MO:Multi-objective, Cov:Coverage, D:Distance, T:Time, E:Equity, R:Reliability, S:Satisfaction, AoRT:Amount over Response Time

NF:Number of Facilities, P:Preference, AF:Arc Failure, DP:Destruction Probability, Sc:Scenario, Cont:Continuous Distribution

by Chang *et al.* (2007) and Li *et al.* (2011) within this group of studies.

The majority of the literature consists of the problems where facility location, flow distribution and inventory prepositioning decisions are made (L/FD/IP). Balcik and Beamon (2008), Duran *et al.* (2011), and Renkli and Duran (2015) study stochastic models where the objectives are maximization of distance-based coverage, minimization of time and minimization of distance, respectively. Unlike others, Paul and MacDonald (2016) focus only on the facility location and item preposition aspects, and minimize total cost which includes the cost of expected fatalities.

Two stage stochastic (2SS) programming is a mainstream modeling approach for humanitarian relief problems in the preparedness stage (Grass and Fischer, 2016). In 2SS programming, first stage decisions are made before the realization of random parameters. Based on the first stage decisions, second stage recourse variables are determined depending on a realization of the random parameters. Objective function usually minimizes the sum of the first stage and the expected second stage costs. Mete and Zabinsky (2010), Rawls and Turnquist (2010), Rawls and Turnquist (2011), and Rawls and Turnquist (2012) study 2SS programs where the objective is minimization of cost, including the penalty cost for shortage. Among these, Rawls and Turnquist (2012) integrate pre-event planning actions and dynamic distribution decisions, where the demand information evolves over a discrete planning horizon. Döyen *et al.* (2012) make the facility location decisions for regional relief centers in the first stage, and for local relief centers on the second stage. Hong *et al.* (2015) study a chance constrained model to satisfy the demand probabilistically, and enforce the same reliability level for all demand regions. Pradhananga *et al.* (2016) minimize the sum of logistics and deprivation costs of the beneficiaries. Finally, Tofghi *et al.* (2016) and Mohammadi *et al.* (2016) study multi-objective models, where travel time, coverage and equity objectives are considered along with cost minimization.

Noyan (2012) and Elçi and Noyan (2018) argue that the risk neutral approach of 2SS programming and minimization of expected value are justified in the long-run for decisions that are of repetitive nature; however, risk measures should be incorporated

into models for non-repetitive decision making under uncertainty to obtain more robust solutions. Noyan (2012) use the 2SS model of Rawls and Turnquist (2010) as a base, and incorporate conditional-value-at-risk (CVaR) as a risk measure to have risk-averse solutions. Elçi and Noyan (2018) extend this model by enforcing a joint probabilistic constraint on the feasibility of the second-stage problem. There are also studies that incorporate solution and/or model robustness in their 2SS models. Solution robustness aims to have nearly optimal solutions in all scenarios whereas model robustness seeks nearly feasible solution in all scenarios (Mulvey *et al.*, 1995). Bozorgi-Amiri *et al.* (2012), Bozorgi-Amiri *et al.* (2013) and Rezaei-Malek *et al.* (2016) incorporate solution robustness by adding absolute cost variance terms in the objective function along with the expected cost. Rezaei-Malek *et al.* (2016) also use a term that penalizes infeasibilities to incorporate model robustness. Dalal and Üster (2017) consider the worst-case transportation cost among scenarios along with the expected transportation cost.

2.1.1. Discussion

One of the fundamental distinctions regarding business supply chains and humanitarian relief chains lies in the significance of unsatisfied demand. Thus, we will begin our discussion of the literature by discussing how demand is handled in the preparedness models. It can be seen in Table 2.1 that an overwhelming majority of the studies adopts the classical business supply chain approach and allows demand shortages subject to penalty cost. While it is relatively easy to determine quantitative penalty costs associated with not satisfying one unit of demand for different items in scale to operational/fixed costs in the context of a business supply chain, this is an utter challenge in the context of disasters where human suffering is in question. Yet this challenge is hardly considered in many of these studies.

There are a few studies that maximize the total demand covered (Balcik and Beamon, 2008; Mohammadi *et al.*, 2016). Among these, Balcik and Beamon (2008) follow the approach of Berman and Krass (2002) who define coverage level as a decreasing step function of the distance to the closest facility (thus, k coverage levels and coverage radii are defined for each demand node) that they address. Balcik and

Beamon (2008) assign weights to each item type to represent relative criticality and maximize the expected weighted demand coverage over the scenarios. However, each of their scenarios contains a single demand point, thus fairness is not an issue. Murali *et al.* (2012) utilize a similar coverage idea in their response stage model where a single item is distributed. They maximize the total amount distributed, where the amount of supply from a facility to a demand point is limited by a fraction of the requirement of the demand point. This fraction is a decreasing step function of the distance.

In the few studies that enforce demand satisfaction (e.g., Horner and Downs (2010), Görmez *et al.* (2011), Horner and Widener (2011), Chapman and Mitchell (2018), Kılıcı *et al.* (2015) and Üster and Dalal (2017)) the uncertainty aspect of the problem is overlooked. The hybrid risk-averse 2SS model proposed by Elçi and Noyan (2018) can enforce the feasibility of the second-stage problem under each scenario when certain risk parameters are fixed at specific values.

Relying on expected performance is another pervasive approach. Not only using expected values for rare events may result in very poor performance under certain realizations depending on problem parameters (Elçi and Noyan, 2018), but also extrapolating scenario probabilities based on historical observations (as in Balcik and Beamon (2008), Duran *et al.* (2011) and Rezaei-Malek *et al.* (2016)) may become problematic in case of rare events like earthquakes (Battarra *et al.*, 2018). In the few studies that incorporate robustness or risk-averse concepts (Bozorgi-Amiri *et al.*, 2012, 2013; Rezaei-Malek *et al.*, 2016; Noyan, 2012; Dalal and Üster, 2017; Elçi and Noyan, 2018) it is assumed that scenario probabilities are known. As far as we are aware, there are no studies with a robust optimization model that do not need scenario probability information and focus on model robustness where the decisions are feasible—i.e. ensure demand satisfaction—regardless of the scenario realization.

Another important observation is that cost minimization is the most common objective function. In spite of the studies such as Holguín-Veras *et al.* (2012) and Gralla *et al.* (2014) that foster the need to introduce the trade-offs between efficiency, effectiveness and equity into the humanitarian logistics models, studies which put the main concern beyond cost minimization are still relatively sparse, especially in the domain of preparedness stage. Among those which include fairness aspects, some use hard constraints, while others use objective functions for this purpose. Eleven studies among the papers reviewed utilize the first approach. Döyen *et al.* (2012), Kılıcı *et al.* (2015), Renkli and Duran (2015), Salman and Yücel (2015), and Elçi and Noyan (2018) limit the allocation distances whereas Hong *et al.* (2015) ensure that all regions will observe the same reliability level. Kılıcı *et al.* (2015), Rezaei-Malek *et al.* (2016), and Noham and Tzur (2018) constrain the service level differences among beneficiaries and Arnette and Zobel (2019) limit the minimum coverage. Demand points are assigned to the closest available facility in Horner and Widener (2011), Kılıcı *et al.* (2015), Noham and Tzur (2018), and Kinay *et al.* (2018). There are ten studies in the second group which either use multiple objectives or objective function terms to encourage fairness. One of them is by Chapman and Mitchell (2018) who employ non-linear cost of walking distance and a term regarding their disparity in the objective function of their clustering/location model. Holguín-Veras *et al.* (2013) introduced the *deprivation cost*, which increases exponentially with the delivery time of the goods, resulting from a multi-period delivery plan for the post-disaster stage. Pradhananga *et al.* (2016) use deprivation cost in the objective function of their preparedness stage model together with the logistics and pre-disaster costs. In their study, the non-linear deprivation cost coefficients are calculated in a preprocessing step and the solution is sensitive to the parameters of this function. Drezner *et al.* (2006) use minimization of variance in the distance in their multi-objective mixed integer non-linear problem. Bozorgi-Amiri *et al.* (2013) use maximization of the minimum satisfaction level, and Mohammadi *et al.* (2016) use minimization of maximum satisfaction level difference as one of the objectives in their multi-objective models. Üster and Dalal (2017), Dalal and Üster (2017), and Tofghi *et al.* (2016) minimize the maximum distance or time as one of the objectives in their multi-objective approaches. Among these multi-objective

approaches, Mohammadi *et al.* (2016) obtain a pareto front, Üster and Dalal (2017) use ε -constraint method, and the rest use weighted sum of objectives. Mostajabdaveh *et al.* (2019) use an inequity-averse objective function and Arnette and Zobel (2019) minimize maximum risk.

Finally, the majority of the papers rely on a single case study and do not experiment on problem instances of different sizes or different topological characteristics to test the performance of their models and solution techniques.

Our study, which is shown as the last entry in Table 2.1, targets the two echelon C/L/FD/IP problem. The uncertainty in demand is captured by a set of scenarios but the model does not employ any scenario probabilities. The proposed MILP model ensures demand satisfaction under any scenario with minimum preparedness cost. The model assigns people to the closest open facilities and limits maximum walking distance in the first echelon, while recognizing the dependence of coverage level to distance for item distribution in the second echelon. In this way, the resulting relief network implies the existence of an effective and fair post-disaster distribution plan.

2.2. Response Stage

In the response stage of disaster relief operations the main decision component is the routing (R) decisions, where there are studies that consider the vehicles explicitly or aggregated as number of vehicles on arcs. Some studies consider location routing models where the facility opening decisions (L) are made simultaneously. Acquisition of the vehicles (V) and inventory (IP) are also considered in some papers. Moreover there are studies that consider debris removal (DR) without considering the routing of the work crew. Table 2.2 gives a broad summary for the response stage models reviewed in this study in terms of their main decision components, optimization types, objective function components, uncertainty type, and equity aspects. The abbreviations used in the table are explained under the table. Table 2.2 organizes the reviewed studies mainly by their main decision components, and then by their year of publication within a group. Our discussion herein generally keeps to this order as well.

Table 2.2. Overview of studies on disaster response stage.

	Decisions	Optimization Type	Objectives	Uncertainty	Equity Aspect
Barbarosoglu and Arda (2004)	NF	2SS/LP	Cost	Sc	-
Huang <i>et al.</i> (2015)	NF	Det/CQNF	(MO) S/DC/E	-	Sum of squared distance to ideal fill rate
Anaya-Arenas <i>et al.</i> (2018)	NF	Det/MIP	(MO) S/T/E	-	Minmax satisfaction difference, piecewise convex shortage cost function
Aksu and Özdamar (2014)	DR	Det/MIP	TWE	-	-
Özdamar <i>et al.</i> (2014)	DR/R	Det/MINLP	(MO) IA/T	-	-
Sahin <i>et al.</i> (2016)	DR/R	Det/MIP	T	-	Minmax arrival time
Berktaş <i>et al.</i> (2016)	DR/R	Det/MIP	T	-	Minmax arrival time
Kasaei and Salman (2016)	DR/R	Det/MIP	T and PC	-	-
Akbari and Salman (2017a)	DR/R	Det/MIP	T	-	Minmax arrival time
Akbari and Salman (2017b)	DR/R	Det/MIP	PC	-	-
Ajam <i>et al.</i> (2019)	DR/R	Det/MIP	T	-	-
Tzeng <i>et al.</i> (2007)	L/NF	Det/MIP	(MO) Cost/T/S	-	Maximin satisfaction
Salmerón and Apte (2010)	L/NF	2SS/MIP	(MO) NC/S	Sc	-
Afshar and Haghani (2012)	L/R	Det/MIP	S	-	Satisfaction limit
Rath and Gujjahr (2014)	L/R	Det/MIP	(MO) Cost/S	-	-
Tricoire <i>et al.</i> (2012)	L/A/R	2SS/MIP	(MO) Cost/S	Sc	Closest assignment
Ahmadi <i>et al.</i> (2015)	L/R	Det/MIP and 2SS/MIP	(MO) T/Cost	Sc	Latest arrival time limit

Table 2.2. Overview of studies on disaster response stage. (cont.)

	Decisions	Optimization Type	Objectives	Uncertainty	Equity Aspect
Caunhye <i>et al.</i> (2016)	L/R/IP	2SS/MIP	(MO) T/Cost	Sc	-
Alem <i>et al.</i> (2016)	NF/IP/V	2SS/Rob/MIP	Cost and (MO)Cost/Risk	Sc	-
Moreno <i>et al.</i> (2016)	L/NF/V	2SS/MIP	Cost	Sc	-
Moreno <i>et al.</i> (2018)	L/NF/V	2SS/MIP	Cost	Sc	Deprivation cost
Haghani and Oh (1996)	R	Det/MIP	Cost	-	-
De Angelis <i>et al.</i> (2007)	R	Det/MIP	S	-	Satisfaction limit
Yi and Kumar (2007)	R	Det/MIP	S	-	-
Balcik <i>et al.</i> (2008)	R	Det/MIP	Cost	-	Minmax shortage penalty
Özdamar (2011)	R	Det/MIP	T	-	-
Berkoune <i>et al.</i> (2012)	R	Det/MIP	T	-	-
Özdamar and Demir (2012)	R/IP	Det/MIP	T	-	-
Huang <i>et al.</i> (2012)	R	Det/MIP	D and T and E	-	Time weighted convex disutility
Lin <i>et al.</i> (2011)	R	Det/MIP	(MO) S/Cost/E	-	Penalty for maximum absolute satisfaction difference
Lin <i>et al.</i> (2012)	L/R	Det/MIP	Cost	-	Penalty for maximum absolute satisfaction difference, distance limit
Rottkemper <i>et al.</i> (2012)	R	Stoc/MIP	Cost	F	Increasing penalty cost with deprivation length
Battini <i>et al.</i> (2014)	R	Det/MIP	Cost	-	-
Garrido <i>et al.</i> (2015)	R/IP	Stoc/MIP	Cost	CC	-

Table 2.2. Overview of studies on disaster response stage. (cont.)

	Decisions	Optimization Type	Objectives	Uncertainty	Equity Aspect
Pérez-Rodríguez and Holguín-Veras (2015)	R	Det/MINLP	Cost	-	Deprivation cost
Rivera-Royero <i>et al.</i> (2016)	R	Det/MIP	E	-	Deprivation cost
Özdamar <i>et al.</i> (2018)	R	Det/MIP	S	-	-
Penna <i>et al.</i> (2018)	R	Det/MIP	Cost	-	-
Li and Chung (2019)	R	Det/Rob/MIP	(MO) V/T	Sc	Minmax arrival time
<i>This study</i>	R	Det/MIP	Prx	-	Penalties based on satisfaction differences

NF:Network Flow, DR:Debris Removal, R:Routing, L:Location, A:Allocation, IP:Inventory Prepositioning, V:Vehicle Procurement

Det:Deterministic, 2SS:Two stage stochastic, Rob:Robust, CQNF:Convex Quadratic Network Flow, MO:Multi-objective

S:Satisfaction, DC:Delay Cost, E:Equity, T:Time, TWE:Total Weighted Earliness, IA:Inaccessibility, PC:Prize to Collect

NC:Number of Casualties, D:Distance, Prx:Proxy Measure, Sc:Scenario, F:Forecast, CC:Chance Constraint

Barbarosoglu and Arda (2004) give a two-stage stochastic linear program for transportation planning, which is a network flow problem. Huang *et al.* (2015) solve a convex quadratic network flow problem on a time-space network without vehicle consideration. They consider efficiency (delay cost), effectiveness (lifesaving utility) and equality objectives in a multi-objective optimization problem. The importance of fairness in disaster relief is studied by Anaya-Arenas *et al.* (2018) in a recent study. They discuss performance metrics for equity and state that fairness related objectives are still not common. Then a network flow model for periodical deliveries of relief items and three alternative multi-objective functions are proposed. The first one minimizes the sum of shortage penalty and the cost of trips required. The second one includes range objective along with the others. The last objective minimizes the cost of trips, and the penalty of unsatisfied demand which is modeled with a piecewise linear convex disutility function.

There are studies that consider debris removal and/or restoration of arcs on the network after a disaster occurrence to ensure that all beneficiaries are accessible. Aksu and Özdamar (2014) give a tactical model where they decide in which periods which arc will be cleaned without considering the routing of work crews. Özdamar *et al.* (2014) study a similar problem where they minimize inaccessibility and makespan, where inaccessibility is recursively determined depending on the cleaning operations. Sahin *et al.* (2016), Berktaş *et al.* (2016) and Ajam *et al.* (2019) study road clearance operations where a single vehicle needs to visit all critical nodes while opening damaged roads if necessary. Kasaei and Salman (2016) study single vehicle arc routing problem to repair network connectivity. Their first model minimize the total time, whereas the second model maximizes the total collected prize while minimizing the total time as a secondary objective. Akbari and Salman (2017a) and Akbari and Salman (2017b) solve multi-vehicle an arc routing problem to repair network connectivity by removing debris where objectives are makespan minimization and maximizing the total prize collected given a time limit, respectively.

Location decisions are simultaneously considered with routing decisions in some of the studies in the response stage. Tzeng *et al.* (2007) provide multi-period, multi-

commodity, multi-objective relief distribution model that is based on a two tier network structure. Model decides on warehouse locations, and the flow amounts from suppliers to warehouses and from warehouses to demand points at each time period. There are three objective functions as minimizing total cost, minimizing travel time and maximizing the minimum demand satisfaction. They assert that the first two objectives aim for efficiency whereas the last one has a fairness goal. Salmerón and Apte (2010) develop a two stage stochastic model where the first stage deals with capacity expansion decisions and the second stage addresses the network flow on the multiple transportation modes. Apart from models that use general network definitions, Afshar and Haghani (2012) give a model that complies with the complex network structure of Federal Emergency Management Agency (FEMA). They develop the model to handle multiple types of items and multiple modes of transportation. The model decides on the locations of the temporary facilities, flows of items and flows of vehicles explicitly. The single objective minimizes the total amount of weighted unmet demand, while obeying the limit on the maximum number of facilities to be opened. They also define equity constraints to increase fairness by imposing lower limits on satisfaction levels. Rath and Gutjahr (2014) define a location-routing problem network structure there are intermediate warehouses in between the supply and demand points. Decisions are made for selecting a set of depot locations, amounts of items that are shipped, and the tours of vehicles while obeying budget, capacity and driving time limitations. Tricoire *et al.* (2012) extend the maximal covering tour problem. They decide on the opened distribution centers, closest assignment of demand points to distribution centers, tours, and the amount of items carried. Caunhye *et al.* (2016) also propose a two stage stochastic location-routing model, where the location of warehouses and amount of inventories are determined in the first stage, and a homogenous set of vehicles are routed for each scenario in the second stage. Ahmadi *et al.* (2015) study operational multi-depot location-routing problem where local depots are selected and vehicles are assigned to them along with the routing decisions. In the model, they include a limit on the latest arrival time.

Alem *et al.* (2016) propose a two stage stochastic problem where the inventory prepositioning and vehicle procurement decisions are made as well. They consider

minmax regret, CVaR, and semi-deviation as risk measures along with their risk neutral model. Similarly, Moreno *et al.* (2016) study the problem where location of depots and vehicle assignment to them are considered. The set of heterogeneous capacitated vehicle types exist where they transfer relief items in each time bucket. Later Moreno *et al.* (2018) extend this model to consider deprivation cost in their objective function.

Among the studies that consider routing operations, Haghani and Oh (1996) model a multi-commodity, multi-modal network flow problem with time windows where the objective minimizes the total cost of vehicle and item flow, inventory, late delivery and transportation mode change. De Angelis *et al.* (2007) aim to maximize the demand served and considers the detailed constraints of the existing air deliveries of World Food Programme in Angola. They also include a constraint to make sure to satisfy a fraction of the demand of each client for equity. Yi and Kumar (2007) propose a model that focuses on dispatching the items and evacuating wounded people from the affected areas. The multiperiod model keeps track of the flow of items, vehicles, and wounded people on the network. Also, weights on item types and wounded people are assigned to prioritize, and the objective function minimizes the total weighted sum of unsatisfied demand and unserved injured people. Balcik *et al.* (2008) focus on last mile distribution. They define two types of items depending on the nature of demand, and rolling horizon framework suggested to capture the dynamic nature of the problem. In the objective function, the sum of operational costs and penalty cost due to the maximum shortage is minimized. Later, Battini *et al.* (2014) provide a model which is a modified version of the one given by Balcik *et al.* (2008) by disallowing end of planning horizon shortages and incorporating resource capacity. Özdamar (2011) describes a two-step planning system where helicopter logistics in disaster relief is considered. The deterministic model tries to minimize the total time required to complete all tasks, and decides on the deliveries of medical items and the evacuation of the injured people at an aggregate level, obeying helicopter operational limitations. In this way, vehicle, item and injured people flows are obtained and the explicit vehicle routes are generated at the post-processing stage. Berkoune *et al.* (2012) transport multiple types of relief goods using back and forth trips between demand points and depots.

Özdamar and Demir (2012) consider inventory allocation decisions along with the distribution. They define the relief routing problem hierarchically where they first cluster the beneficiaries and solve the network flow problem for the top level. Then the clusters are subdivided further and the result of the top level problem is used as an input. The routes of individual vehicles are not tracked explicitly, but the available vehicles of different types are assigned to arcs. Model handles carrying of commodities and injured people. A study that focuses on flood emergencies is given by Garrido *et al.* (2015) where the flood occurrence is represented by a spatio-temporal stochastic process. They define the demand occurrence probabilistically at every time period, where the severity of the disaster is also a random variable. The model keeps track of the flow of products and vehicles, along with the inventory held at each location at each period, while minimizing the total cost.

The objective function selection in disaster response is an important issue and there exist other important factors than total cost. Huang *et al.* (2012) define three performance metrics for efficiency, efficacy and equity. In their notation, efficiency objective minimizes total travel cost, efficacy minimizes the sum of items' arrival times, and equity deals with capturing the discrepancy in efficiency among demand points. Lin *et al.* (2011) decides on the tours of vehicles and the amount of items satisfied in these tours. Three objective functions are defined, which are all converted into cost units using penalty parameters as a weighted sum. The first objective minimizes total unsatisfied demand penalty and the second one minimizes total travel cost. The third objective aims for fairness by minimizing the maximum absolute difference of satisfaction levels. Later, Lin *et al.* (2012) extend the model to considers location decisions as well. Instead of assigning tours from the central depots, they decide on a predetermined number of temporary facility locations. Also a distance limit between demand point and its assigned temporary is defined.

The time until the relief goods are received by the beneficiaries is critical in humanitarian logistics since they affect the well being of the people. Rottkemper *et al.* (2012) study the inventory relocation problem where a sudden change in demand occurs. The demand forecasts in the rolling horizon approach introduce uncertainty.

Model minimizes the total cost of operations and the penalty cost of unsatisfied demand. However, the penalty parameter increases as the number of periods in deprivation increases. Pérez-Rodríguez and Holguín-Veras (2015) develop a routing model that considers the fairness aspect among beneficiaries. They use the findings in Holguín-Veras *et al.* (2013) as base and the objective function minimizes the so called “social cost”, which is the sum of transportation and nonlinear deprivation costs. Rivera-Royero *et al.* (2016) propose a dynamic routing model run in a rolling horizon setting, with different vehicle types and different urgencies of demand points. They keep track of the number of round trips for each vehicle between nodes in each time period. The objective is to minimize the unmet demand weighted by the priorities that are based on deprivation costs.

More recently, Özdamar *et al.* (2018) provide an extension to arc routing problem with profits, where arc capacities are considered as well. Trucks deliver goods to the affected population who cannot walk to distribution centers, and the aim is to maximize the total population served by the trucks and the number of people that leave the neighborhood by their cars. Penna *et al.* (2018) study last mile distribution for the response stage with a rich vehicle routing problem (Rich-VRP). They consider multiple depots and multiple trip heterogeneous fleet where site dependencies are present for the vehicles. They minimize the total travel and fixed cost to satisfy all demand in their objective function. Li and Chung (2019) study robust (worst-case) versions of capacitated vehicle routing problem (CVRP) and split delivery vehicle routing problem (SDVRP) considering five objectives and compares them. The objective functions are to provide efficient (number of vehicles and total travel time cost), and fast and fair (sum of arrival times, demand weighted arrival times and the last arrival time) distribution.

Finally, the extensions of the well-known vehicle routing problem (VRP) can be of interest in the response stage. One can refer to Braekers *et al.* (2016) for a survey on VRP variants. More specifically, Lahyani *et al.* (2015) and Caceres-Cruz *et al.* (2015) review rich vehicle routing problems. Koç *et al.* (2016) focus on heterogeneous VRP and Montoya-Torres *et al.* (2015) can be referred to for a review on VRP with multiple

depots.

2.2.1. Discussion

We can mainly categorize the reviewed response stage studies into three as the ones that consider debris removal, network flow, and routing decisions. Debris removal activities appear less frequently in the reviewed studies, Aksu and Özdamar (2014) consider it without explicit vehicle consideration, whereas others include vehicular considerations (Özdamar *et al.*, 2014; Sahin *et al.*, 2016; Berktaş *et al.*, 2016; Kasaei and Salman, 2016; Akbari and Salman, 2017a,b; Ajam *et al.*, 2019). Network flow models do not explicitly model the vehicle flows, however the amount flows can be converted into the required number of vehicles to perform trips given the vehicle capacities (Alem *et al.*, 2016; Moreno *et al.*, 2016, 2018).

Since the locations of the facilities to keep inventory affect the performance when distributing relief goods to the beneficiaries, there are studies that integrate location and/or inventory prepositioning decisions into their response stage models. More than a quarter of the studies that are reviewed integrate location decisions with routing or network flow components. On the other hand, inventory decisions are considered by fewer studies as an integral part of the model (Caunhye *et al.*, 2016; Alem *et al.*, 2016; Özdamar and Demir, 2012; Garrido *et al.*, 2015).

The majority of the studies outlined in Section 2.2 provide mixed integer programs (MIP) and they assume the parameters are uncertain at the response stage and the decision makers can collect data after the disaster accurately. However, there are studies that consider uncertainty, mainly by defining a set of disaster scenarios. Disaster scenarios are used in a two stage stochastic programming (2SS) setting with a location decision component except for two, namely Barbarosoglu and Arda (2004) and Alem *et al.* (2016). Moreover, robustness is rarely incorporated in the response stage models. Alem *et al.* (2016) consider minmax regret, CVaR, and semi-deviation as robustness measures whereas Li and Chung (2019) consider the worst case.

Although fairness is an important aspect of humanitarian logistics operations, half of the studies ignore the equity aspect in their models and focus on time and cost related efficiency and effectiveness measures. Among the ones that introduce hard constraints to improve fairness, Afshar and Haghani (2012) and De Angelis *et al.* (2007) limit the minimum satisfaction levels of the beneficiaries. Ahmadi *et al.* (2015) place a bound on the latest arrival time and Lin *et al.* (2012) add a constraint on maximum distance. Maximizing minimum utility (or minimizing maximum disutility) is used in six studies as a fairness related objective. Anaya-Arenas *et al.* (2018) minimize maximum satisfaction difference whereas Tzeng *et al.* (2007) consider maximizing the minimum satisfaction in their multi-objective model. Apart from these, maximum shortage penalty is minimized (Balcik *et al.*, 2008), and maximum arrival time is minimized (Sahin *et al.*, 2016; Berktaş *et al.*, 2016; Akbari and Salman, 2017a; Li and Chung, 2019) in the other papers.

There are nine studies that model equity in their objective function in a more direct way. Huang *et al.* (2015) use sum of squared distances to ideal fill rate as one of the objectives in their multi-objective model. Huang *et al.* (2012) use a piecewise linear convex function to calculate time weighted disutility, and Anaya-Arenas *et al.* (2018) later use the idea to calculate shortage costs. Rottkemper *et al.* (2012) minimize cost of unsatisfied demand along with the operational costs, where the unsatisfied demand penalty increases as the time span to receive goods increases. Lin *et al.* (2011) and Lin *et al.* (2012) use the penalty cost due to the maximum absolute satisfaction difference among the demand points. Finally, Pérez-Rodríguez and Holguín-Veras (2015), Rivera-Royero *et al.* (2016), and Moreno *et al.* (2018) utilize the deprivation cost concept which is introduced by Holguín-Veras *et al.* (2013). Deprivation cost converts the unsatisfied demand to cost by utilizing an exponentially increasing function with the delivery time of the goods. Among these studies Pérez-Rodríguez and Holguín-Veras (2015) provide a nonlinear objective, whereas the other two has a linear objective functions since they consider discretized time segments. Although Holguín-Veras *et al.* (2016) provide an estimation process for the parameters of the deprivation cost, note that it depends on the economic estimation of the value of human lives and different parameter values may result in different solutions. Apart from that recently, Gutjahr and Fischer (2018)

analyze the deprivation cost objective and show that it may lead to unfair solutions under a fixed budget. Therefore they claim that deprivation cost concept should be extended to take equity into account as well.

Our study, which is shown as the last entry in Table 2.2, targets the response stage problem in disaster relief operations by considering the routing explicitly and in detail. Assuming the preparedness stage actions are already taken (warehouses are built and inventories are prepositioned in them, TF locations where the affected people will be gathering are determined), the model decides on the routes of the vehicles and how much of inventory is carried between nodes, thus keeping track of the satisfaction levels at each TF node at each time period. Since efficiency, effectiveness and equity are important at the same time, we define proxy objective functions that are based on the satisfaction rates of TFs at each time segments, such that they will perform adequately for these conflicting objectives simultaneously.

2.3. Fairness Concern

In the delivery of disaster relief items to the affected population, a fair distribution of goods in terms of amount and timeliness is crucial. It is at least as important as the equity provided in other public services since human lives may be at stake. Many disciplines (including economics, political science, and operations research among others) are interested in the equity concept (Leclerc *et al.*, 2012). In economics literature, several studies on the equity and efficiency trade-off and its applications can be found. One can refer to Sen and Foster (1997) and Young (1995) for books on the subject with the economics point of view. Savas (1978) discuss efficiency, effectiveness and equity as three performance measures in public service deliverance. They define efficiency as how much output is obtained compared to the input, effectiveness as the satisfaction provided by the service relative to the needs, and define equity as “fairness, impartiality, or equality of service”. Savas (1978) also elaborates alternative approaches to allocate public services equitably as equal payments, equal outputs, equal inputs, and equal satisfaction of demand. Marsh and Schilling (1994) provide a review on the subject and present 20 different equity measures, then build a framework and analyze their

characteristics. Mandell (1991), Bertsimas *et al.* (2011), and Bertsimas *et al.* (2012) provide studies that investigate the trade-off between efficiency and fairness. Apart from these, Mulligan (1991) and Kalcsics *et al.* (2015) provide studies on equity in the facility location problem setting.

Balcik *et al.* (2011), Ogryczak *et al.* (2014), Karsu and Morton (2015) and Matl *et al.* (2016) provide reviews on the fair optimization models. Balcik *et al.* (2011) focus on nonprofit and public sector with a vehicle routing perspective. Ogryczak *et al.* (2014) review equity on network models. They present “max-min fairness” and “lexicographic maximin” as equity measures. Then they state minimization of inequality measures may lead to inferior solutions since it contradicts maximization of individual utilities of the beneficiaries. Therefore it is needed to focus on fair optimization which considers both equity and efficiency rather than inequality minimization. They provide a review on objectives that can be used for this purpose, and on the fair optimization models in communication networks and location and allocation models. Karsu and Morton (2015) provide a systematic review on inequity averse optimization in operational research. They mainly focus on equitability and balance issues. The main difference between equitability and balance is the anonymity among entities, i.e. equitability compares identical individuals whereas balance concerns with entities with different needs and preferences. They review the allocation, location, vehicle routing, scheduling, transportation and network design, and other studies in terms of equitability concerns. Then they categorize different ways to handle fairness issue. Matl *et al.* (2016) focus on equity objectives in vehicle routing perspective. They classified the literature in vehicle routing into five groups. The first two are “vehicle routing problem with route balancing” (VRPRB) and its time window extension. VRPRB models are bi-objective where the second objective minimizes range of distance traveled for equity. The third group, “min-max VRP” contains the models that include a single objective to incorporate equity. Then they define other methods, and application papers as the remaining classes. Matl *et al.* (2016) also provide theoretical and numerical analysis on inequality measures and their effects on the solutions.

2.3.1. Approaches to Handle Equity

Assuming $y = (y_1, y_2, \dots, y_m)$ is a vector of utilities of beneficiaries (Let y_i be the outcome of a given distribution for beneficiary $i \in I$, $I = \{1, 2, \dots, m\}$), the utilitarian solution maximizes $\sum_{i \in I} y_i$ among feasible solutions. It is a natural choice where the system efficiency is measured by the total utilities. Although in most cases the total system utility reduces under a fairness consideration, the nature of the problem may require a fairness scheme in some cases. However there is no universally accepted scheme of equity since its interpretation is subjective and problem specific (Bertsimas *et al.*, 2011). The most widely used approaches to handle equity can be summarized below (Karsu and Morton, 2015; Ogryczak *et al.*, 2014; Matl *et al.*, 2016).

2.3.1.1. The Rawlsian Approach. It is one of the simplest and most commonly used approaches. It is also referred as “max-min fairness” since it maximizes $\min_{i \in I} y_i$ to provide equity. However this approach cannot differentiate among distributions as long as they have the same utility level for the most unfavorable entity (e.g. utility vectors (1,1,9) and (1,5,5) are equivalent for the Rawlsian approach).

Lexicographic approach is an extension to the Rawlsian approach, which aims to alleviate the problem of not being able to differentiate the differences among the entities except the worst one, i.e. the max-min approach. After maximizing the smallest utility level, it considers the next worst-off entity, and moves on for the next ones.

2.3.1.2. Inequality Index Based Approach. Inequality indices are the functions that assign a scalar value to a given utility vector. They are usually utilized in multi-objective models since they only consider equitability, and ignore efficiency concerns. The most commonly used inequality indices can be given as follows:

- *Range*: The difference between highest and lowest utilities ($\max_{i \in I} y_i - \min_{i \in I} y_i$).
- *Deviation*: The deviation from the mean. Total absolute deviation ($\sum_{i \in I} |y_i - \bar{y}|$) or maximum deviation ($\max_{i \in I} |y_i - \bar{y}|$) can be considered.

- *Variance*: The variance of utilities of the entities $(\sum_{i \in I} (y_i - \bar{y})^2 / |I|)$.
- *Gini coefficient*: It is one of the most widely used index in economics. Gini coefficient $(\frac{\sum_{i \in I} \sum_{j \in I} |y_i - y_j|}{2|I| \sum_{i \in I} y_i})$ takes values between 0 and 1, and the smaller the gini index is, the lower is the inequality.
- *Sum of pairwise absolute differences*: The sum of pairwise absolute differences among all entities $(\sum_{i \in I} \sum_{j \in I} |y_i - y_j|)$

2.3.1.3. Inequity-averse Aggregation Function Based Approach. In order to achieve equity-efficiency trade-off, a function $U : \mathbb{R}^m \mapsto \mathbb{R}$ that concerns both equity and efficiency can be used. In this case, the original problem is modified as $\max\{U(y) : y \in Y\}$ where $Y \in \mathbb{R}^m$ is set of feasible solutions.

A function needs to satisfy the following properties to be inequity-averse (Karsu and Morton, 2015):

- If $y^1 < y^2$ then $U(y^1) < U(y^2) \quad \forall y^1, y^2 \in Y$ (Function U is strictly increasing with respect to every coordinate).
- $U(y) = U(\Pi^l(y))$, where $\Pi^l(y)$ is an arbitrary permutation of the y vector (Function U is symmetric).
- If $y_j > y_i$ then $U(y) < U(y - \varepsilon \mathbf{e}_j + \varepsilon \mathbf{e}_i) \quad \forall y \in \mathbb{R}^m$, where $0 < \varepsilon < y_j - y_i$, and $\mathbf{e}_j, \mathbf{e}_i$ are the j^{th} and i^{th} unit vectors in $\mathbb{R}^m$ (Function U satisfies Pigou-Dalton principle of transfers).

A general fairness scheme, “ α -fairness” (Atkinson, 1970), defines a parametric class of utility functions as given in Equation 2.1.

$$U_\alpha(y) = \begin{cases} \sum_{i \in I} \frac{y_i^{1-\alpha}}{1-\alpha} & \alpha \geq 0, \alpha \neq 1 \\ \sum_{i \in I} \log(y_i) & \alpha = 1 \end{cases} \quad (2.1)$$

Moreover, proportional fairness scheme (for which a transfer of a resource between entities is favorable only if the percentage increase in the utility of the receiving end is higher than the percentage decrease in the utility of the other) and max-min fairness schemes are captured as the special cases of α -fairness for $\alpha = 1$ and $\alpha \rightarrow \infty$, respectively. For the case $\alpha = 0$, α -fairness scheme is equivalent to the utilitarian approach. Therefore α parameter can be used to change the attitude on efficiency-fairness trade-off and it is called the inequality aversion parameter (Bertsimas *et al.*, 2012).

2.3.2. Efficiency-Fairness Trade-off

It is obvious that any fair solution concept is a probable cause of deterioration in the total system efficiency. Bertsimas *et al.* (2011) and Bertsimas *et al.* (2012) provide means to discuss the relation of efficiency loss and fairness increase. Let $S(Y)$ be the objective of the utilitarian solution for the set of feasible solutions $Y \in \mathbb{R}^m$, and $F(Y)$ be the objective of a fair solution under a certain fairness scheme, for maximization case. Then they define “price of fairness” (POF) as the relative efficiency loss under an imposed fairness scheme, given in Equation 2.2. POF is bounded between zero and one, where the efficiency loss is smaller for the smaller values. They also derive theoretical bounds for price of fairness under α -fairness scheme as a function of the number of entities and inequality aversion parameter.

$$POF(Y) = \frac{S(Y) - F(Y)}{S(Y)} \quad (2.2)$$

3. A ROBUST DISASTER PREPAREDNESS MODEL FOR EFFECTIVE AND FAIR DISASTER RESPONSE²

In this chapter, we will summarize the distinguishing properties of the proposed preparedness stage model and present the model itself. All of the model properties and assumptions are validated by consulting subject experts in AFAD (Republic of Turkey Disaster and Emergency Management Authority). AFAD is the state institution responsible for averting disasters and minimizing damage that occurs after disasters. They plan and organize post-disaster response efforts nationwide, and try achieve co-operation among different government agencies. The model is designed such that the required parameters are either available or can be estimated by AFAD experts.

3.1. Model Properties

The properties of the proposed model are as follows:

Network structure: There is a given set of permanent facility (PF) candidate locations that can be used to store relief items before disaster occurrence. Also, a set of size (capacity) options for the PFs are given. The model chooses the locations and the sizes of PFs. The amount of items to preposition at each PF is also determined by the model. Items that are prepositioned in PFs are transported to temporary facilities (TFs) in the event of a disaster, and affected people receive relief items at TFs. Public facilities such as schools or sport centers determine the set of TF candidate locations. The model chooses which of these candidate locations are to be used as TFs. The assignment of demand points to TFs (clustering) is an output of the model where each demand point must be assigned to the closest selected TF location. Figure 3.1 below depicts the network structure and the decisions.

²This chapter appears in Erbeyoğlu and Bilge (2019) as a part of its content.

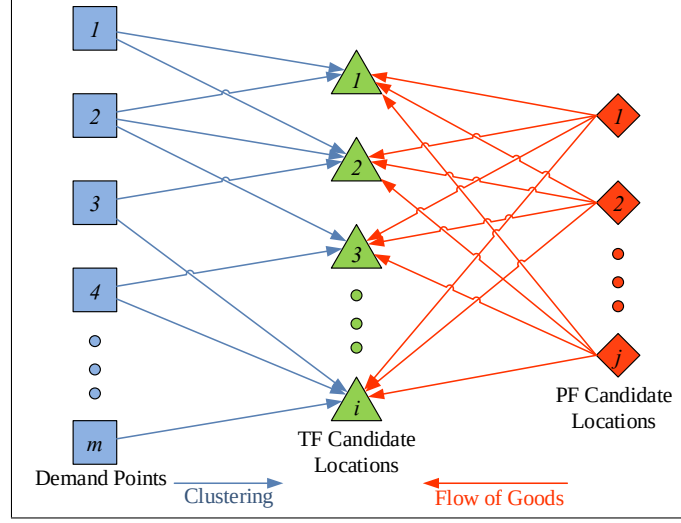


Figure 3.1. Network structure.

Clustering with closest assignment property: The proposed model incorporates clustering decisions instead of assuming it as a preprocessed step. When clustering the demand points to TFs, we set a limit on the distance between the demand point and its assigned TF location, and we impose the closest assignment policy.

Gerrard and Church (1996) state that the closest assignment policy is a requirement for emergency response. Equity and efficacy of the emergency services affect the public confidence and the acceptance of location decisions, and the closest assignment policy is a legitimate and sensible allocation rule to achieve them. Most people would oppose being assigned to a non-closest facility, even if within an acceptable distance. Although the closest assignment property is usually a requirement for emergency response, or for cases where the clients are distance minimizers, this approach is used in four studies in the disaster preparedness literature, namely Horner and Widener (2011), Kılıcı *et al.* (2015), Noham and Tzur (2018), and Kınay *et al.* (2018). In this study, we assign the demand points to the closest open TF location to define a realistic problem setting.

Demand satisfaction: As discussed in Section 2.1.1, most studies on the preparedness stage minimize costs which include a shortage penalty. However, one may argue that trying to minimize the cost or staying within a budget at expense of shortage should not be the primary concern in a pre-disaster setting. Instead, decision makers

should be informed about the actions they should take to provide relief to all affected. In the model we propose, all demand is satisfied without a limit on the number of facilities or the total amount that can be prepositioned. This approach in demand satisfaction together with our robustness and scenario handling, explained next, complement each other and define the perspective in this study.

Robustness and disaster scenarios: We are interested in the occurrence of rare disasters such as earthquakes. The expected value of the performance measures may mean little for such rare and non-repetitive disasters, even if it were possible to obtain realistic estimates of scenario probabilities. Instead, we use a model robustness approach that ensures feasibility across all disaster scenarios (i.e. all demand is guaranteed to be satisfied under any disaster scenario). A representative set of disaster scenarios model the uncertainty in the size and geographical distribution of the affected population. Probability information on these scenarios is assumed unavailable or unreliable. Each disaster scenario is associated with a different earthquake epicenter. Based on seismic analyses as well as the level of destruction expected for different probable disaster magnitudes at each selected epicenter, governmental authorities, who are guided by scientists and humanitarian experts, specify a magnitude against which the population in question will be protected. A possible approach for determining the disaster intensity against which protection will be sought is suggested in Battarra *et al.* (2018). Once the level of protection is determined, preparedness plans will be based on achieving this protection. Hence, decision making in this disaster preparedness setting needs to be conservative by nature, and planning for shortages is deliberately avoided as it can be seen contradictory to the term “preparedness”.

It should be noted that ensuring feasibility in all scenarios does not boil down to merging the scenarios into one by using the highest demand values for a demand point among all scenarios. To illustrate, consider a case where there are two TFs and a single PF location. Assume the demand requirements with respect to each scenario are 0 and 50 at the first TF, and 50 and 0 at the second. In our model, prepositioning 50 items is sufficient to serve the whole demand, but 100 items would be needed if we were to use the highest values over the scenarios.

Service coverage windows: The experts with whom we are consulting use timely and fair satisfaction of demand as their conceptual aim when judging the quality and performance of a humanitarian response plan. This is represented mainly by how much of the need is actually fulfilled, how the deliveries are spread over time relative to the generation of the need, and whether there are sections of the affected population that are neglected or are receiving poor service relative to the rest as a result of the policies used. The evaluation of the distribution plan developed in the response stage will be based on these factors. Thus, the proposed model aims to design a network that is suitable for effective and fair response plans that score well on these factors. This is achieved mainly by imposing a demand covering scheme referred as “service coverage windows.” A set of time frames is defined as service coverage windows (SCW), and the proportion of demand of each item type that needs to be satisfied within each time frame are specified by the decision maker (e.g. 30% of the total demand of the first item type and 10% of the second item type should be satisfied within 10 hours, 60% of the first item type and 30% of the second item type should be met within 24 hours, and all demand must be served within 48 hours). Note that this approach, which our experts found as an intuitive, direct, and natural way to express their conceptual service requirements, is also in agreement with the choices of the much larger and diverse humanitarian experts group that Gralla *et al.* (2014) work with in assessing the trade-offs among multiple humanitarian objectives.

We impose SCWs as hard constraints unlike the studies that maximize the total demand covered by utilizing the coverage level concept, such as Balcik and Beamon (2008) and Mohammadi *et al.* (2016). This aims to assist achieving a more effective and fair distribution in the response stage by ensuring that for every TF location there are close enough PF locations to meet the service requirements set by humanitarian experts. Moreover, this approach eliminates the challenge of having to come up with workable penalty and/or urgency coefficients. The humanitarian experts we consult do not feel at ease in determining such parameters, especially when these terms will be used together with several other cost coefficients. Furthermore, using urgency weights or shortage penalties may result in an imbalance among transported item types (i.e. a model may choose to transport a large number of less important items, instead of

more important item types depending on the parameter values).

Pursuit of humanitarian objectives: The objective function of the model is the minimization of the disaster preparedness cost. Having said this, it is not the driving force of the model. Any feasible solution to our model ensures that every TF location will receive all of the required items in a timely manner under any disaster scenario. Therefore, the cost objective is utilized in order to obtain non-dominated solutions. This approach is in accord with the findings of Gralla *et al.* (2014) in their study for assessing the trade-offs among humanitarian objectives using expert preferences. The authors state that effectiveness is the primary concern followed by equity, whereas cost is the least important goal. In our case, SCWs ensure that the requirements for amount and speed of service can be met under any scenario, hence effectiveness is the main driver. Moreover, enforcing SCWs over each and every opened TF will result in a network design that can facilitate a fair solution in the response stage. The model also incorporates fairness concern during beneficiaries' access to TFs. By employing the closest assignment policy during clustering the affected population, cases where one of two neighbors being assigned to a farther TF will be avoided. Finally, limiting the maximum distance for the assignment of demand points to TFs limits total walking distance of the most disadvantageous beneficiary (worst-case).

3.2. *CLFDIP* Mathematical Model

Definitions of sets, parameters and decision variables are given as follows, and the mixed integer programming (MIP) model is defined in Equations 3.1 – 3.14.

The problem and the model is named *CLFDIP* since it contains clustering, location, flow distribution and inventory prepositioning decisions that are introduced in Section 2.1. In this formulation, the objective function 3.1 minimizes the total pre-disaster cost due to opening permanent facilities, and the acquisition and holding cost of prepositioned inventory. Temporary facilities do not incur costs since AFAD experts state that public facilities will be used as TFs and personnel working there will be public servants and volunteers. Constraints 3.2 make sure that each demand point under

Sets:

I	Set of temporary facility (TF) locations
J	Set of permanent facility (PF) locations
K	Set of service coverage windows
T^P	Set of PF sizes
S	Set of scenarios
L	Set of items
J_i^k	Set of PFs that can serve TF i within SCW k ($J_i^k \subseteq J_i^{k'}$, for $k < k'$)
M_s	Set of demand points under disaster scenario s
I_m	Set of TFs that are close enough to serve demand point m

Parameters:

d_{ml}^s	Demand of point m for item l under scenario s
r_{kl}	Proportion of demand for item l to be satisfied within service coverage window k
K_t^P	Capacity of a PF of size t
K_i^T	Capacity of the TF at location i
u_l	Capacity consumption of item l
h_l	Acquisition, expected inventory holding and wastage costs cost of item l
c_{jt}	Fixed cost of PF at location j of size t
δ_{im}	Distance between TF i and demand point m

Decision variables:

X_{im}^s	Binary variable indicating clustering decisions, i.e. if demand point m is assigned to TF i for scenario s
Y_i^s	Binary variable indicating if TF i is opened under scenario s
F_{jil}^s	Amount of item l transported from PF j to TF i under scenario s
Z_{jt}	Binary variable indicating if PF j of size t is opened
H_{jl}	Prepositioned inventory amount of item l at PF j

CLFDIP:

$$\min \quad \sum_{j \in J} \sum_{t \in T^P} c_{jt} Z_{jt} + \sum_{j \in J} \sum_{l \in L} h_l H_{jl} \quad (3.1)$$

$$\text{s.t.} \quad \sum_{i \in I_m} X_{im}^s = 1 \quad s \in S, m \in M_s \quad (3.2)$$

$$X_{im}^s \leq Y_i^s \quad s \in S, m \in M_s, i \in I_m \quad (3.3)$$

$$\sum_{l \in L} u_l \sum_{m \in M_s} d_{ml}^s X_{im}^s \leq K_i^T Y_i^s \quad s \in S, i \in I \quad (3.4)$$

$$\sum_{n \in I_m | \delta_{nm} \leq \delta_{im}} X_{nm}^s \geq Y_i^s \quad s \in S, m \in M_s, i \in I_m \quad (3.5)$$

$$\sum_{j \in J_i^k} F_{jil}^s \geq r_{kl} \sum_{m \in M_s} d_{ml}^s X_{im}^s \quad s \in S, i \in I, k \in K, l \in L \quad (3.6)$$

$$\sum_{l \in L} u_l H_{jl} \leq \sum_{t \in T^P} K_t^P Z_{jt} \quad j \in J \quad (3.7)$$

$$\sum_{i \in I} F_{jil}^s \leq H_{jl} \quad j \in J, l \in L, s \in S \quad (3.8)$$

$$\sum_{t \in T^P} Z_{jt} \leq 1 \quad j \in J \quad (3.9)$$

$$X_{im}^s \in \{0, 1\} \quad s \in S, i \in I, m \in M_s \quad (3.10)$$

$$Y_i^s \in \{0, 1\} \quad s \in S, i \in I \quad (3.11)$$

$$F_{jil}^s \geq 0 \quad s \in S, j \in J, i \in I, l \in L \quad (3.12)$$

$$Z_{jt} \in \{0, 1\} \quad j \in J, t \in T^P \quad (3.13)$$

$$H_{jl} \geq 0 \quad j \in J, l \in L \quad (3.14)$$

each scenario is assigned to one of the TFs in the I_m set, which contains the facilities that are close enough to serve the demand point. Constraints 3.3 allow demand point assignments only to the opened TFs, and 3.4 ensure that TF capacity is not violated. Although constraints 3.3 become redundant along with 3.4, they are kept to obtain a tighter linear relaxation of the model. Assignments of demand points to the closest available TF is provided by equations 3.5, using the closest assignment constraints defined by Church and Cohon (1976). Constraints 3.6 state that for each item at a

TF under a scenario, r_{kl} proportion of the total demand must be satisfied within k^{th} service coverage window. Figure 3.2 below illustrates the SCWs and corresponding J_i^k sets. Note that the windows define only upper limits on the distance to avoid being over-restrictive, therefore the demand regarding the largest window can be satisfied by the PFs that are within the smaller windows ($J_i^1 \subseteq J_i^2 \subseteq J_i^3$). Constraints 3.7 limit the amount of prepositioned items by the PF capacity if it is opened. Constraints 3.8 state the amount of items that can be shipped from a PF under each scenario is limited by the prepositioned amount, and 3.9 force the model to open at most one size of PF at each candidate location. Finally, equations 3.10 – 3.14 define the binary and positive variables. In the model, F_{jl}^s and H_{jl} variables are left as continuous variables to reduce the number of integer variables. This can be justified since the flow variables will not be the actual amount that is carried in a disaster situation and a post-disaster routing model will be deciding the real transportation amount. Although the inventory decisions will be executed right away, rounding the inventory values could be insignificant compared to fixed cost of facilities in a realistic setting.

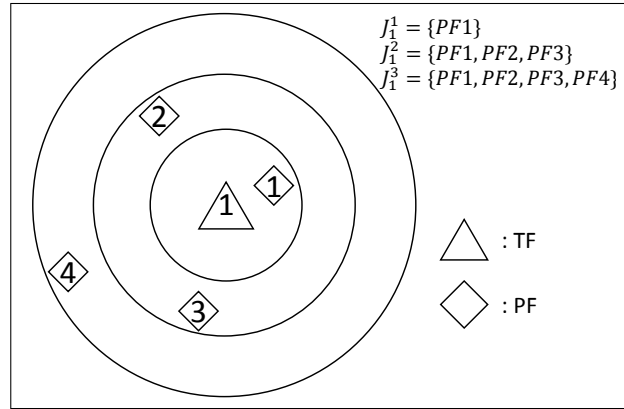


Figure 3.2. Illustration of SCWs and corresponding J_i^k sets.

3.2.1. Valid Inequality Sets

Three valid inequality sets are defined to tighten the linear relaxation of *CLFDIP*. The first valid inequality set is a corollary of constraints 3.2 and it makes sure that there is an eligible TF location that is opened, for each demand point under each

scenario. Equation 3.15 defines the corresponding expression.

$$\sum_{i \in I_m} Y_i^s \geq 1 \quad s \in S, m \in M_s \quad (3.15)$$

The second valid inequality set benefits from the SCW definition and is a corollary of constraints 3.6. It makes sure that for each opened TF there is at least one selected PF location of any size within the smallest SCW. Equation 3.16 defines the valid inequality where $k = 1$ is assumed to be the smallest window.

$$\sum_{j \in J_i^1} \sum_{t \in T^P} Z_{jt} \geq Y_i^s \quad s \in S, i \in I \quad (3.16)$$

The last valid inequality set is defined as a consequence of the demand satisfaction property. Equation 3.17 defines the valid inequality set, which ensures that for each scenario and item type, the total amount of stored is enough to cover all demand.

$$\sum_{j \in J} H_{jl} \geq \sum_{m \in M_s} d_{ml}^s \quad s \in S, l \in L \quad (3.17)$$

3.2.2. Use Cases as a Decision Tool

This model is basically designed to make strategic pre-disaster decisions, i.e. PF location/capacity selection and inventory pre-positioning. Hence, the model can be re-run by the decision maker to perform additional analysis in order to comprehend the nature of the problem, the topology of the case, and sensitivity to parameters. Besides these, three more use cases for the model are described below.

When solving the model, the closest assignment constraints and service coverage windows may cause infeasibilities depending on the instance at hand. Such infeasibilities imply physical inadequacies in the network structure, and decision makers should

address these issues in the preparedness stage by specifying new candidate facility locations and/or expanding their capacities. In order to aid this issue, *CLFDIP* can be adapted and used in a preprocessing stage to find out the demand points that cannot receive relief under the given instance. For this purpose, we can solve the model to minimize the total number of people that will not receive service. This requires a new binary variable that indicates if a demand point m under scenario s is not assigned to any TF. Furthermore, the demand point assignment constraints 3.2 and closest assignment constraints 3.5 should be adapted accordingly. In this way, the decision maker will obtain information about the required actions to resolve infeasibility, i.e. by observing regions with unsatisfied demand on the map and searching for new candidate facility locations accordingly.

After solving *CLFDIP*, only the pre-disaster decisions, PF selection (Z_{jt}) and inventory prepositioning (H_{jl}), will be executed right away. TF locations (Y_i^s) and demand point clustering (X_{im}^s) decisions are scenario dependent post-disaster decisions. Furthermore, given the first-stage decisions, usually multiple-optima exists for these decisions. Therefore, the second-stage decisions can be refined in a post-optimization step by re-using our model given the strategic decisions. *CLFDIP* becomes separable over scenarios after fixing the Z_{jt} and H_{jl} variables, and the second-stage decisions can be refined for each scenario using an appropriate objective such as minimization of the total weighted distance or the number of TF points to open. If an earthquake occurs, the TF locations of the scenario that is the most similar to actual one will be used. In fact, if the decision maker can collect data regarding the earthquake fast enough, *CLFDIP* with fixed Z_{jt} and H_{jl} variables can be solved for the actual demand realizations in a very short time as well.

In *CLFDIP*, selection of the TF locations and demand point assignments are dependent on the scenarios (i.e. a different set of TFs are selected for each disaster scenario). Therefore it is not possible to inform the population regarding the TF locations that they are assigned to prior to the disaster. If the decision maker prefers to determine a single set of TF locations and announce it in the preparedness stage, then *CLFDIP_EarlyNotify* model which is a modification of *CLFDIP* can be used.

The only different set used in *CLFDIP_EarlyNotify* is M which is the set of demand points that are affected in any one of the scenarios ($M = \bigcup_{s \in S} M_s$). Also, X_{im} and Y_i binary decision variables are used instead of X_{im}^s and Y_i^s , and they become scenario independent. They are the binary variables indicating if demand point m is assigned to TF i , and if TF i is opened, respectively. Then *CLFDIP_EarlyNotify* can be obtained by rearranging the clustering constraints 3.2 – 3.5 and SCW constraints 3.6 accordingly. In fact, *CLFDIP_EarlyNotify* is equivalent to the case where the constraint given in Equation 3.18 is added on the *CLFDIP* model. Finally, the valid inequalities can be easily modified to fit the *CLFDIP_EarlyNotify* model.

$$Y_i^{s_1} = Y_i^{s_2} \quad s_1 \in S, s_2 \in S, i \in I \quad (3.18)$$

3.3. Problem Complexity

The problem that we define here for the preparedness stage (*CLFDIP*) is NP-hard. In order to prove this claim, we first introduce a close relative of the ordinary Knapsack Problem (*KP*), which we call as Knapsack Problem Complement (*KPC*): “Given a set $N = \{1, 2, \dots, n\}$ of items with sizes $s_j \in \mathbb{Z}_+$ and utilities $u_j \in \mathbb{Z}_+$ for $j \in N$, and two positive integers A and B , is there a subset $S' \subseteq N$ such that $\sum_{j \in S'} s_j \geq \sum_{j \in N} s_j - B$ and $\sum_{j \in S'} u_j \leq \sum_{j \in N} u_j - A$?”.

Recall that *KP*, which is known to be NP-Complete (Garey and Johnson, 1979), is based on the following decision question: “Given a set $N = \{1, 2, \dots, n\}$ of items with sizes $s_j \in \mathbb{Z}_+$ and utilities $u_j \in \mathbb{Z}_+$ for $j \in N$, and two positive integers A and B , is there a subset $S \subseteq N$ such that $\sum_{j \in S} s_j \leq B$ and $\sum_{j \in S} u_j \geq A$?”. Then, it is possible to observe that for any given subset S , we can construct the complement $S' = N \setminus S$ in polynomial time. Moreover, S leads to a “yes” answer for *KP* on a given instance if and only if its complement S' leads also to a “yes” answer for *KPC* on the same instance. Hence, *KP* polynomially transforms to *KPC*, which makes *KPC* NP-complete as well.

Theorem 3.1. *The preparedness stage problem (CLFDIP) is NP-hard.*

Proof. The decision problem of *CLFDIP* can be formulated as the question “Are there subsets $J' \subseteq J$ and $I' \subseteq I$ such that capacity limitations are satisfied and the items prepositioned in the selected PF locations J' are sufficient to satisfy the SCW requirements of the selected TF locations I' under each scenario $s \in S$, where demands are determined by assigning each demand point $m \in M_s$ to the closest open TF $i \in I' \cap I_m$, while having total inventory prepositioning and facility opening costs less than or equal to a given integer limit A ?”

It suffices to show that *KPC* is a particular case of *CLFDIP* to complete the proof. For this purpose we consider the case where $|I| = 1, |M| = 1, |S| = 1, |K| = 1, |T| = 1, |L| = 1, J_i^k = J, r_{kl} = 1$. We let the single TF location be within the distance limit of the demand point so that it is assigned to the TF, and set the capacity of PFs as the item sizes in *KPC* (i.e. $K_{jt}^P = s_j$) and the fixed cost of PFs as the utilities in *KPC* (i.e. $c_{jl} = u_j$). Besides we make inventory costs $h_l = 0$ and capacity consumptions $u_l = 1$. Finally, we let the TF's capacity and demand of the demand point to be $\sum_{j=1}^n s_j - B$.

In the following we explain how this particular class of *CLFDIP* is equivalent to *KPC*. For this particular restriction, *CLFDIP* decision problem seeks a subset of PFs, such that the overall capacity of the selected PFs is sufficient to cover the demand of the TF, and the total cost is below the given limit A . Then, a feasible solution of the restricted *CLFDIP* is also a feasible solution of *KPC*, where the selected PFs correspond to the selected items S' . Similarly, given a feasible solution to *KPC* we can construct a feasible solution of the restricted *CLFDIP* by opening PF locations that correspond to the selected items, opening the single TF location and assigning the single demand point to the TF, and prepositioning a total of $\sum_{j=1}^n s_j - B$ items to the opened PFs while satisfying the capacity limitations. Therefore, if this particular restricted class of *CLFDIP* can be solved in polynomial time, then *KPC* can be solved in polynomial time. Consequently *CLFDIP* is at least as difficult as *KPC*, and the

optimization problem of *CLFDIP* is NP-hard. $\square$

3.4. Exact Solution with Logic-based Benders Decomposition

Benders decomposition is a solution technique for large-scale optimization problems where the problem becomes easier by fixing some of the complicating variables (Benders, 1962). The main problem is decomposed into a master problem and sub-problems, and some of the master problem variables are assigned a trial solution. Then, the sub-problems provide feedback (Benders cuts) regarding the feasibility and the objective function value, until the procedure converges to the optimal solution. Logic-based Benders decomposition (LBBD) is a generalization of the technique which is introduced by Hooker (2000) and developed further in a general framework by Hooker and Ottosson (2003). LBBD is similar to classical Benders approach: It decomposes the original problem into a master problem and sub-problems, and the feasible region of the relaxed master problem is tightened gradually by introducing Benders cuts. However, unlike classical Benders decomposition, LBBD does not require the sub-problems to be linear programs since an inference dual is used to generate cuts instead of duality based cuts. Therefore, the valid cuts need to be hand-tailored considering the underlying structure of the problem. Also, the logic-based cuts are simpler in the cases where the sub-problems are feasibility problems rather than optimization problems (Hooker, 2007). A valid cut eliminates the current master problem solution, but does not exclude any feasible solution of the global problem (Chu and Xia, 2004).

The LBBD method is applied to various problems, including planning and scheduling (Hooker, 2007), multicore architecture optimization (Benini *et al.*, 2008), transportation network design (Peterson and Trick, 2009), aircraft maintenance scheduling (Bajestani and Beck, 2011), location and routing (Fazel-Zarandi and Beck, 2012), inventory-location problem (Wheatley *et al.*, 2015), among others. In disaster relief context, Dalal and Üster (2017), Üster and Dalal (2017), and Elçi and Noyan (2018) utilize classical Benders decomposition as their solution techniques. Apart from that, Rawls and Turnquist (2010), Li *et al.* (2011), and Noyan (2012) develop solution

algorithms based on L-shaped method (Van Slyke and Wets, 1969), which is a Benders decomposition application in the stochastic programming domain. However, to the best of our knowledge, LBBD has not been employed in a disaster relief context up to the date of this study.

The main idea behind our LBBD approach can be outlined as follows: In *CLFDIP*, determining the locations of PFs and TFs, and the amount of inventory to hold in each PF are the main decisions, whereas the assignment of demand points to TFs and the flow decisions can be called auxiliary control variables since they determine if the selection of main decisions are feasible or not. Given the closest assignment property, the demand points can be trivially clustered to a TF if the locations of the selected ones are provided. Similarly, once we determine the inventory levels and clusters, we can check whether or not the SCW constraints are satisfied. Therefore, we can reformulate *CLFDIP* conceptually as given in *CLFDIP_R*. We decompose *CLFDIP* into a location and inventory prepositioning master problem (*LIPMP*); and two sub-problems as a clustering sub-problem (*CSP*) and a flow distribution sub-problem (*FDSP*). *CSP* is separable over scenarios, and *FDSP* is separable over scenarios and item types. If a feasible solution of the *LIPMP* is also feasible for *CSP* and *FDSP* sub-problems, it is also feasible for the original *CLFDIP* problem. The details related to the LBBD that we propose are given in the following subsections.

CLFDIP_R:

$$\min \quad (3.1)$$

$$\text{s.t.} \quad (3.7), (3.9), (3.11), (3.13), (3.14)$$

$$Y_i^s \text{ corresponds to a feasible cluster} \quad s \in S$$

$$Y_i^s \text{ and } H_{jl} \text{ correspond to a feasible flow distribution} \quad s \in S, l \in L$$

3.4.1. Location and Inventory Prepositioning Master Problem

We decompose *CLFDIP* such that the TF and PF locations are selected and the amount of inventory held in the PFs are determined in the master problem *LIPMP*, while minimizing the total cost. *LIPMP* is defined below, where all of the equations that are composed of the Z_{jt} , Y_i^s and H_{jl} variables remain, and the valid inequalities that are defined in Section 3.2.1 are included. Excluding the X_{im}^s and F_{jil}^s variables in the master problem relaxes the solution space of *LIPMP*, therefore the valid inequalities become crucial to tighten the initial feasible region. Note here that the objective function of *LIPMP* is equivalent to the objective function of *CLFDIP*; therefore the sub-problems generate only feasibility cuts, when necessary.

LIPMP:

$$\begin{aligned} \min \quad & (3.1) \\ \text{s.t.} \quad & (3.7), (3.9), (3.11), (3.13), (3.14), (3.15), (3.16), (3.17) \end{aligned}$$

3.4.2. Clustering Sub-problem and Logic-based Benders Cuts

The clustering sub-problem only deals with the feasibility of Y_i^s variables. The feasibility of a given $\overline{Y_i^s}$ vector in terms of TF capacities can be checked by solving *CSP*, which is separated over scenarios. However, one can observe that *CSP* can be solved algorithmically instead of solving the integer program. Satisfaction of constraints 3.19 is ensured by valid inequalities 3.15 in *LIPMP*. Constraints 3.20 and 3.22 dictate the assignment of the demand points to the closest available facility. Therefore, we can assign demand points to the closest TF i that is opened to obtain $\overline{X_{im}^s}$ vector. Then, we can check if the TF capacity constraints 3.21 are satisfied for each scenario s .

CSP($s, \overline{Y_i^s}$):

$$\begin{aligned} \min \quad & 0 \\ \text{s.t.} \quad & \sum_{i \in I_m} X_{im}^s = 1 \quad m \in M_s \end{aligned} \quad (3.19)$$

$$X_{im}^s \leq \overline{Y}_i^s \quad m \in M_s, i \in I_m \quad (3.20)$$

$$\sum_{l \in L} u_l \sum_{m \in M_s} d_{ml}^s X_{im}^s \leq K_i^T \overline{Y}_i^s \quad i \in I \quad (3.21)$$

$$\sum_{n \in I_m | \delta_{nm} \leq \delta_{im}} X_{nm}^s \geq \overline{Y}_i^s \quad m \in M_s, i \in I_m \quad (3.22)$$

$$X_{im}^s \in \{0, 1\} \quad i \in I, m \in M_s \quad (3.23)$$

It should be noted that there may be more than one equidistantly closest available TFs for some of the demand points. In this case, different clusters can be obtained by assigning these demand points to different alternatives. Therefore, if we end up with an infeasible cluster after all demand points are assigned to a closest facility, we need to check if there is a feasible alternative cluster. For this purpose, we define the reduced clustering sub-problem *ReducedCSP* given below. *ReducedCSP* is equivalent to *CSP* after fixing the values of the X_{im}^s variables for which a unique closest TF exist. We define M'_s as the set of demand points having alternative closest available TFs; K'_{si} as the remaining capacity of TF i after assigning the demand points that have unique closest TF; and I'_{sm} as the set of equidistant TFs for a demand point $m \in M'_s$. Although *ReducedCSP* is an integer program, the number of variables and constraints are relatively small and it is a feasibility problem; therefore the solution times are relatively small.

ReducedCSP($s, M'_s, K'_{si}, I'_{sm}$):

$$\begin{aligned} \min \quad & 0 \\ \text{s.t.} \quad & \sum_{i \in I'_{sm}} X_{im}^s = 1 \quad m \in M'_s \end{aligned} \quad (3.24)$$

$$\sum_{l \in L} u_l \sum_{m \in M'_s} d_{ml}^s X_{im}^s \leq K'_{si} \quad i \in \cup I'_{sm} \quad (3.25)$$

$$X_{im}^s \in \{0, 1\} \quad m \in M'_s, i \in I'_{sm} \quad (3.26)$$

If *ReducedCSP* fails to find a feasible solution, then we can conclude that the $\overline{Y}_i^s$ vector does not correspond to a feasible cluster, and we need to eliminate it in *LIPMP*.

Since CSP is composed of binary variables, one cannot define duality based feasibility cuts. Let S' be the set of scenarios for which infeasible clusters obtained, and $P_1(s)$ be the set of TFs whose capacity is violated under scenario $s \in S'$. Also define $P_2(s, i)$ as the set of previously closed TF locations which are closer to at least one demand point assigned to TF i in scenario $s \in S'$. For a given TF $i \in P_1(s)$, one way to resolve the infeasibility is to close down the facility i . The other option is to open at least one TF $p \in P_2(s, i)$ and reducing the load of TF i due to closest assignment property. Using this idea, the logic-based feasibility cut set is defined in equation 3.27.

$$\sum_{p \in P_2(s, i)} Y_p^s \geq Y_i^s \quad s \in S', i \in P_1(s) \quad (3.27)$$

A logical expression needs to exclude the current solution from the master problem, and it must not eliminate any feasible solution to the original problem to be a valid Benders cut, and to guarantee convergence to optimality (Chu and Xia, 2004). These two conditions are shown to hold in the following theorems:

Theorem 3.2. *The logic-based feasibility cuts 3.27 eliminate all solutions containing $\overline{Y}_i^s$ vector from the feasible region of LIPMP.*

Proof. The definition of $P_1(s)$ and $P_2(s, i)$ sets ensure that $\overline{Y}_i^s = 1$ and $\overline{Y}_p^s = 0$, for each $i \in P_1(s)$ and $p \in P_2(s, i)$ for a given scenario s . Therefore, the current master problem solution $\overline{Y}_i^s$ does not satisfy cuts 3.27, and it is excluded from all subsequent master problem solutions. $\square$

Theorem 3.3. *The logic-based feasibility cuts 3.27 do not remove any feasible solution of the original problem CLFDIP.*

Proof. To prove Theorem 2, we need to show the given $\overline{Y}_i^s$ vector cannot be a part of a feasible solution for CLFDIP (i.e. feasible $\overline{X}_{im}^s$ cannot be obtained). For scenario s and $\overline{Y}_i^s$, let $\widetilde{M}_{is}$ be the set of demand points that must be assigned to available TF i due to closest assignment property. Also let us define $\widetilde{Q}_{mis} = I_m \setminus (P_1(s) \cup P_2(s, i))$,

namely the set of TF points that demand point m can be assigned to, but farther to m than TF i . Given the definition of the sets, and that $\overline{Y}_i^s$ is infeasible to the *CSP*, equations 3.28 – 3.29 hold.

$$\delta_{pm} \leq \delta_{im} \leq \delta_{qm} \quad s \in S, \ m \in \widetilde{M}_{is}, \ i \in P_1(s), \ p \in P_2(s, i), \ q \in \widetilde{Q}_{mis} \quad (3.28)$$

$$\sum_{l \in L} u_l \sum_{m \in \widetilde{M}_{is}} d_{ml}^s > K_i^T \quad s \in S, \ i \in P_1(s) \quad (3.29)$$

Assuming $\overline{Y}_i^s$ is a feasible vector, for any scenario s , $i \in P_1(s)$, and $m \in \widetilde{M}_{is}$, $X_{pm}^s = 0$ must hold for all $p \in P_2(s, i)$ in *CLFDIP*. Furthermore, $X_{qm}^s = 0$ for $q \in \widetilde{Q}_{mis}$ must hold because of constraint 3.5 and equation 3.28. Therefore $X_{im}^s = 1$ must hold due to constraints 3.2 – 3.3. However in this case, equation 3.29 contradicts constraint 3.4. Therefore, $\overline{Y}_i^s$ vector cannot be a part of feasible solution vector for *CLFDIP*. $\square$

3.4.3. Flow Distribution Sub-problem and Duality-based Benders Cuts

If *CSP* has a feasible solution, then all that remains is to check whether there exists a feasible flow distribution with respect to the given TF locations ($\overline{Y}_i^s$) and inventory levels ($\overline{H}_{jl}$) from the master problem, and demand allocations ($\overline{X}_{im}^s$) obtained from the clustering sub-problem. The second sub-problem *FDSP* is given below, where the total demand for item l in TF i is defined as $\overline{D}_{il}^s = \sum_{m \in M_s} d_{ml}^s \overline{X}_{im}^s$. Note that constraints 3.6 and 3.8 are separable over scenarios and item types, therefore *FDSP* is defined for each scenario s and item type l .

$$\begin{aligned} & FDSP(s, l, \overline{Y}_i^s, \overline{H}_{jl}, \overline{D}_{il}^s) : \\ & \min \quad 0 \\ & \text{s.t.} \quad \sum_{j \in J_i^k} F_{jil}^s \geq r_{kl} \overline{D}_{il}^s \overline{Y}_i^s \quad i \in I, k \in K \end{aligned} \quad (3.30)$$

$$\sum_{i \in I} F_{jil}^s \leq \overline{H_{jl}} \quad j \in J \quad (3.31)$$

$$F_{jil}^s \geq 0 \quad j \in J, i \in I \quad (3.32)$$

If *FDSP* has a feasible solution for all scenarios and item types, then the solution to *LIPMP* is also a feasible solution to the original problem. Otherwise duality-based feasibility cuts are generated and added to the master problem. The dual formulation of *FDSP* is used to check the feasibility of the second sub-problem and to generate feasibility cuts if needed. *DFDSP* is defined in Equations 3.33 – 3.36, where θ_{ik} and ϕ_j are the dual variables corresponding to constraints 3.30 and 3.31, respectively.

$$DFDSP(s, l, \overline{Y_i^s}, \overline{H_{jl}}, \overline{D_{il}^s}) :$$

$$\max \quad \sum_{j \in J} \phi_j \overline{H_{jl}} + \sum_{i \in I} \sum_{k \in K} \theta_{ik} r_{kl} \overline{D_{il}^s} \overline{Y_i^s} \quad (3.33)$$

$$\text{s.t.} \quad \sum_{k: j \in J_i^k} \theta_{ik} + \phi_j \leq 0 \quad j \in J, i \in I \quad (3.34)$$

$$\theta_{ik} \geq 0 \quad i \in I, k \in K \quad (3.35)$$

$$\phi_j \leq 0 \quad j \in J \quad (3.36)$$

Since *DFDSP* has a trivial feasible solution, its solution can either be finite optimum or unbounded. If there is a finite optimum solution, this means *FDSP* is also feasible and thus solution to the master problem is the solution for the overall problem. Otherwise, an unbounded solution to the *DFDSP* indicates the infeasibility of the *FDSP*. For each (s, l) couple where *FDSP* is unbounded, we generate the feasibility cut given in 3.37 and add it to the master problem, where $(\theta_{ik}^r, \phi_j^r)$ is an extreme ray of the unbounded solution.

$$\sum_{j \in J} \phi_j^r \overline{H_{jl}} + \sum_{i \in I} \sum_{k \in K} \theta_{ik}^r r_{kl} \overline{D_{il}^s} \overline{Y_i^s} \leq 0 \quad (3.37)$$

3.4.4. Implementation Details

In classical Benders decomposition, the master problem is solved to optimality at each iteration. Since constructing the branch-and-bound tree from scratch at each iteration can be time consuming, we use *Branch-and-Benders-cut* strategy that builds a single search tree and generates Benders cuts within the tree (Rahmaniani *et al.*, 2017). We employ CPLEX solver to implement our models. Using the *LazyConstraintCallback* functionality of CPLEX, we solve the sub-problems whenever an incumbent is obtained in the search tree. If the solution is a feasible one, then it is accepted as the new incumbent. Otherwise logic-based or duality-based feasibility cuts are generated and added to the branch-and-bound tree globally. Figure 3.3 summarizes the algorithm of the LBBD approach we propose.

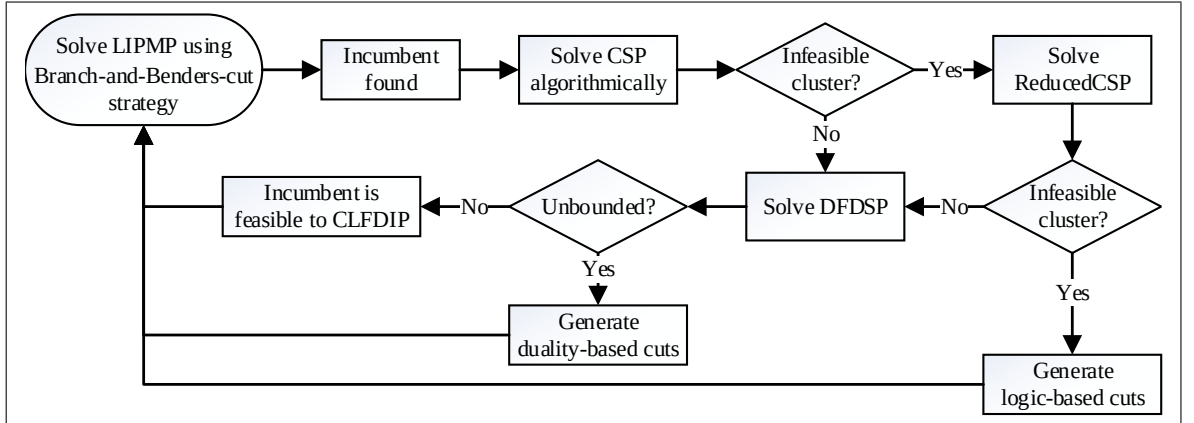


Figure 3.3. The algorithm of the LBBD approach.

Apart from using *Branch-and-Benders-cut* strategy, two other strategies are utilized to improve solution time. In the presence of *LazyConstraintCallback*, CPLEX disables parallel computing by default in order to ensure thread safety since the callback functions may modify globally shared data simultaneously. In order to benefit from parallel computing, we ensure that local variables are used in callback functions, and there is a dedicated dual sub-problem object for each thread. In this way, we used 8 parallel threads without risking the correctness of the solution.

Secondly, we observe that the tightened variable bounds during the presolve phase for *CLFDIP* is beneficial to speed up the procedure. However, the solver turns off the dual presolve reductions in the presence of *LazyConstraintCallback* since the master problem is not complete and new constraints will be included later on. Therefore, before running the LBBD procedure, we build the *CLFDIP* model and let the solver apply presolve on the full model. Then the variable bounds obtained in the presolve phase are used as the variable bounds in the master problem.

Finally, note that the LBBD procedure can easily be applied for the *CLFDIP_EarlyNotify* model, which is a use case of the original problem given in Section 3.2.2, by redefining the sub-problems appropriately.

3.5. Experimental Results

In this section we analyze the performance of the proposed LBBD, the effect of integrating clustering decisions in the model, the sensitivity of pre-disaster costs with respect to the SCW distance limits. For this purpose, a set of test problems with different sizes are generated. These instances are solved using our LBBD implementation, and off-the-shelf solution strategies of the solver package. The LBBD algorithm is implemented using C# programming language. We then conclude our numerical studies with an example based on the Anatolian Side of İstanbul.

3.5.1. Test Instances

There are several sophisticated techniques in the earthquake engineering literature to assess disaster damage (e.g. Yazar *et al.*, 1984; Erdik *et al.*, 2010). Here we use a practical and simplified approach to generate self-consistent artificial instances with stylized realism. The data generation tool we use to generate problem sets and parameters is explained in detail in Appendix A.1.1. The data generation scheme is parametrized and enables the decision maker to generate self-consistent instances with different characteristics. Different topological features such as the number of cities, their sizes, orientations and relative positions; as well as disaster-related factors

such as epicenters, magnitudes and affected populations can be obtained using this tool. In order to validate our data generation scheme, we consulted Boğaziçi University Kandilli Observatory and Earthquake Research Institute (KOERI). The subject expert confirmed that the data generation scheme is a valid abstraction of the problem.

To test the numerical performance, twelve test problems with different sizes are generated randomly. These cases include two, three, and four cities. For each case, there are four independent instances. The general properties of the instances are shown in Table 3.1, where the first column identifies problem names and the second column states the number of cities generated in the instance. Instances are referred to as “ $Px-y$ ”, where x stands for the number of cities and y for the instance number. The next column indicates the total population living in the hypothetical region. The fourth column gives the number of demand points (affected buildings) in each scenario, separated by semicolons. The number of demand points is given for the four-scenario case, so the first two (three) values are valid for two- (three-) scenario cases. The next two columns identify the number of PF and TF candidate locations. Finally, the last two columns give the number of variables in each instance for two-, three- and four-scenario cases. Table 3.1 provides a broad picture of the difficulty of the test instances. Note also that even the smallest instances can be representative of real-life cases.

As discussed in Section 3.1, we model for the worst case, so the subject expert we consulted confirmed that the number of disaster scenarios does not need to be high since each scenario corresponds to a disaster epicenter. In addition, it should be noted that the number of disaster scenarios considered in the report by Japan International Cooperation Agency (JICA, 2002) is four for İstanbul. However, to demonstrate the scalability of the LBBD approach, we generate cases with 10 scenarios for all instances as well.

3.5.2. Results and Discussion

CLFDIP is solved for the given test instances by using IBM ILOG CPLEX 12.8. In this version of the solver package, the classical Benders decomposition algorithm is

Table 3.1. General properties of the test instances.

	#City	Pop.	$ M_s $	$ J $	$ I $	#Binary Variables	#Cont. Variables
P2-1	2	155458	485;543;1045;626	35	77	19535;41915;55635	16275;24360;32445
P2-2	2	243400	600;695;683;418	21	81	27006;42672;49041	10269;15372;20475
P2-3	2	283173	1041;757;689;1072	32	120	43283;59872;84617	23136;34656;46176
P2-4	2	390767	993;357;348;785	48	133	33059;41141;59015	38448;57600;76752
P3-1	3	301000	581;584;857;515	41	114	25222;43690;54939	28167;42189;56211
P3-2	3	281821	379;400;1004;864	57	111	16274;35141;52552	38133;57114;76095
P3-3	3	501707	716;379;1167;471	61	171	23978;53321;65758	62769;94062;125355
P3-4	3	441097	664;1423;1001;644	71	201	58167;83421;97373	85839;128652;171465
P4-1	4	388283	1314;993;675;851	44	167	51973;65904;86325	44220;66264;88308
P4-2	4	423098	399;582;1003;1294	54	203	26696;47374;77563	65934;98820;131706
P4-3	4	530200	1001;1149;1190;1721	60	232	54643;81053;127117	83700;125460;167220
P4-4	4	723861	1220;1225;431;736	118	310	66844;78183;95511	219834;329574;439314

also implemented as a solution strategy. We therefore present the results with three solution strategies. The first strategy uses the default parameters of the solver package and is denoted in this manuscript as “regularCplex”. The second one, which we denote as “bendersCplex”, utilizes the CPLEX implementation of the classical Benders decomposition, where all integer variables are left in the master problem and the continuous variables are placed in the sub-problem. The last strategy is our implementation of LBBD with *Branch-and-Benders-cut* strategy. In regularCplex and bendersCplex strategies, Z_{jt} variables have the highest branching priority, followed by Y_i^s and X_{mi}^s variables. In LBBD, Z_{jt} variables have a higher branching priority. Although the valid inequalities do not affect the performance of regularCplex and bendersCplex significantly in our preliminary experiments, we present numerical results where they are kept in the model. Run times are limited to 8 hours as a stopping condition and the number of threads that the solver can utilize is set to 8. All experiments are carried out on a PC with 3.30 GHz CPU and 16 GB RAM, running under 64-bit Windows 7 operating system.

Table 3.2. Numerical performance comparison for *CLFDIP*.

	regularCplex		bendersCplex		LBBD	
Problem	Gap%	Time	Gap%	Time	Gap%	Time
P2-1-s2	0.00	1982.0	0.00	38.0	0.00	27.9
P2-1-s3	0.00	24947.5	0.00	121.3	0.00	62.8
P2-1-s4	9.32	28800.5	0.00	141.7	0.00	97.4
P2-1-s10	36.86	28800.7	0.00	941.5	0.00	482.3
P2-2-s2	0.00	5700.4	0.00	652.8	0.00	48.5
P2-2-s3	0.00	21198.6	0.00	3555.7	0.00	88.0
P2-2-s4	32.37	28800.3	0.00	861.9	0.00	114.8
P2-2-s10	78.62	28800.4	0.00	3357.7	0.00	419.0
P2-3-s2	0.00	16153.3	0.00	409.5	0.00	88.8
P2-3-s3	17.01	28801.0	0.00	249.4	0.00	131.6
P2-3-s4	31.33	28800.4	0.00	1950.9	0.00	210.6
P2-3-s10	79.81	28801.1	17.79	28801.1	0.00	2440.4
P2-4-s2	13.73	28800.3	4.20	28800.4	0.00	96.9
P2-4-s3	13.82	28800.4	9.16	28800.2	0.00	106.0
P2-4-s4	42.33	28800.5	7.43	28800.3	0.00	215.4
P2-4-s10	86.69	28800.6	25.95	28805.5	0.00	1202.7
P3-1-s2	0.00	26795.8	0.00	22309.2	0.00	494.1
P3-1-s3	24.87	28800.2	0.00	2657.2	0.00	93.3
P3-1-s4	0.00	22338.5	0.00	12261.8	0.00	184.9
P3-1-s10	78.24	28800.3	32.02	28800.5	0.00	637.2
P3-2-s2	0.00	19465.5	0.00	421.8	0.00	64.8
P3-2-s3	14.60	28800.3	0.00	3849.3	0.00	88.9
P3-2-s4	15.98	28800.4	4.22	28800.7	0.00	191.3
P3-2-s10	40.64	28800.6	16.37	28801.3	0.00	468.6
P3-3-s2	25.18	28800.2	0.00	14696.0	0.00	509.9
P3-3-s3	18.81	28800.5	1.85	28800.8	2.99	28800.3
P3-3-s4	62.28	28800.3	6.83	28801.1	1.09	28800.2
P3-3-s10	89.44	28800.8	26.30	28801.3	0.00	4866.1
P3-4-s2	33.74	28800.3	35.67	28800.6	1.18	28800.6
P3-4-s3	90.88	28800.6	12.40	28801.2	0.00	1233.2
P3-4-s4	91.16	28800.5	26.19	28801.4	1.25	28803.8
P3-4-s10	91.37	28801.4	88.44	28801.2	0.89	28800.6
P4-1-s2	25.16	28800.5	0.00	3539.4	0.00	271.0
P4-1-s3	38.89	28800.4	0.00	1531.5	0.00	308.0
P4-1-s4	54.55	28800.4	23.18	28800.9	0.00	415.7
P4-1-s10	89.36	28801.0	50.17	28805.8	0.00	2661.2
P4-2-s2	0.00	9571.0	0.00	2130.4	0.00	194.8
P4-2-s3	32.26	28800.6	0.00	2009.8	0.00	275.9
P4-2-s4	83.66	28800.4	0.00	2078.0	0.00	622.6
P4-2-s10	90.40	28801.0	85.11	28801.0	0.00	3330.2
P4-3-s2	64.71	28800.5	27.33	28800.4	0.00	614.1
P4-3-s3	93.71	28800.3	41.28	28801.3	8.19	28803.2
P4-3-s4	77.70	28800.4	6.05	28801.7	0.00	2066.7
P4-3-s10	90.35	28801.1	70.70	28805.5	0.87	28804.4
P4-4-s2	94.46	28800.4	32.14	28800.5	0.00	1835.4
P4-4-s3	94.98	28800.6	58.22	28801.3	0.00	6866.2
P4-4-s4	95.04	28800.8	49.18	28801.7	0.00	8571.4
P4-4-s10	95.15	28807.1	86.58	28804.5	13.72	28803.2

Table 3.2 presents a summary of the results of regularCplex, bendersCplex and LBBD. The first column provides the instance name, and the subsequent columns indicate the optimality gap percentages and the durations for solution strategies. The problem names are given as “ $Px-y-sz$ ”, where x stands for the number of cities, y for the instance number, and z for the number of scenarios.

Table 3.2 indicates that optimality gaps tend to increase with the problem size (both in terms of number of cities and city sizes) and the number of scenarios. Apart from that, Table 3.2 shows that the performance of regularCplex deteriorates very quickly with the problem size. Only in 9 out of 48 instances an optimal solution is found, but these are mostly among instances with two cities or two scenarios. One can also observe that optimality gaps can be greater than 90%, which indicates poor performance.

Although bendersCplex yields better results than the regularCplex, its performance is still behind LBBD as depicted in Table 3.2. There are 22 instances for which the optimal solution is found with bendersCplex, with shorter run times than with regularCplex. However, as the problem sizes increase, bendersCplex fails to find the optimum solution within the given time limit.

Finally, as displayed in the last two columns of Table 3.2 the optimum solutions can be attained for 40 instances out of 48 with LBBD. Moreover, the run times are much shorter than those of other methods. Solution speed with the LBBD approach is fast, especially considering the strategic nature of the problem. For cases where the procedure is interrupted by the time limit, the optimality gaps are small, and there is only one instance where the optimality gap is higher than 10%. There is also only one instance where LBBD is outperformed by bendersCplex, namely P3-3-s3.

It should be noted that any feasible solution to the problem satisfies the requirements of all affected people under all scenarios. Therefore, decision makers can use the best solution obtained without jeopardizing the quality of service. However, a sub-optimal solution compromises cost effectiveness. A large optimality gap means a severe

economic loss considering the high investment costs. Thus, although a standard solver provides feasible solutions, the results show that our customized LBBD method significantly improves the quality of the suggested relief network design within a shorter run time.

In Section 3.2.2 *CLFDIP_EarlyNotify* model is explained, which modifies *CLFDIP* by selecting the TFs independent of the scenarios, thus allowing decision makers to announce these locations prior to a disaster. The numerical studies are performed for this alternative version with the same set of problems and the results (which are parallel to the results of *CLFDIP*) are presented in Table B.1 in Appendix B.1.

3.5.3. The Effect of Integrated Clustering Decisions

Our model treats clustering of the demand points as an integral part of the problem to improve the solution quality in terms of cost. We test this claim by means of a cluster-first approach, where we decompose *CLFDIP* into two stages: first the individual demand points are clustered into TFs for each scenario, then the PF locations and prepositioned inventory amounts are found given the TFs.

The cluster-first (CF) model consist of constraints 3.2 – 3.5. As the first option of an objective function, we minimize the total distance traversed by the affected population. This choice is in parallel to the literature (Görmez *et al.*, 2011; Chang *et al.*, 2007), and tends to open as much TF as possible while closest assignment and capacity constraints are obeyed. As the second option, we minimize the number of TFs that are opened. Here, the average distances will be higher but still within the limits defined by I_m sets. Cluster-first model is separable over scenarios, we can therefore find a feasible clustering solution for each scenario s and obtain the values of Y_i^s and X_{im}^s variables. As the next step, *CLFDIP* is solved by fixing the values of Y_i^s and X_{im}^s variables to obtain the remaining decisions.

To analyze the benefit of integrated clustering decisions, we use the instances for which the optimum solutions are found. Table 3.3 provides the comparison in

terms of the number of selected PFs and cost increase for CF approach under both objective functions. The integrated clustering decisions allow the model to alter the selected TF locations. Then it may be possible to select less number of PFs, PFs with smaller sizes, or PFs with less fixed costs by adjusting the selected TF locations since warehouses must comply with the SCWs of the TFs. Therefore, the optimal objective function is worsened in most of the instances, especially for the distance minimization case. Also, cost increase can be observed even for the cases where the number of PFs remains the same. One can thus conclude that it is beneficial to consider these decisions simultaneously, even though this increases the problem complexity.

Table 3.3. Cost and the number of PFs comparison for cluster-first (CF) approach.

Problem	LBB	CF-Min Distance	CF-Min TFC		Count	Problem	LBB	CF-Min Distance	CF-Min TFC		Count
	#PF	#PF	Cost Incr %	#PF	Cost Incr %		#PF	#PF	Cost Incr %	#PF	Cost Incr %
P2-1-s2	2	2	0.0	2	0.0	P3-2-s2	3	3	15.5	3	0.0
P2-1-s3	3	3	0.0	3	0.0	P3-2-s3	3	4	6.6	3	4.0
P2-1-s4	3	3	2.3	3	0.0	P3-2-s4	3	4	6.6	3	4.0
P2-1-s10	3	3	2.3	3	0.0	P3-2-s10	3	3	10.2	3	4.0
P2-2-s2	2	4	34.6	2	0.0	P3-3-s2	3	4	16.6	4	3.7
P2-2-s3	2	4	34.6	2	0.0	P3-3-s10	3	4	6.7	4	6.7
P2-2-s4	2	4	34.6	2	0.0	P3-4-s3	3	5	16.7	4	14.7
P2-2-s10	2	4	24.4	4	24.4	P4-1-s2	3	5	22.8	4	9.1
P2-3-s2	2	3	21.0	2	0.0	P4-1-s3	3	6	28.7	4	9.1
P2-3-s3	2	3	21.0	2	0.0	P4-1-s4	3	6	28.7	4	9.1
P2-3-s4	2	3	21.0	2	0.0	P4-1-s10	3	6	31.4	5	20.1
P2-3-s10	3	3	8.4	3	0.0	P4-2-s2	3	4	33.4	3	5.7
P2-4-s2	3	4	9.8	3	7.2	P4-2-s3	4	5	27.4	4	8.1
P2-4-s3	3	4	11.4	3	7.2	P4-2-s4	4	5	16.5	4	6.8
P2-4-s4	3	4	11.4	3	7.2	P4-2-s10	4	5	16.5	4	6.8
P2-4-s10	3	4	12.4	4	11.0	P4-3-s2	3	5	32.5	4	20.1
P3-1-s2	3	5	40.8	3	11.7	P4-3-s4	4	5	12.9	5	4.8
P3-1-s3	3	5	26.1	3	7.7	P4-4-s2	4	6	26.6	6	22.7
P3-1-s4	3	5	26.1	3	7.7	P4-4-s3	5	7	23.7	6	9.2
P3-1-s10	3	5	25.6	4	15.0	P4-4-s4	5	7	25.7	6	17.6

Finally note that, although we do not observe this in our test instances, there is a possibility that the selected TF locations may not provide a feasible solution for the overall problem since the CF model is not informed about the SCWs.

3.5.4. Cost Sensitivity to SCWs

CLFDIP ensures that for each TF there are PFs at locations from which demand can be filled within the required response times by imposing SCWs. We expect this characteristic to assist in finding better relief distribution solutions in the response stage in terms of effectiveness and fairness. In this section, we analyze the change in the preparedness stage costs as the SCW distance limits are changed. As in Section 3.5.3, the problem instances for which the optimum solution is found are used for the analysis.

Keeping all other parameters constant, the SCW distance limits are increased and decreased by 5%, 10%, 20% and 30%. Each of these changes redefines the elements in the J_i^k sets. For further analysis, we eliminate all SCW constraints (i.e. we set distance limits to infinity) by replacing Equation 3.6 in *CLFDIP* with the demand satisfaction constraints given in Equation 3.38 below.

$$\sum_{j \in J} F_{jil}^s \geq \sum_{m \in M_s} d_{ml}^s X_{im}^s \quad s \in S, i \in I, l \in L \quad (3.38)$$

Table 3.4 provides the average percentage of cost change in two-, three- and four-city instances, and in all instances as SCW size limits are changed. One can observe that the preparedness cost increases as SCW size limits are tightened and decreases as they are increased. This behavior is expected given that increasing SCW distance limits increases the number of candidate PF locations that can serve a TF within a specified window. By contrast, tightening SCWs reduces the number of candidate PF locations, and either the cost increases or the problem becomes infeasible. When distance limits are decreased by 20% and 30%, there are four and five instances where

the problem becomes infeasible, respectively. Those instances are excluded from the analysis.

Table 3.4. Sensitivity of solutions to SCW distance limits.

		SCW size change (%)								
		-30	-20	-10	-5	+5	+10	+20	+30	No SCW
Cost change (%)	P2	14.17	10.27	4.72	2.14	-0.21	-1.02	-3.39	-3.39	-7.72
	P3	13.98	8.01	4.35	2.85	-0.62	-0.81	-6.67	-12.88	-18.97
	P4	19.23	10.64	7.39	3.01	-0.28	-1.97	-6.55	-8.40	-20.76
	All	15.99	10.04	5.41	2.60	-0.35	-1.25	-5.32	-7.49	-15.05

As an extreme case, SCWs can be eliminated altogether, in which case the average cost saving goes up to 15.05%. It should be noted that more than 70% of distribution centers cannot receive adequate service within the required time limits when SCWs are eliminated from the model. This result indicates that using SCWs improves the network significantly at the expense of such an increase in the pre-disaster cost. On the opposite extreme, all problems become infeasible as we further tighten the window limits. However the preparedness cost is relatively insensitive to small changes in SCW distance limits.

Another parameter related to the SCWs is r_{kl} , which determines the proportion of demand for item l to be satisfied within service coverage window k . In our experiments, the costs are insensitive to changes in the r_{kl} parameter in almost all instances. Note that this is due to mostly having non-binding PF capacities in our instances and obeying the distance limits of SCWs dominates the cost.

3.5.5. An Example Based on İstanbul Anatolian Side

Before concluding our computational studies for the preparedness stage, we present a case study to provide some insight on the model performance on a real setting. İstanbul is the largest city in Turkey and one of the biggest metropolitan cities

in the world. Our case study is for developing a logistics network for the Anatolian side of İstanbul, which is a highly populated residential area separated from the European side of the city by the Bosphorus strait. We base our case on the report by Japan International Cooperation Agency (JICA, 2002). Damage estimations are provided for the two models in the JICA report, and the distribution of demand points among the districts of the area under concern are obtained from there for each scenario. The JICA report also provides the number of TF points required in each district. We use the facility locations provided by Disaster Coordination Center (AKOM) of İstanbul Metropolitan Municipality, and used by Görmez *et al.* (2011), for the potential PF locations. The neighborhoods within each district are also specified by AKOM. We randomly select a subset of these neighborhoods and use the neighborhood center coordinates of each as a candidate TF location. The resulting case consists of 18 PFs and 104 TF candidate locations, 12270 demand points in the first scenario, and 13930 demand points in the second scenario. The details of the case generation is provided in Appendix A.1.2.

The optimal solution for the case of İstanbul Anatolian Side is found in 224 seconds using the proposed LBBD approach. Figure 3.4 provides the corresponding results. In Figure 3.4, blue triangles represent the TF locations and red diamonds correspond to potential PFs. The model selects two PFs to be built, in Tuzla and Ümraniye, which are presented in larger diamonds. There are 37 TF locations selected in each of the scenarios, and the selected TFs for the first scenario are shown in larger triangles in Figure 3.4. With these results, the average walking distances of the beneficiaries are 1689.7 and 1574.1 meters for each scenario. Similarly, the average distance between PFs and TFs weighted by the flows are 12152.4 and 12168.9 meters for each scenario.

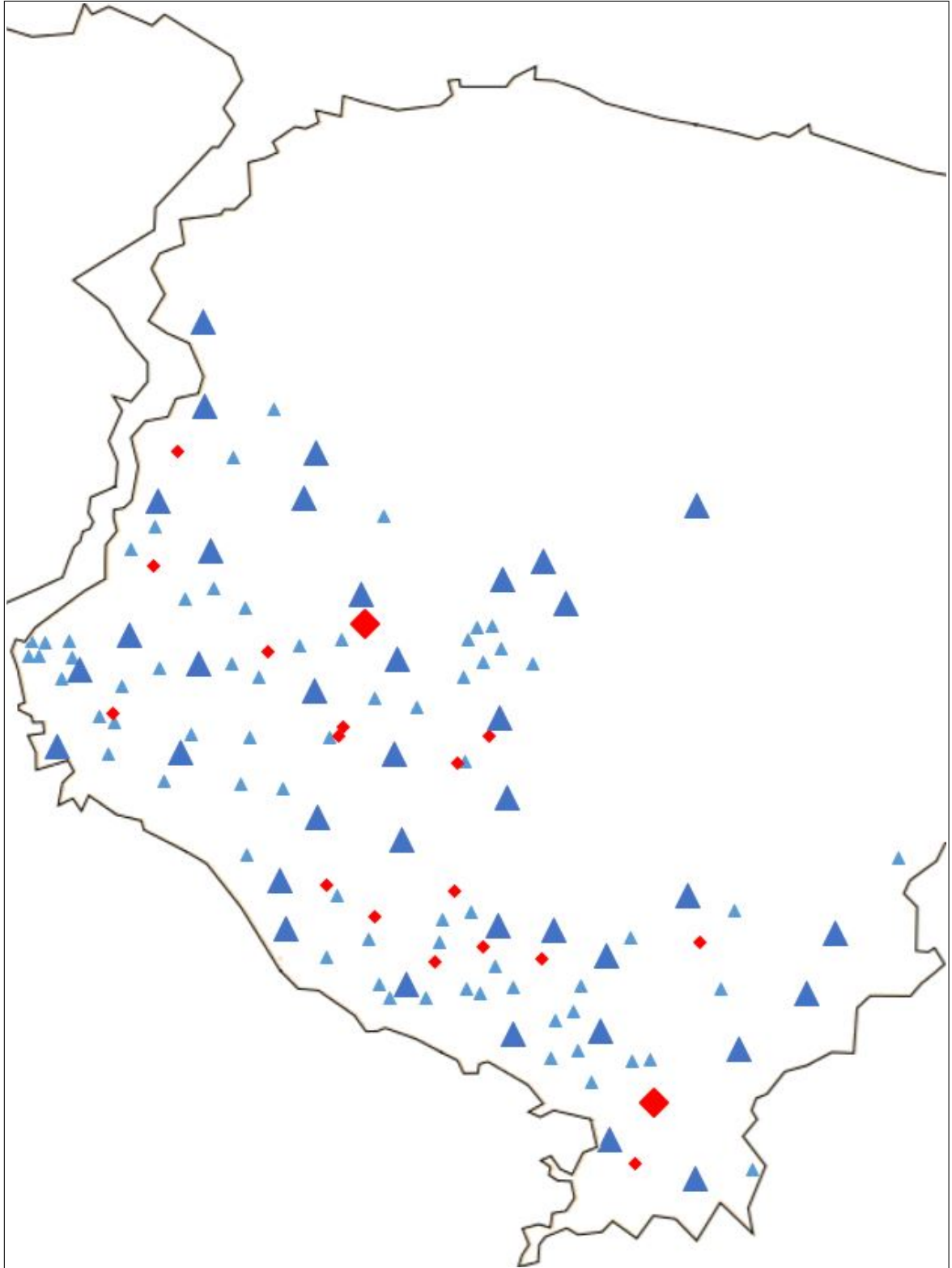


Figure 3.4. The results of the first scenario for the İstanbul Anatolian side case.

4. A RICH-VRP MODEL TO PURSUE EFFECTIVENESS AND FAIRNESS TRADE-OFF IN DISASTER RESPONSE

In this chapter, we address the response stage problem of distributing the relief items that are stored in multiple depots to the affected population gathered at relief centers, by means of a Rich-VRP model. One of our major research concerns is to propose suitable linear objective functions for the model for managing the effectiveness-fairness trade-off. We then turn our efforts to develop solution methods for the resulting model that displays a very challenging nature.

The chapter opens with a discussion of the basic properties and assumptions of the model, followed by the model itself. We then introduce the alternative objective functions and compare them. Next the matheuristics proposed to solve the problem are presented. Finally, numerical studies conclude the chapter.

4.1. Model Properties

The model, which we call *ResponseModel*, is a multi-depot, heterogeneous-vehicle with multiple use, capacitated, open vehicle routing problem with split deliveries, and the basic properties are discussed below. Note that similar to *CLFDIP*, the model properties and assumptions are validated by consulting subject experts at AFAD.

The problem properties of the *ResponseModel* are as follows:

Network structure: PF nodes are the existing warehouses for which the locations and the initial inventory amounts are determined in the preparedness stage. Similarly, TF locations are also determined in the preparedness stage, and they are the gathering points for affected people to receive relief goods. Therefore TFs are the aggregated demand points where the demand values are determined by the number of people that are assigned to them. As a result, the node set ($N = I \cup J$) is composed of two types,

namely PF nodes (J) and TF nodes (I). The set of directional arcs $A = (I \times I \cup J \times I)$ exist among all nodes, except there are no direct arcs between two PFs. Discretized time segments determine the planning horizon, and the symmetric arc lengths are determined as the shortest time that it takes to travel between two nodes. A given set of vehicles with different capacities exist, and the node and the time period that each of them will be available for service is predetermined.

Demand satisfaction: We assume a single item to distribute. Even if there are multiple item types, we assume that they can be bundled to meet the requirements of a beneficiary. In this way, the need to determine item weights is eliminated. Requirements at TFs do not have to be observed at time zero, demand arrivals can be realized during the planning horizon due to recurrent demand. We assume there are enough items available in the PFs to cover the total demand. This may be because we provide a robust plan in the preparedness stage, thus there will be no shortages in the TF points at the end of the planning horizon. Otherwise, we assume that replenishments are exogenous and outside the scope of the model.

Pursuit of humanitarian objectives: As mentioned before, all demand requirements are satisfied at the end of the planning horizon. Therefore the deliveries must be made as much as possible in a timely manner, while the demand satisfaction levels among the affected people should differ as small as possible throughout the horizon to improve fairness. Therefore the model should aim for efficiency, effectiveness and fairness at the same time. In order to capture this we propose different objectives that mimic inequity-averse objective functions. In this study, effectiveness considers the timeliness of the distribution, while fairness is related with the discrepancy in satisfaction among TFs during the horizon. Efficiency is defined as the length of the planning horizon, which implicitly reflects cost consideration as well.

Policy assumptions and limitations: Response stage is the phase when the execution of the relief operations are performed given the preparedness decisions. While the deliveries should be sufficient, timely and fair, the model should be flexible in operational decisions and represent them in as much detail as possible. In order to improve

the solution quality, vehicles are not assigned to depots or demand points. Tours are not mandatory, vehicles can visit any node as many times as they require. Vehicles can collect items from different depots, inventory can be relocated among PFs, and split deliveries in TFs are allowed. Finally, we prevent a vehicle to visit a TF node without satisfying any demand there. As limitations, we assume a closed system where outside purchase of vehicles or items are not allowed. Also, we do not explicitly model the pickup and delivery operations in the nodes and their durations are assumed to be included in the travel times.

Rich-VRP attributes: The problem we define here is a combination of different vehicle routing problem (VRP) extensions at the same time. We consider a model with “Heterogeneous fleet VRP with multiple use of vehicles” (HVRPM), “Multiple Depots VRP” (MDVRP), “Open VRP” (OVRP), “Split-delivery VRP” (SDVRP) (Caceres-Cruz *et al.*, 2015), and also vehicles do not have assigned depots. Hasle *et al.* (2006) define a Rich-VRP model as “a non-idealized model that represents the application at hand in an adequate way by including all important optimization criteria, constraints, and preferences”. Similarly, Rieck and Zimmermann (2010) state that extending the basic capacitated VRP models by including additional complex constraints or different objective functions is required to define a Rich-VRP. Therefore the *ResponseModel* we define is classified as a Rich-VRP problem.

4.2. Mathematical Model

Since we propose and implement alternative candidate objective functions, a base model that satisfies the properties given in Section 4.1 is provided. The required sets, parameters and the decision variables are given below, and Equations 4.1 – 4.23 define the *ResponseModel*.

Sets:

T	Set of time segments, $T = \{0, 1, \dots, T_h \}$
I	Set of temporary facility (TF) nodes
J	Set of permanent facility (PF) nodes
N	Set of all nodes, $I \cup J = N$
A	Set of arcs, $A = (I \times I \cup J \times I)$
V	Set of vehicles

Parameters:

d_{it}	Demand generated at TF i at time t
τ_{nm}	Number of time segments it takes to travel on arc $(n, m) \in A$
c_v	Capacity of vehicle v , in number of items
s_j	Amount of items initially held at PF j
B_{vnt}	$= \begin{cases} 1 & \text{If vehicle } v \text{ starts at node } n \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$

Decision variables:

X_{vnmt}	Binary variable indicating if vehicle v that traveled on arc (n, m) arrived to node m at time t
Y_{vnmt}	Amount of items carried on vehicle v that traveled on arc (n, m) arrived to node m at time t
H_{jt}	Remaining amount of inventory at PF j at the beginning of time t
Z_{vit}	Amount of items delivered to TF i by vehicle v at time t
G_{vnt}	Binary variable indicating if vehicle v finishes its service at node n at time t
P_{it}	The percentage of the satisfied cumulative demand in TF i at time t
Q_{it}	Binary auxiliary variable indicating if the cumulative amount carried to TF i up to time t is larger than the cumulative demand requirement until then

ResponseModel:

$$\min \quad f(X, Y, Z, H, P) \quad (4.1)$$

s.t.

$$X_{vnm t} = 0 \quad v \in V, (n, m) \in A, t = 0 \quad (4.2)$$

$$H_{j t} = s_j \quad j \in J, t = 0 \quad (4.3)$$

$$B_{v n t} + \sum_{m: (n, m) \in A} X_{v m n t} = \sum_{m: (n, m) \in A} X_{v n m (t + \tau_{n m})} + G_{v n t} \quad v \in V, n \in N, t \in T \quad (4.4)$$

$$Y_{v n m t} \leq c_v X_{v n m t} \quad v \in V, (n, m) \in A, t \in T \quad (4.5)$$

$$H_{j t} + \sum_{v \in V} \sum_{n: (n, j) \in A} Y_{v n j t} = H_{j (t+1)} + \sum_{v \in V} \sum_{n: (j, n) \in A} Y_{v j n (t + \tau_{j n})} \quad j \in J, t \in T \quad (4.6)$$

$$\sum_{n: (n, i) \in A} Y_{v n i t} = Z_{v i t} + \sum_{n: (i, n) \in A} Y_{v i n (t + \tau_{i n})} \quad v \in V, i \in I, t \in T \quad (4.7)$$

$$\sum_{v \in V} \sum_{t \in T} Z_{v i t} = \sum_{t \in T} d_{i t} \quad i \in I \quad (4.8)$$

$$\sum_{n \in N} \sum_{t \in T} G_{v n t} = 1 \quad v \in V \quad (4.9)$$

$$Z_{v i t} \geq \sum_{n: (n, i) \in A} X_{v n i t} \quad v \in V, i \in I, t \in T \quad (4.10)$$

$$\frac{\sum_{v \in V} \sum_{t'=0}^t Z_{v i t'}}{\sum_{t'=0}^t d_{i t'}} \leq 1 + Q_{i t} \sum_{t' \in T} d_{i t'} \quad i \in I, t \in T \quad (4.11)$$

$$\frac{\sum_{v \in V} \sum_{t'=0}^t Z_{v i t'}}{\sum_{t'=0}^t d_{i t'}} \geq Q_{i t} \quad i \in I, t \in T \quad (4.12)$$

$$P_{i t} \leq \frac{\sum_{v \in V} \sum_{t'=0}^t Z_{v i t'}}{\sum_{t'=0}^t d_{i t'}} + Q_{i t} \quad i \in I, t \in T \quad (4.13)$$

$$P_{i t} \leq 2 - Q_{i t} \quad i \in I, t \in T \quad (4.14)$$

$$P_{i t} \geq \frac{\sum_{v \in V} \sum_{t'=0}^t Z_{v i t'}}{\sum_{t'=0}^t d_{i t'}} - Q_{i t} \sum_{t' \in T} d_{i t'} \quad i \in I, t \in T \quad (4.15)$$

$$P_{i t} \geq Q_{i t} \quad i \in I, t \in T \quad (4.16)$$

$$X_{v n m t} \in \{0, 1\} \quad v \in V, (n, m) \in A, t \in T \quad (4.17)$$

$$c_v \geq Y_{v n m t} \geq 0 \quad v \in V, (n, m) \in A, t \in T \quad (4.18)$$

$$s_j \geq H_{j t} \geq 0 \quad j \in J, t \in T \quad (4.19)$$

$$Z_{v i t} \in \{0\} \cup \mathbb{Z}^+ \quad v \in V, i \in I, t \in T \quad (4.20)$$

$$1 \geq G_{v n t} \geq 0 \quad v \in V, n \in N, t \in T \quad (4.21)$$

$$Q_{it} \in \{0, 1\} \quad i \in I, t \in T \quad (4.22)$$

$$1 \geq P_{it} \geq 0 \quad i \in I, t \in T \quad (4.23)$$

In *ResponseModel* only the constraints are presented since alternative objective functions will be given in the following sections. Constraints 4.2 and 4.3 set the initial values for the variables related to vehicle and inventory levels in the first time segment, which are implemented as variable bounds instead of explicit constraints. Constraints 4.4 ensure vehicle conservation, and 4.5 limit the amount that can be transported on a vehicle by its capacity. Equations 4.6 define inventory balance constraints for PFs. Note that this set of constraints allow inventory relocation among PFs. Similarly, equation set 4.7 is the inventory balance constraints for TFs. Constraints 4.8 make sure that all of the demand is satisfied at the end of the planning horizon for all TFs. Equations 4.9 ensure all vehicles will leave the network, which is required for constraints 4.4 to work properly. Constraints 4.10 are added to improve effectiveness by making sure that if a vehicle visits a demand point, it has to satisfy some demand there. Equations 4.11 and 4.12 determine the value of auxiliary Q_{ilt} variables. Constraints 4.13 – 4.16 calculate the percentage of satisfied demand in TF i at time t , such that its value is bounded between 0 and 1 even if the amount of item carried to that TF i is higher than the cumulative demand up to time t . Lastly, equations 4.17 – 4.23 define the decision variables. $Y_{vnm t}$, H_{jlt} , and G_{vnt} are left as continuous variables since they will obtain integer values due to the definition of the constraints given integer values for the parameters.

4.2.1. Valid Inequality Set

A set of valid inequalities that considers the earliest entrance time to a node by a vehicle is defined to improve the solution quality. The valid inequality set eliminates all $X_{vnm t}$ and $Y_{vnm t}$ variables that cannot obtain a positive value due to initial paths of vehicles, and it is defined in equation 4.24 below, where $\tilde{\tau}_{nm}$ defines the shortest distance between nodes n and m . Note that $\tilde{\tau}_{nm}$ definition is required since we assume

there are no direct arcs between two PF nodes.

$$\sum_{n' \in N} \sum_{m: (m, n') \in A} \sum_{t'=0}^{\bar{t} + \bar{\tau}_{\bar{n}m} + \tau_{mn'} - 1} Y_{\bar{v}mn't'} + X_{\bar{v}mn't'} = 0 \quad \bar{v} \in V, \bar{n} \in N, \bar{t} \in T : B_{\bar{v}\bar{n}\bar{t}} = 1 \quad (4.24)$$

4.3. Proposed Objective Functions

One of the important questions in humanitarian relief delivery is to define an appropriate objective function. In a disaster response setting the minimization of inequality between demand points may lead to inferior solutions on its own since it contradicts the maximization of individual utilities of the beneficiaries. Therefore, we need to focus on fair optimization which considers equity, effectiveness and efficiency rather than inequality minimization. However note that efficiency, effectiveness and equity can usually be conflicting (Gralla *et al.*, 2014). It should also be noted that the properties of inequity-averse functions that are stated in Section 2.3 deal with allocation of resources in a static environment. However, in relief distribution we work with a multi-period problem, and the problem structure (e.g. number of vehicles and their capacities, distances between nodes) constrain the time and the quantity of items that can be distributed. Therefore, the utility vector y can not be defined as the allocation amounts for each entity as in Section 2.3, but as a vector of satisfaction percentages for each time period. As a result of that we are unable to come up with an inequity-averse aggregation function that satisfies the properties of inequity-averse functions. However, the objective functions that we propose try to capture both the satisfaction levels and their times in a way that their progression is important, rather than their final values. Therefore the model and objective function features (guaranteed demand satisfaction, penalizing unsatisfied demands with an increasing function of time) helps us to observe similar properties.

The *ResponseModel* given in Section 4.2 ensures all demand requirements will be satisfied at the end of the planning horizon, assuming the total inventory held in the

PFs is sufficient to cover all cumulative demands of TFs and the planning horizon is long enough. Therefore, the effectiveness consideration is related with the timeliness of the distribution, and the fairness consideration is related with the discrepancy among TFs during the horizon. Efficiency consideration is related to the duration of the planning horizon, which implicitly reflects cost consideration as well. In fact, makespan effects all three.

The satisfaction levels of TFs at the end of the planning horizon is not a performance measure and we consider the progression of the satisfaction levels in each time period. Moreover, we cannot use demand weighted arrival times since the demand generation is not completed at time zero, and satisfaction levels of a TF may reduce as new demand requirements occur. We define the “*disutility*” of each TF i as $\sum_{t \in T} (1 - P_{it})$, which can be interpreted as the area above the satisfaction level curve for that TF. With these in mind, we propose alternative objective functions in the following subsections that try to capture efficiency, effectiveness and equity considerations simultaneously. Moreover, a trade-off parameter α is used to adjust the emphasis on fairness and effectiveness.

4.3.1. ResponseModelObj₁

In the first objective, we consider the discrepancy among the disutilities of TF points at each time period. One can assert that it is unfair for TF i and TF j to have different disutilities. Using this idea, we penalize the satisfaction ratio differences between TFs at each time periods. Moreover, we can suggest that the differences that are observed closer to the end of the planning horizon are more important than the earlier ones. Therefore *ResponseModelObj₁* minimizes the total sum of differences between the dissatisfaction levels weighted by t^α multiplier, where α is the trade-off parameter.

The additional decision variable set and *ResponseModelObj₁* are given below.

Additional decision variables:

D_{ijt} Difference between the satisfaction levels of TF i and TF j at time t

ResponseModelObj₁:

$$\min \sum_{i \in I} \sum_{\substack{j \in I \\ j \neq i}} \sum_{t \in T} t^\alpha D_{ijt} \quad (4.25)$$

s.t.

$$(4.2 - 4.23)$$

$$P_{it} - P_{jt} \leq D_{ijt} \quad i \in I, j \in I, j \neq i, t \in T \quad (4.26)$$

$$D_{ijt} \geq 0 \quad i \in I, j \in I, j \neq i, t \in T \quad (4.27)$$

Intuitively, one would expect that the discrepancies between TFs should be smaller in the last periods as the value of α increases. Therefore effectiveness emphasis will be higher as the value of α increases since the decision maker can ignore earlier disutility differences rather than trying to maintain a balance among TFs. Also, efficiency is implicitly considered since the penalties in the objective function increases with time and shorter realized planning horizons will be preferred. Finally, it should be noted that this objective is equivalent to “sum of pairwise absolute differences” when $\alpha = 0$ is selected.

4.3.2. ResponseModelObj₂

The second objective function is based on multi-objective optimization where effectiveness can be defined by the total unsatisfied demand percentages throughout the planning horizon, and fairness can be given as the total pairwise differences between the disutilities of TFs. Therefore *Obj₂* is an extension of the first objective by considering the effectiveness term as well. The corresponding *ResponseModelObj₂* model is given below where $f(\alpha, t)$ is the trade-off parameter which is a function of time.

Additional decision variables:

D_{ijt} Difference between the satisfaction levels of TF i and TF j at time t

ResponseModelObj₂:

$$\min \quad \sum_{i \in I} \sum_{t \in T} (1 - P_{it}) + \sum_{i \in I} \sum_{\substack{j \in I \\ j \neq i}} \sum_{t \in T} f(\alpha, t) D_{ijt} \quad (4.28)$$

s.t.

$$(4.2 - 4.23)$$

$$P_{it} - P_{jt} \leq D_{ijt} \quad i \in I, j \in I, j \neq i, t \in T \quad (4.29)$$

$$D_{ijt} \geq 0 \quad i \in I, j \in I, j \neq i, t \in T \quad (4.30)$$

Unlike Obj_1 , this objective includes the effectiveness term as well. Moreover, we can define different $f(\alpha, t)$ functions that can perform differently. We can define $f_1(\alpha, t) = t^\alpha$ to obtain $Obj_{2.1}$, or it can linearly increase from zero to 2α (i.e. $f_2(\alpha, t) = \frac{2\alpha t}{T}$) to define $Obj_{2.2}$. Furthermore, by defining the objective function as in Equation 4.31, we obtain $Obj_{2.3}$ which can emphasize effectiveness in earlier periods, and equality in the latter periods.

$$\sum_{i \in I} \sum_{t \in T} (2\alpha - f_2(\alpha, t))(1 - P_{it}) + \sum_{i \in I} \sum_{\substack{j \in I \\ j \neq i}} \sum_{t \in T} f_2(\alpha, t) D_{ijt} \quad (4.31)$$

Intuitively, one would expect that the discrepancies between TFs should be smaller in the last periods as the value of α increases. Similarly, the model focuses more on effectiveness as the value of $f(\alpha, t)$ reduces. It should be noted that objective $Obj_{2.2}$ is equivalent to the “utilitarian” objective if $\alpha = 0$.

4.3.3. ResponseModelObj₃

The third objective function is inspired by the “Rawlsian” approach. However, unlike Rawlsian approach that uses a single utility value for each TF, we consider the minimum satisfaction level among all TFs at each time period. The corresponding *ResponseModelObj₃* is given below where t^α term tries to increase effectiveness and efficiency by pushing the model to satisfy the all demands as early as possible as the α parameter increases. Also note that the Q_{it} binary variables are not needed to define P_{it} variables correctly in this model.

Additional decision variables:

D_t The minimum satisfaction level among all TFs at time t

ResponseModelObj₃:

$$\min \sum_{t \in T} (1 - D_t) t^\alpha \quad (4.32)$$

s.t.

$$(4.2 - 4.10), (4.17 - 4.21), (4.23)$$

$$P_{it} \geq \frac{\sum_{v \in V} \sum_{t'=0}^t Z_{vit'}}{\sum_{t'=0}^t d_{it'}} \quad i \in I, t \in T \quad (4.33)$$

$$P_{it} \geq D_t \quad i \in I, t \in T \quad (4.34)$$

$$D_t \geq 0 \quad t \in T \quad (4.35)$$

4.4. Objective Functions Adapted from the Literature

In this section, we present the four objective functions that are adapted from the literature to use in our *ResponseModel*. One of them, namely *ObjHSB*, considers the satisfaction percentages of TF points at each time period, whereas the rest uses a single utility definition for each demand point (i.e. $y_i = \sum_{t \in T} (1 - P_{it})$).

4.4.1. ResponseModelObjHSB

Huang *et al.* (2012) solve a vehicle routing problem for the last-mile distribution from a warehouse to demand points. For this model, they define an equity objective, which calculates the fraction of the total unsatisfied demand at each time period for demand nodes, and converts it into disutility using a piecewise linear convex function as demonstrated in Figure 4.1 below. In this way, they aim to prioritize the worst-off demand points before others. The additional parameters and variables, and

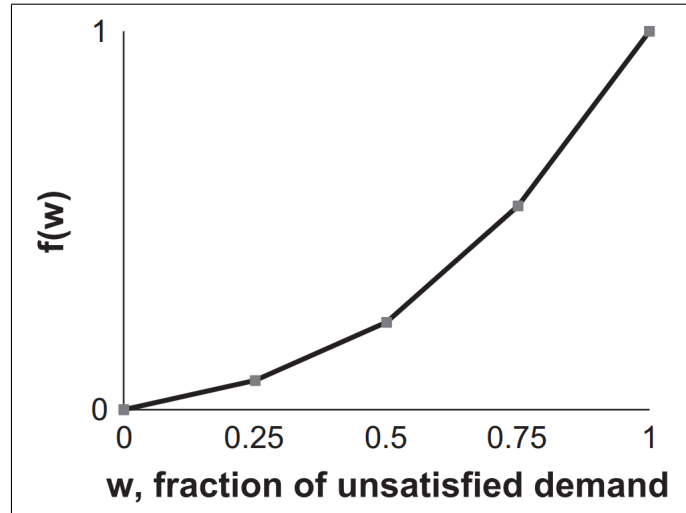


Figure 4.1. An example piecewise linear disutility function (Huang *et al.*, 2012).

ResponseModelObjHSB model that is resulted is given below.

Additional parameters:

a_p Parameter value that defines the slope of the linear constraint in p^{th} segment. $a_p = \{4/13, 8/13, 16/13, 24/13\}$

b_p Parameter value that defines the intercept of the linear constraint in p^{th} segment. $b_p = \{0, -1/13, -5/13, -11/13\}$

Additional decision variables:

F_{it} The disutility of TF i in time t

ResponseModelObjHSB:

$$\min \quad \sum_{i \in I} \sum_{t \in T} F_{it} \quad (4.36)$$

s.t.

$$(4.2 - 4.23)$$

$$F_{it} \geq a_p(1 - P_{it}) + b_p \quad i \in I, t \in T, p \in P \quad (4.37)$$

$$F_{it} \geq 0 \quad i \in I, t \in T \quad (4.38)$$

4.4.2. ResponseModelPiecewisePropFair

In Section 2.3, proportional fairness is introduced as a special case of α -fairness. Since it maximizes a nonlinear function ($\sum_{i \in I} U_i = \sum_{i \in I} \log(y_i)$), we adapt it to our problem using a piecewise linear approximation, where the utility y_i is defined as $y_i = \frac{\sum_{t \in T} P_{it}}{|T|}$ (i.e. normalized area under the satisfaction curve of TF i). The piecewise linear function that we use is given in Figure 4.2 below, where the horizontal axis represent y_i and the vertical axis represent U_i . Then the corresponding *ResponseModelPiecewisePropFair* is given below.

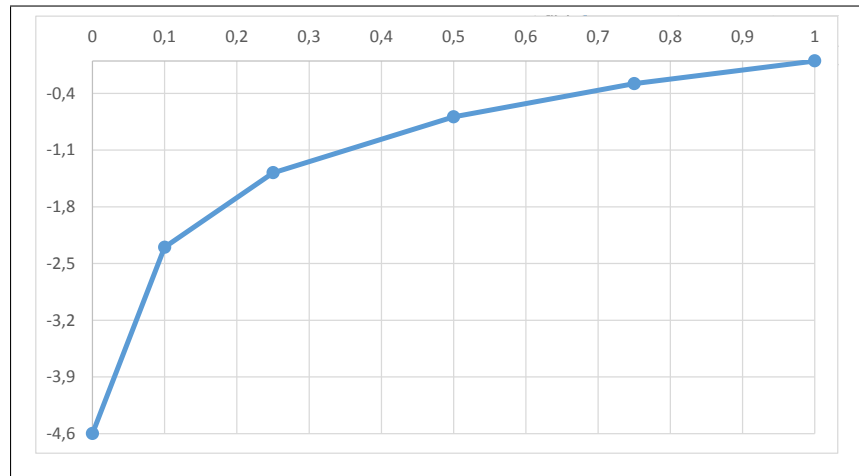


Figure 4.2. Piecewise linear approximation to the proportional fairness.

Additional parameters:

- a_p Parameter value that defines the slope of the linear constraint in p^{th} segment. $a_p = \{23, 92/15, 69/25, 41/25, 28/25\}$
- b_p Parameter value that defines the intercept of the linear constraint in p^{th} segment. $b_p = \{-23/5, -437/150, -207/100, -151/100, -28/25\}$

Additional decision variables:

- U_i Approximated logarithm of the utility of TF i

ResponseModelPiecewisePropFair:

$$\min \quad - \sum_{i \in I} U_i \quad (4.39)$$

s.t.

(4.2 – 4.23)

$$U_i \leq a_p \frac{\sum_{t \in T} P_{it}}{|T|} + b_p \quad i \in I, p \in P \quad (4.40)$$

$$U_i \geq 0 \quad i \in I \quad (4.41)$$

4.4.3. ResponseModelRange

The range objective is a pure equality objective where the difference in the maximum and minimum disutilities are minimized. The corresponding *ResponseModelRange* is given below.

Additional decision variables:

- R_1 The maximum disutility among TFs
- R_2 The minimum disutility among TFs

ResponseModelRange:

$$\min \quad R_1 - R_2 \quad (4.42)$$

s.t.

(4.2 – 4.23)

$$R_1 \geq \sum_{t \in T} (1 - P_{it}) \quad i \in I \quad (4.43)$$

$$R_2 \leq \sum_{t \in T} (1 - P_{it}) \quad i \in I \quad (4.44)$$

$$R_1, R_2 \geq 0 \quad (4.45)$$

4.4.4. ResponseModelRawlsian

The Rawlsian objective is another pure equality objective where the maximum disutility is minimized. The corresponding *ResponseModelRawlsian* is given below.

Additional decision variables:

R The maximum disutility among TFs

ResponseModelRawlsian:

$$\min \quad R \quad (4.46)$$

s.t.

(4.2 – 4.23)

$$R \geq \sum_{t \in T} (1 - P_{it}) \quad i \in I \quad (4.47)$$

$$R \geq 0 \quad (4.48)$$

4.5. Objective Function Selection

Before moving onto the solution methods and their numerical performances, we first evaluate the behavior of the alternative objective functions using metrics that range from utilitarian to egalitarian approaches. In this way, we select a few number objective functions that perform well under both effectiveness and fairness related

metrics to continue with our studies. For this purpose, we generate 20 small instances randomly as explained in Appendix A.2.1. The instances have 2 or 3 PFs; 4, 6, 7, or 8 TFs; 3 or 4 vehicles; and 16, 20 or 23 time segments. Instances are named as “P- j - i - v - t ”, where j , i , v , and t represent the number of PFs, TFs, vehicles and time segments, respectively. Since using optimal or near optimal results will be more accurate for comparing objective function alternatives, we only use the instances where the optimal solution is found for all objective function types in this analysis.

ResponseModel is solved for the given test instances with each objective by using IBM ILOG CPLEX 12.8. In all models, X_{vnmt} variables have the highest branching priority. Run times are limited to 8 hours and 1% relative optimality gap is imposed as a stopping condition. The number of threads that the solver can utilize is set to 8. Finally, for *ObjRange*, a 0.01 absolute optimality gap is defined to avoid numerical problems. All experiments are carried out on a PC with 3.30 GHz CPU and 16 GB RAM, running under 64-bit Windows 7 operating system.

As the first step, *ResponseModel* is solved with the objectives adapted from the literature, and with the proposed objectives by setting $\alpha = 0$, $\alpha = 1$, $\alpha = 2$, and $\alpha = 3$. The optimality gaps and the run times for the proposed objective functions with different trade-off parameters, and the corresponding results for the objective functions adapted from the literature are provided in Tables B.2–B.6 in Appendix B.2. In Tables B.2–B.6, the results are italicized if the stopping criteria for the optimality gap is attained before the time limit. One can observe that even small instances may be hard to solve to optimality by CPLEX in 8 hours of run time, which is generous for the response stage. In general, we can observe up to 100% percent optimality gaps, which are caused by poor lower bounds. Also, we observe that the proposed objectives are harder to solve compared to the ones adapted from the literature.

To analyze the effect of the trade-off parameter, the output of *ResponseModel* with given objective functions and α values are evaluated with 11 metrics in the literature. These performance measures are: *utility*, α -*fairness* with $\alpha = \{1, 2, 3\}$, *range*, *Rawlsian*, *sum of pairwise absolute differences*, *total absolute deviation*, *maximum de-*

violation, *gini coefficient*, and *deprivation cost*. The parameters for deprivation cost calculations are based on the econometric estimation of deprivation cost by Holguín-Veras *et al.* (2016), where deprivation cost with terminal point is used while value of life is set to one million dollars.

In order to make the comparison easier, the percentage deviation of each instance in each performance measure from the average over different α values are calculated. Then the average of these deviations are taken over the instances for each performance metric. As mentioned before, we only use the instances where the optimal solution is found for all objective function types in such analyses. The comparisons are presented on a radar chart, where smaller values are better since all objectives are of minimization type. In each axis, the alternatives can be compared within each other. Since the performance metrics range from purely utilitarian to pure equality metrics, an objective alternative where all metrics are very small would be an ideal one. However, since utility and equality are conflicting measures, we look for the best compromise which perform relatively well among all.

Figures 4.3 to 4.7 present the effect of different α values on each of the proposed objectives, respectively. Note that $\alpha = 0$ is not defined for $Obj_{2,3}$. As mentioned before, a tight and balanced loop around the origin indicates the given objective performs well in all performance metrics. For Obj_1 , we can conclude that $\alpha = 0$ performs usually well on equality metrics, whereas the performance is worsened for the utilitarian terms. On the other hand, with $\alpha = 2$ and $\alpha = 3$ the exact opposite is true. Therefore we choose $\alpha = 1$ which is more balanced compared to the others. The discussion on $Obj_{2,1}$ is in parallel with Obj_1 , and $\alpha = 1$ is chosen for $Obj_{2,1}$ as well. For $Obj_{2,2}$, $\alpha = 0$ performs well in utilitarian metrics (since it is equivalent to the utilitarian objective) and performs poorly on equality metrics. Despite having a smaller deterioration, the opposite is true for $\alpha = 2$ and $\alpha = 3$. However, we observe that $\alpha = 1$ provides a nice trade-off among utilitarian and equality metrics, therefore we choose that. For $Obj_{2,3}$, it is observed that the trade-off parameter has almost no effect on the results due to the structure of the objective function, and we choose $\alpha = 1$. Finally $\alpha = 1$ is chosen for Obj_3 as well since it provides a compromise between utilitarian and egalitarian metrics.

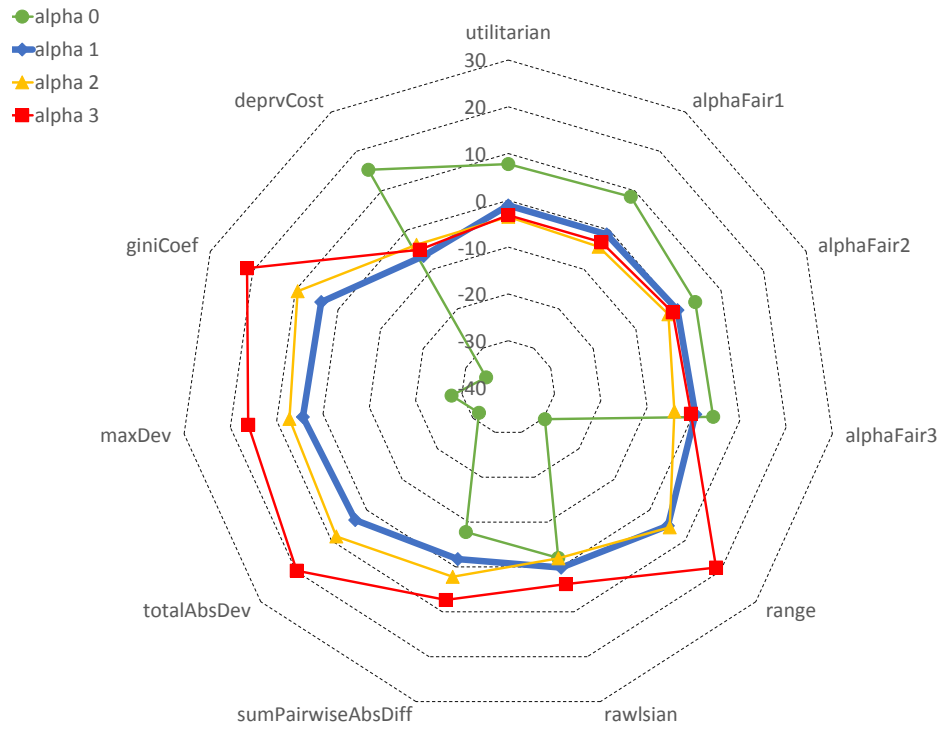


Figure 4.3. Comparison of Obj_1 with different α values.

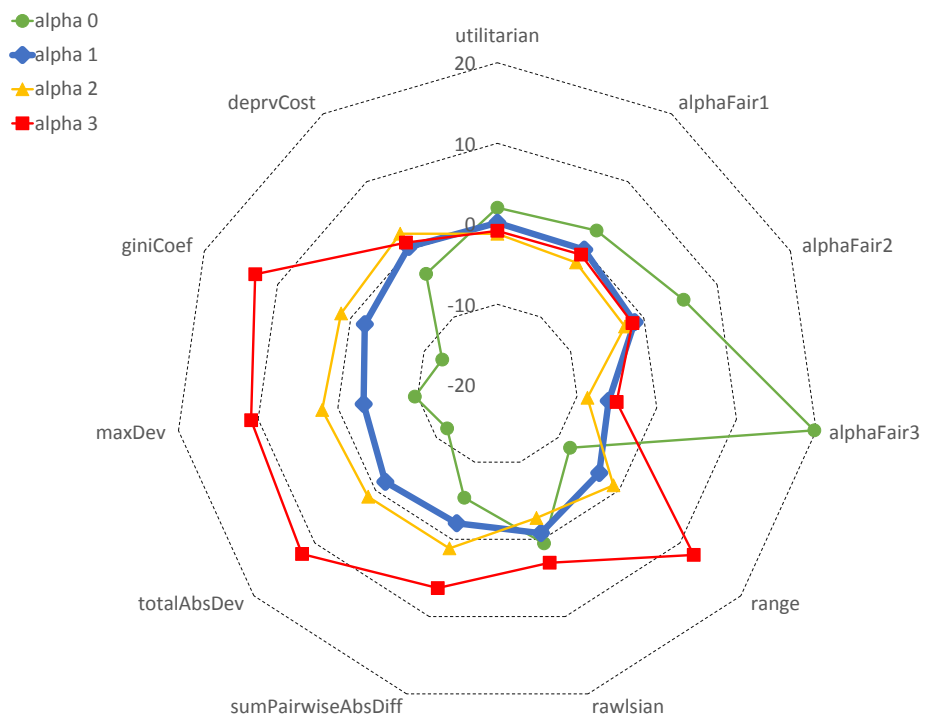


Figure 4.4. Comparison of $Obj_{2.1}$ with different α values.

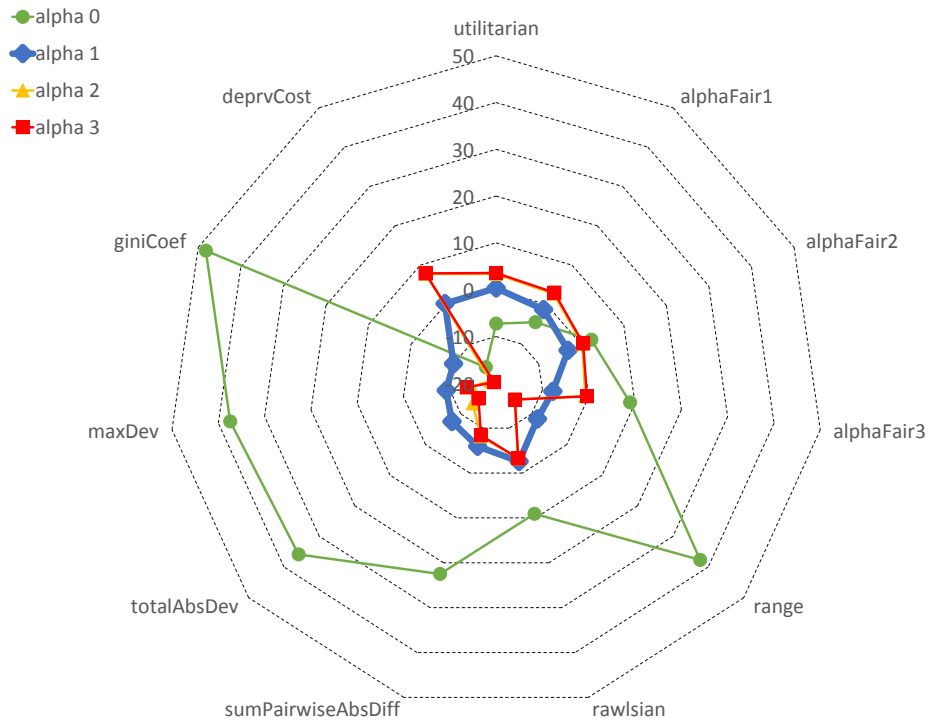


Figure 4.5. Comparison of $Obj_{2.2}$ with different α values.

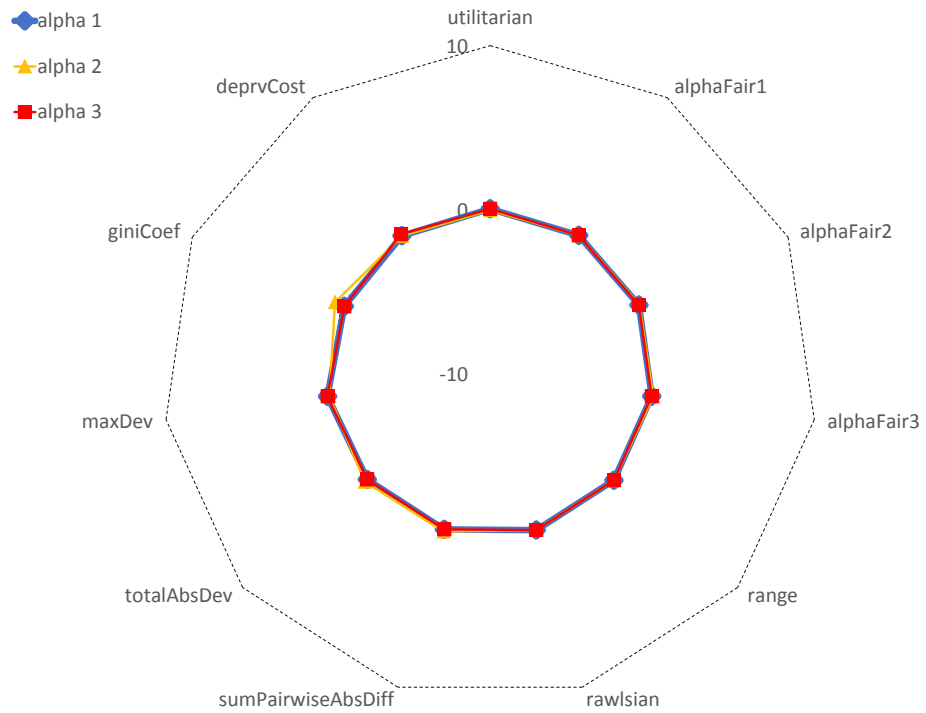


Figure 4.6. Comparison of $Obj_{2.3}$ with different α values.

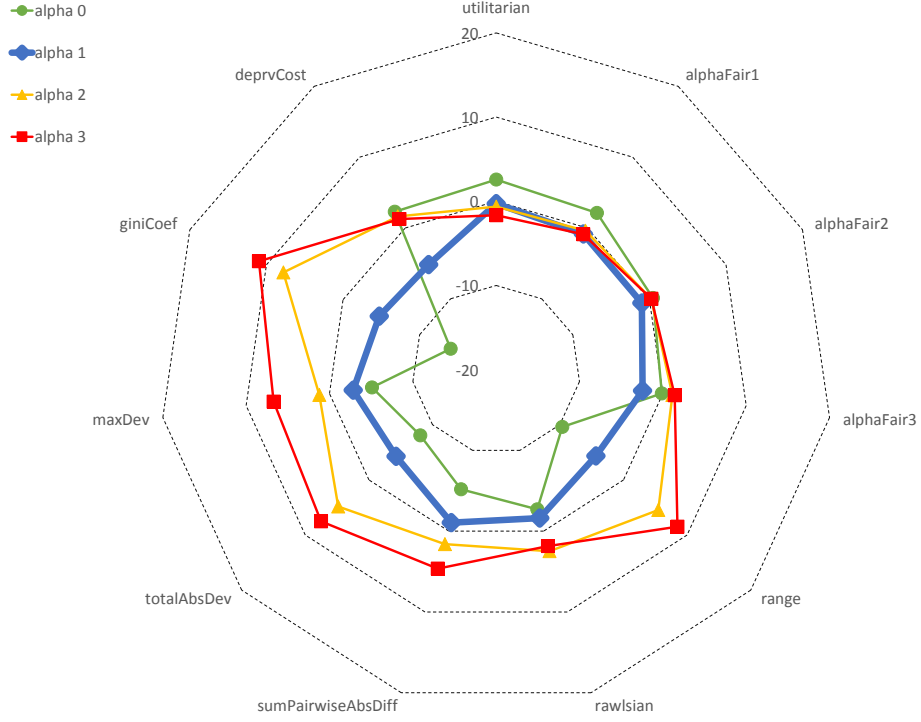


Figure 4.7. Comparison of Obj_3 with different α values.

The next step in the analysis is to compare all proposed objectives with the selected α values to the objective functions in the literature using the same approach as before. Figure 4.8 provides the comparison among all objectives. Figure 4.8 reflects that the proposed objectives are balanced among performance metrics in general. Among the proposed objectives, Obj_1 and $Obj_{2,1}$ focuses slightly more on equality, whereas $Obj_{2,3}$ and Obj_3 are stronger on the utilitarian metrics compared to the others. An important observation is that Obj_{HSB} and $Obj_{PiecewisePropFair}$ yield very good results for utilitarian metrics, whereas they perform poorly on equality metrics. Obj_{Range} performed well on equality metrics and performed poorly on the others, where the opposite is valid for $Obj_{Utilitarian}$, as expected. Finally, $Obj_{Rawlsian}$ also yields a good compromise between equality and utility metrics. Figure 4.9 emphasizes the performance of the selected best three alternatives, namely Obj_1 , $Obj_{2,2}$, and $Obj_{Rawlsian}$, that provide a good trade-off between utilitarian and egalitarian metrics.

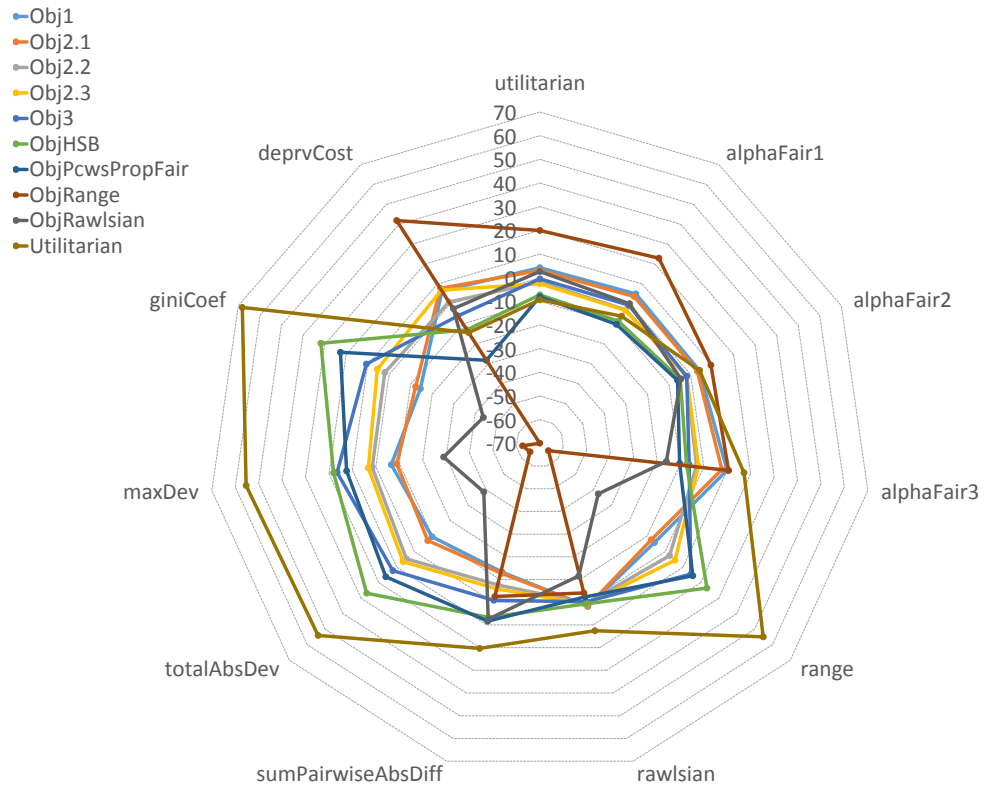


Figure 4.8. Comparison of all objectives.

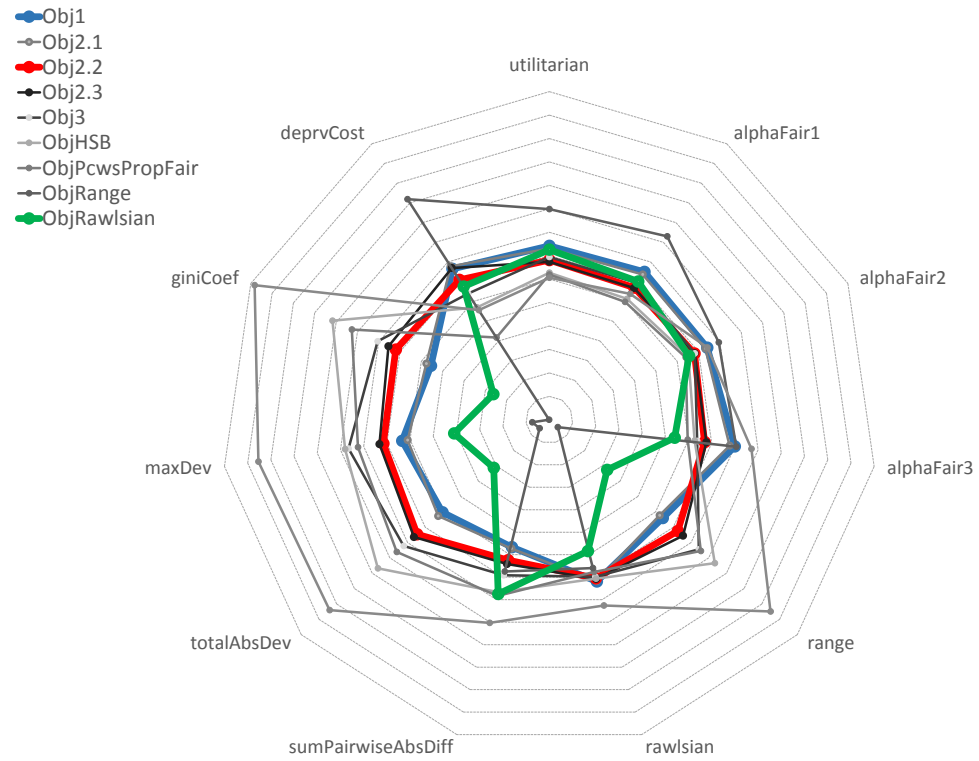


Figure 4.9. Comparison of selected best objectives.

As the final step, we calculate the price of fairness (POF) as introduced in Section 2.3.2. The POF for each objective alternative for all considered problems are given in Table 4.1 along with their average. Table 4.1 indicates *ObjHSB* and *ObjPiecewisePropFair* are close to the utilitarian, as observed in Figure 4.8. Also among the selected objectives, *Obj_{2.2}* has a relatively small price of fairness.

Table 4.1. Price of fairness for each objective.

Problem	<i>Obj₁</i>	<i>Obj_{2.1}</i>	<i>Obj_{2.2}</i>	<i>Obj_{2.3}</i>	<i>Obj₃</i>	<i>ObjHSB</i>	<i>ObjPcwsPrFair</i>	<i>ObjRange</i>	<i>ObjRawls</i>
P-3-4-3-16	-0.36	-0.18	-0.18	-0.18	-0.15	-0.04	-0.03	-0.33	-0.15
P-3-4-4-16	-0.20	-0.20	-0.14	-0.14	-0.07	-0.02	-0.02	-0.26	-0.11
P-3-4-3-20	-0.33	-0.31	-0.10	-0.12	-0.06	-0.06	-0.01	-0.36	-0.15
P-3-6-3-16	-0.39	-0.06	-0.01	-0.03	-0.07	0.00	0.00	-0.37	-0.17
P-2-6-2-20	-0.11	-0.02	-0.03	-0.03	-0.09	-0.03	-0.01	-0.55	-0.12
P-2-8-2-20	-0.26	-0.22	0.00	0.00	-0.11	0.00	0.00	-0.26	-0.08
P-2-8-2-23	-0.13	-0.13	-0.13	-0.03	-0.14	-0.03	-0.03	-0.14	-0.14
Average	-0.25	-0.16	-0.08	-0.08	-0.10	-0.02	-0.01	-0.32	-0.13

4.6. Solution Methods

The response stage problem that we deal with is an extension of the vehicle routing problem (VRP), which is classified as NP-hard (Archetti *et al.*, 2011). Also in our experimentation in Section 4.5, we observed that the CPLEX solver fails to find the solution in a reasonable amount of time even for very few number of nodes. Furthermore, as seen in our preliminary studies, the model does not lend itself to decomposition methods such as logic-based-Benders-decomposition or Branch & Price. Therefore, we focus on two matheuristic methods, namely *feasible sequence generation heuristic* and *adaptive large neighborhood search* (ALNS). The following subsections provide details on the heuristic methods.

In the heuristic methods that we study, the need to predetermine the length of the planning horizon can be relaxed, unlike the mathematical model. In this way, the planning horizon will be an output of the solution methods. Note that while this

approach increases the solution space of the problem, it eliminates the possibility of selecting a planning horizon that is too short to obtain a feasible solution.

4.6.1. Feasible Sequence Generation Model and Heuristic

4.6.1.1. Feasible Sequence Generation Model. Since we deal with a problem with complex structure (e.g. having multiple heterogeneous capacitated vehicles, multiple shared depots, split deliveries, and complex objective functions), even finding a feasible solution vector that can satisfy the demands of all TFs can be problematic. Even if we are given a sequence of visits for each vehicle, the need to ensure demand satisfaction while obeying vehicle capacities and supply amounts may result in an infeasible solution vector. Therefore, we build a MIP that can provide feasible vehicle routes by considering the sequence of the nodes that are visited, while such constraints are present. However, in this case we need to introduce the parameter K_v , which is the number of visits that vehicle v is allowed to perform, and this parameter will limit the solution space similar to the planning horizon in *ResponseModel*.

The sets, parameters and the decision variables are given below and constraints 4.49 – 4.58 define *FeasSeqModel*.

Sets:

V	Set of vehicles
K_v	Set of available visiting slots for vehicle v , $K_v = \{1, \dots, K_v \}$
I	Set of temporary facility (TF) nodes
J	Set of permanent facility (PF) nodes

Parameters:

d_i	Total demand generated at TF i through the planning horizon
c_v	Capacity of vehicle v , in number of items
s_j	Amount of items initially held at PF j

Decision variables:

X_{vnk}	Binary variable indicating if node n is k^{th} in the sequence of vehicle v
Y_{vjk}	Amount of items collected by vehicle v from PF j that is k^{th} in the sequence
Z_{vik}	Amount of items satisfied by vehicle v at TF i that is k^{th} in the sequence

FeasSeqModel:

$$\min \quad 0$$

s.t.

$$\sum_{n \in I \cup J} X_{vnk} \leq 1 \quad v \in V, k \in K_v \quad (4.49)$$

$$Y_{vjk} \leq c_v X_{vjk} \quad v \in V, j \in J, k \in K_v \quad (4.50)$$

$$Z_{vik} \leq c_v X_{vik} \quad v \in V, i \in I, k \in K_v \quad (4.51)$$

$$0 \leq \sum_{j \in J} \sum_{k'=1}^k Y_{vjk'} - \sum_{i \in I} \sum_{k'=1}^k Z_{vik'} \leq c_v \quad v \in V, k \in K_v \quad (4.52)$$

$$\sum_{v \in V} \sum_{k \in K_v} Y_{vjk} \leq s_j \quad j \in J \quad (4.53)$$

$$\sum_{v \in V} \sum_{k \in K_v} Z_{vik} \geq d_i \quad i \in I \quad (4.54)$$

$$\sum_{j \in J} X_{vjk} + \sum_{j \in J} X_{vjk+1} \leq 1 \quad v \in V, k \in K_v \quad (4.55)$$

$$X_{vnk} \in \{0, 1\} \quad v \in V, n \in I \cup J, k \in K_v \quad (4.56)$$

$$Y_{vjk} \geq 0 \quad v \in V, j \in J, k \in K_v \quad (4.57)$$

$$Z_{vik} \geq 0 \quad v \in V, i \in I, k \in K_v \quad (4.58)$$

FeasSeqModel is a feasibility problem, therefore no objective function is given. Constraint 4.49 ensures at most one node can be assigned to each slot of the vehicles. Note that a vehicle is allowed not to visit any node for some k in its sequence. Constraints 4.50 and 4.51 define the logical connection between variables, and equations 4.52 define the total supply/demand feasibility at each step of each vehicle. In this way, we ensure that vehicles do not carry more than their capacity and items cannot be used to satisfy demand at TFs if they are not collected from previously visited PFs. Constraints 4.53 and 4.54 limit the total supply amount of each PF, and ensure demand satisfaction at each TF. Equations 4.55 prevent two PFs to be visited consecutively since it is prohibited by the original problem. Finally, equations 4.56 – 4.58 define the variables. Note that the first visit (i.e. $k = 1$) for the X_{vnk} variables are initialized such that the vehicles will start their sequence at the node that they are initialized by

the decision maker.

In order to reduce the solution space of the problem, we define the following two sets of valid inequalities for *FeasSeqModel*. The first valid inequality set 4.59 ensures that a TF node will be visited as the second in any sequence since a vehicle has to visit a TF node after being initialized at a PF node. The second valid inequality given in 4.60 is to reduce symmetry if there are two vehicles of the same capacity that are initialized at the same node at the same time. In this case, the vehicle with the smaller index will visit a node that has a smaller index. In equation 4.60, $\tilde{V}$ defines the set of (v_1, v_2) vehicle couples with the same capacity that are initialized at the same node at the same time.

$$\sum_{i \in I} X_{vi2} = 1 \quad v \in V \quad (4.59)$$

$$\sum_{i \in I \cup J} X_{v_1 i 2} \leq \sum_{i \in I \cup J} X_{v_2 i 2} \quad (v_1, v_2) \in \tilde{V} \quad (4.60)$$

Note that X_{vnk} solution may not correspond to a feasible solution as it is, and it requires post-processing. As mentioned before we allow a slot for a vehicle to be empty, and the model does not prevent two consecutive slots to have the same node. Moreover for some visits, corresponding Y_{vjk} or Z_{vik} values may be equal to zero. If an empty slot or such nodes appear in the X_{vnk} solution vector, we eliminate them in the post-processing step. Then we can evaluate the performance of the solution vector by converting it into X_{vnmt} variables and fixing them in *ResponseModel* with the desired objective.

4.6.1.2. Feasible Sequence Generation Heuristic. Since *FeasSeqModel* is a feasibility model, generating a single solution would probably yield very poor results. Therefore we define *feasible sequence generation heuristic (FSGH)* that generates many feasible solutions within a given time limit, using the “Generic Callback” structure in CPLEX 12.8 with “Candidate” context. In a nutshell, the solver invokes a callback function

whenever a feasible solution is obtained, and we post-process the incumbent and evaluate its performance with the desired objective function of *ResponseModel*. If the incumbent is better than the best result obtained so far, we update the best solution. When running the heuristic, the solver is allowed to utilize up to 8 threads, therefore a different local variable that keep track of the best solution encountered within each thread exists to avoid race conditions.

In order to keep the solver running and generating different candidate solutions, we need to reject the incumbent after its performance is evaluated within the callback function. Although we try the following three methods for this purpose, *SatisfactionBasedReject* is chosen as the best performing one in our preliminary experimentation.

- *NullReject*: We reject the solution without providing any cuts. the solver rejects the solution and continues with the branch-and-bound procedure.
- *MakespanBasedReject*: We provide a cut that violates the incumbent. In this method, we want to avoid long arcs since *FeasSeqModel* is unaware of arc lengths. We provide cut 4.61 to the solver, where $\bar{v}$ is the vehicle that has the longest task duration, and n_1 and n_2 are subsequent nodes in the visiting list of $\bar{v}$, that have the longest arc length.

$$X_{\bar{v}n_1k} + X_{\bar{v}n_2k+1} + X_{\bar{v}n_2k} + X_{\bar{v}n_1k+1} \leq 1 \quad k \in K_{\bar{v}} \quad (4.61)$$

- *SatisfactionBasedReject*: We provide a cut that violates the incumbent. In this case, we calculate the disutility of all TFs with the given objectives, and provide a cut that will encourage solution vectors in which the worst-off TF node appears in earlier visits. The following cut 4.62 is provided to solver, where $n' \in I$ is the worst-off TF, and $\bar{X}_{vnk}$ is the solution vector of the incumbent.

$$\sum_{v \in V} \sum_{k \in K_v} k X_{vn'k} \leq \sum_{v \in V} \sum_{k \in K_v} k \bar{X}_{vn'k} \quad (4.62)$$

The last issue related with the *FSGH* is the selection of the K_v values since its value will affect the solution vectors that are obtained. Assuming average vehicle capacity is defined as $\overline{c_v} = \frac{\sum_v c_v}{|V|}$, we set $K_v = K_{min}$ as initial value, and if a feasible solution cannot be found within 120 seconds it is increased by two until a feasible solution is obtained. Equation 4.63 provides the K_{min} calculation, where the first term in the numerator is the average number of visits to PFs, and the second term is the summation of expected number of visits to all TFs. Finally, the total 8 threads are partitioned into three, and *feasible sequence generation heuristic* run in two threads with $K_v = K_{min}$, in three threads with $K_v = K_{min} + 1$, and with $K_v = K_{min} + 2$ in the last three.

$$K_{min} = \left\lceil \frac{\left\lceil \frac{\sum_i d_i}{\overline{c_v}} \right\rceil + \sum_i \left\lceil \frac{d_i}{\overline{c_v}} \right\rceil}{|V|} \right\rceil \quad (4.63)$$

4.6.2. ALNS Applied to the *ResponseModel*

Adaptive large neighborhood search (ALNS) is introduced by Ropke and Pisinger (2006a) and further improved in Ropke and Pisinger (2006b), and Pisinger and Ropke (2007) for rich pickup and delivery models. It is an extension to the *large neighborhood search* (LNS) framework given by Shaw (1998) by incorporating an adaptive layer, which is based on ruin-and-recreate. ALNS provides a general out of the box framework that can be applied to many vehicle routing problem types and allows to mix various VRP variants.

ALNS is a local search framework, in which destroy and repair heuristics compete to alter the current solution vector. It requires the definition of a set of *destroy neighborhoods* and a set of *repair neighborhoods*. At each iteration, a destroy heuristic is selected, which removes at most q many variables from the solution vector. This is followed by assigning feasible variables to those variables using the selected repair heuristic. This framework is defined within a local search framework (e.g. simulated annealing, tabu search, guided local search), and the generated candidate solution is

accepted if it satisfies the acceptance criteria of the local search framework at the master level. At each iteration, a destroy and a repair heuristic is selected separately using roulette wheel with probabilities determined by the past performance. The adaptive layer of the algorithm updates the performance (scores) of the neighborhoods, and the heuristics that perform better obtains a higher chance to be selected. Pisinger and Ropke (2007) state that neighborhoods are usually searched with fast heuristics, and it could be advantageous to use neighborhoods that can provide diversification.

To solve the *ResponseModel*, we build the ALNS algorithm within Simulated Annealing (SA) framework as a matheuristic, which will be referred as *SA-ALNS*. Solution representation, destroy, repair and move heuristics, the improvement steps that we incorporated, adjustments of the adaptive scores of these heuristics, initial solution generation and other implementation details are given in the following subsections.

4.6.2.1. Solution Representation and Fitness Calculation. The solution vector of the proposed *SA-ALNS* heuristic is composed of $|V|$ many list of visits. For each vehicle, there is a list of node-time pair that represents the sequence of the nodes that will be visited by that vehicle, and their arrival times. Obviously, the first visit in each list is to the node where the corresponding vehicle is initialized. Given a list of nodes to visit and the starting time of a vehicle (i.e. B_{vnt}), and given the problem assumption that vehicles do not wait in nodes, this sequence can be converted into the schedule of the vehicle (i.e. the values of X_{vnm} variables). Then the fitness value of a solution vector can be calculated by solving the remaining mixed integer program (MIP) after fixing the corresponding X_{vnm} variables in *ResponseModel*. However, since we cannot guarantee the feasibility of a solution vector, constraint 4.8 is replaced with the relaxed equation 4.64 below. In constraint 4.64, E_i variables indicate the amount of unsatisfied items for TF i at the end of the planning horizon. Then E_i variables are penalized in the selected objective function with appropriate penalty values. Although the remaining fitness calculation problem is a MIP, it is relatively shorter to solve the reduced problem.

$$\sum_{v \in V} \sum_{t \in T} Z_{vit} + E_i = \sum_{t \in T} d_{it} \quad i \in I \quad (4.64)$$

4.6.2.2. Destroy Heuristics. Six different destroy heuristics are defined for the proposed *SA-ALNS*. Each of the destroy heuristics use *destroyProb* as a parameter that determines neighborhood size.

- *RandomDestroy*: It is the simplest destroy heuristic that takes the solution vector as an input, and removes each visit with *destroyProb* probability. This move helps us to improve diversification in the search.
- *RandomRemovalWOInfNodes*: It is the same as the *RandomDestroy* heuristic, except we do not eliminate the visits to TF nodes that observe $E_i > 0$ in the current solution. In this way we aim to increase diversity of the solution vector while trying to remain/become feasible. This heuristic is ignored in the roulette wheel mechanism if there is no TF that is infeasible at the current solution vector.
- *LongestArcDestroy*: Given the solution vector, visits that it takes longest to travel to are eliminated. The number of removals equals to the *destroyProb* fraction of all visited nodes. By eliminating the longest arcs, we aim to improve effectiveness by arriving TFs earlier and to improve efficiency by reducing makespan.
- *MaxFilledDestroy*: The problem setting allows the demand arrivals to occur at any time in the planning horizon, which result in having some of the nodes that receive more items than the requirement up to the time of the visit. Since the P_{it} values are corrected to $P_{it} = 1$ for these cases, there is a potential to improve other TF points with smaller fill rates without worsening such nodes. Therefore given the solution vector, *destroyProb* fraction of visits corresponding the TFs with highest fill rates are removed. This heuristic is ignored in the roulette wheel mechanism if the highest fill rate among TFs in the current solution vector is less than one.
- *FillRelatedDestroy*: Removing visits that are related to each other from the so-

lution vector has more potential to improve the solution vector in repair (Shaw, 1997). Therefore we may consider visits to TFs with high fill rates (> 1) and low fill rates (< 1) which are close to each other both geographically and time-wise as related. If a visit to a high filled TF is followed by a PF visit, these visits can also be considered as related since the requirements of an another TF could be satisfied before visiting that PF. We can also consider a visit to a low filled TF related to a PF visit that is close in terms of arrival times as related since destroying them together provides opportunities to reconsider their order. Moreover eliminating visits to high and low filled TFs may be beneficial if they are arrived at similar times. Finally for PF visits, other PFs that are geographically close and TF visits with high fill rates can be considered as related. Considering these relationships, we define *FillRelatedDestroy* as given in Figure 4.10. This heuristic is ignored in the roulette wheel mechanism if the highest fill rate among TFs in the current solution vector is less than one.

- *TFClosenessRelatedDestroy*: Similar to *FillRelatedDestroy*, time and geographical closeness of the TF visits are considered as relatedness measure. Two visits of different vehicles that are close both geographically and in arrival times can be swapped to improve the solution. *TFClosenessRelatedDestroy* is given in Figure 4.11, and it is ignored in the roulette wheel mechanism if there are TFs observing infeasibilities at the current solution vector.

4.6.2.3. Repair Heuristics. After a destroy heuristic is applied, the solution vector still remain as a list of nodes for each vehicle. However, consecutive node-time pairs do not constitute a feasible vehicle path. Then, four different repair heuristics are defined for the remaining incomplete solution vector.

- *RandomRepair*: This heuristic randomly selects an available vehicle, then inserts a random visit into a random position to improve diversification. A vehicle becomes unavailable whenever the required time to visit all nodes in its list exceeds the makespan of the current solution.
- *AppearanceLikelihoodGreedyRepair*: In this repair heuristic, we ignore the time

```

 $q = \text{Round}(\text{destroyProb} * \#\text{Visits})$ 
Calculate fill rates for each visit of each vehicle
Sort visits by their fill rates
Set  $i :=$  visit with highest fill rate
Destroy  $i$  in the solution vector,  $\text{DestroyedList} := \text{DestroyedList} \cup i$ 
repeat
    Create an empty EligibleList
    Randomly select a visit  $i$  in DestroyedList
    if  $i$  is a visit to a high-filled TF then
        Add PF visits on the same vehicle with  $i$  and low-filled TF visits on
        other vehicles to EligibleList
    else if  $i$  is a visit to a low-filled TF then
        Add PF visits on the same vehicle with  $i$  and high-filled TF visits on
        other vehicles to EligibleList
    else
        Add PF visits and high-filled TF visits on any vehicle to EligibleList
    end if
    Randomly select  $j \in \text{EligibleList}$  with probabilities determined by the
    geographical distances to visit  $i$ 
    Destroy  $j$  in the solution vector,  $\text{DestroyedList} := \text{DestroyedList} \cup j$ 
until  $|\text{DestroyedList}| = q$ 

```

Figure 4.10. Pseudocode of *FillRelatedDestroy*.

stamps on node-time pairs in the incomplete solution vector. For each TF and PF in the vector, we calculate a so-called *appearance likelihood*. For TFs, *appearance likelihood* means the expected number of appearance for a TF in a feasible solution vector, and it is calculated by dividing its total demand to average vehicle capacity. For PFs, we expect a PF visit to appear in a feasible solution vector $\text{TotalOverallDemand}/\text{AverageVehicleCapacity}$ many times. By multiplying this value with the fraction of supply of a PF among all, we calculate the *appearance likelihood* of a PF. In each iteration, the number of visits to a node in the incomplete solution vector are subtracted from its *appearance likelihood* value

```

 $q = \text{Round}(\text{destroyProb} * \# \text{Visits})$ 
Set  $i :=$  a random visit
Destroy  $i$  in the solution vector,  $\text{DestroyedList} := \text{DestroyedList} \cup i$ 
repeat
    Randomly select a visit  $i$  in  $\text{DestroyedList}$ 
    Calculate  $\text{dist}_j = \tau_{ij} / \max\{\tau_{ij}\}$  for each visit  $j$  in the solution vector
    Calculate  $\text{timeD}_j$  as the normalized time difference between visits  $i$  and  $j$ 
    Choose visit  $k$  with the smallest  $\text{dist}_j * \text{timeD}_j$  value
    Destroy  $k$  in the solution vector,  $\text{DestroyedList} := \text{DestroyedList} \cup k$ 
until  $|\text{DestroyedList}| = q$ 

```

Figure 4.11. Pseudocode of *TFClosenessRelatedDestroy*.

to use as a selection parameter. Apart from that, we calculate *expectedTFrun*, which indicates expected number of consecutive TF nodes in a solution vector of a vehicle before visiting a PF node as $(\sum_i \lceil \frac{d_i}{c_v} \rceil) / \lceil \frac{\sum_i d_i}{c_v} \rceil$, which is the division of expected total number of TF appearances to the expected total number of PF visits. This value is rounded up or down randomly.

Then *AppearanceLikelihoodGreedyRepair* heuristic start to repair the incomplete solution vector by considering the node with the highest *appearance likelihood*. Depending on the type of the currently considered node (TF or PF), and considering the *expectedTFrun* length, we insert the current node into the solution vector position which cause the shortest detour among all eligible insertion points. After each insertion *appearance likelihood* of that node is reduced by one, and procedure continues until all nodes have negative *appearance likelihood* values. As the last step, time-stamps in the node-time pairs in the solution vector are corrected.

- *AppearanceLikelihoodRandomRepair*: Performs in the similar fashion with *AppearanceLikelihoodGreedyRepair* heuristic, except we insert the node with the highest *appearance likelihood* to a random position. In this way we aim to improve diversification.
- *FeasSeqModelRepair*: Since the complete solution vector correspond to a X_{vnk} vector for *FeasSeqModel*, we fix the values of X_{vnk} variables that correspond to the visits in the incomplete solution vector. Then *FSGH* is run for *feasSeqMod-*

elTilim seconds and the best solution is selected as the candidate solution for the next iteration. Note that the selection probability of this repair is multiplied by *feasSeqModelProbMultip* parameter since it takes longer for this repair heuristic to run compared to the others. Also, the first valid inequality set given in 4.59 is not introduced in the model for this repair to have a wider solution space by allowing the slot to remain empty.

4.6.2.4. Move Heuristics. Apart from using destroy and repair heuristics in sequence, we define five move heuristics that moves the current solution within its neighborhood. Therefore move heuristics replace destroy and repair heuristics.

- *ReverseTFSequenceMove*: For each vehicle, selects a TF sequence between two PFs randomly, and reverses it. The move does not violate feasibility if the current solution is already feasible since pickup-delivery amounts for the vehicle can remain the same. The move is ignored in the roulette wheel mechanism if there are TFs observing infeasibilities at the current solution vector.
- *ShiftSequenceMove*: For each vehicle, the solution vector is divided into PF-TF segments that starts with a PF and ends before the next PF. Then a random segment is removed and inserted before another random PF. However to remain feasible, we keep the first segment intact since the vehicle has to start from that PF. This move is inspired from Or-opt move (Or, 1976). *ShiftSequenceMove* move also does not violate feasibility if the current solution is already feasible since pickup-delivery amounts for the vehicle can remain the same. This heuristic is ignored in the roulette wheel mechanism if there are TFs observing infeasibilities at the current solution vector.
- *DemandShortageBasedReorderMove*: In all of our objective functions, the best possible value of the objective functions can be attained if we can satisfy the demands of each TF location at each time period. Therefore one can improve the quality of the solution by visiting the nodes that observe higher shortages earlier.

The shortage amount of each TF are calculated as in Equation 4.65 below.

$$short_i = \sum_t \max\{0, \sum_{t'=0}^t d_{it'} - \sum_{v \in V} \sum_{t'=0}^t Z_{vit'}\} \quad i \in I \quad (4.65)$$

DemandShortageBasedReorderMove keeps the slots for TF and PF visits in the solution vector of a vehicle, however it reorders them. We calculate $short_i$ for each TF and order them nonincreasingly. If a TF node appears more than once, the next appearances are pushed at the back of the list. Then we assign the reordered TFs in the slots that are previously assigned to TFs in the given order. The initial PF remains as the first visit, however we greedily assign the PF that creates the shortest detour in each of the PF slot in the solution vector. Similar to the previous two moves, *DemandShortageBasedReorderMove* is also ignored in the roulette wheel if the current solution vector is not feasible.

- *ShiftSequenceBtwVehiclesMove*: Unlike the other move definitions, *ShiftSequenceBtwVehiclesMove* allow visits to be carried from one vehicle to another. The vehicle with the longest task duration is found, and the PF-TF segment that will cause the shortest reduction in makespan is removed from that vehicle. Then that segment is insterted between PF-TF segments of the vehicle with the shortest task at the point where the shortest detour is created. We repeat the process *destroyProb* percent of the $|V|$ times.
- *FeasSeqModelRevisePFMove*: The other moves that are defined do not alter the slots of PF visits. To be able to reconsider the visited PFs and their slots, we eliminate all PF visits except the initial one from the solution vector, then reorder the solution vector such that there is an empty slot between all visits, and fix the values of corresponding X_{vnk} variables. Then *FSGH* is run for *feasSeqModelTilim* seconds and the best solution is selected as the candidate solution for the next iteration. Note that the selection probability of this repair is multiplied by *feasSeqModelProbMultip* parameter since it takes longer for this repair heuristic to run compared to the others. Also, the first valid inequality set given in 4.59 is not introduced in the model for this move.

4.6.2.5. Improvement Steps. We incorporate four improvement steps in our *SA-ALNS* approach which is not originally present in the ALNS framework. The first three of them are run in the given order at the end of each repair or move operation, whereas the last one is performed whenever the SA procedure accepts the candidate solution.

- *NodeEliminationImprove*: Constraints 4.10 ensure that if a vehicle enters a TF node, it has to satisfy at least one unit of demand there, to improve efficiency in the original formulation. If a repaired solution yields $Z_{vit} = 1$ for a visit to TF i by vehicle v , this indicates that the solution may be improved by not visiting that node. Therefore we eliminate nodes with $Z_{vit} = 1$ from the solution vector update the candidate solution if the objective improves.
- *VehicleWOTaskImprove*: Due to the structure of the destroy and repair operations, we may end up with candidate solutions that do not perform any tasks. Therefore the solution quality can be improved by removing tasks from other vehicles and assigning them to the vehicle without tasks. If such vehicles are observed, we remove the TF visit that cause the longest detour from the vehicle with the highest task duration, and assign it as the first visit of the vehicle with no tasks.
- *SwapVehicleListsImprove*: For each vehicle couple that are initialized at different PFs and have the same capacity, we check if the task completion times of both vehicles can be improved by swapping their entire visit lists after the initial PF visit. In this way we aim to improve the solution quality since the arrival times of every visit will reduce in these vehicles.
- *GreedyMakespanReductionImprove*: In this local improvement attempt, we aim to improve the efficiency along with effectiveness and fairness. The set of visits made by each vehicle is kept the same, but they are reordered. Initial PF visit and the slots assigned to TFs and PFs in the current solution are preserved for a vehicle, and at each empty slot the unassigned visit that is closest to the last visited node is placed.

4.6.2.6. Adjustment of Adaptive Weights. The roulette wheel selection mechanism of the destroy, move and repair heuristics depend on the score of each heuristic. The adaptive layer in the ALNS framework enables better performing heuristics to be selected with a higher probability. The scores are collected within iteration segments, which is defined by *scoreUpdateInterval* parameter. At the beginning of each interval, interval scores are set to zero. Then within the interval, scores of the selected heuristics are incremented by *scoreG*, *scoreI* and *scoreW* for global best solution, improving solution, and accepted worsening solution, respectively. The total interval score of a heuristic is divided by the number of times selected to find its interval score at the end of the time segment. Then the previous scores are smoothed using a smoothing parameter *scoreSmooth* to incorporate the previous scores in the roulette wheel selection.

4.6.2.7. Initial Solution Generation. We construct an initial solution by running the *FSGH* as introduced in Section 4.6.1 for *initTilim* seconds.

4.6.2.8. Other Implementation Details. As mentioned before, ALNS is implemented within SA framework. The SA procedure is run for *tilim* seconds. A temperature value T is initialized, and it is decreased in each iteration by geometric cooling scheme, given in 4.66 where *coolCoef* is the cooling coefficient. At each temperature level, a neighboring solution S' is generated from the current solution S . If the objective value of the neighboring solution, $F(S')$, is an improved value over the current objective value $F(S)$, then the move is always accepted. Moreover, the worsening moves are accepted with the probability function given in 4.67, for the minimization problem case. At high temperatures probability of accepting a worsening move is more than the lower temperature case, and this results in diversification at the beginning where the temperature is high, and intensification at the end of the procedure where temperature is lower. Since selection of the initial temperature affects the solution quality, a set of parameters to calculate initial temperature are used instead of selecting the temperature value. The formula to initialize temperature is given in Equation 4.68. In Equation 4.68, $F(S_0)$ is the objective function value of the initial solution and we select T_0 such that a solution

S' will be selected with γ probability in the first iteration if $F(S') = \beta F(S)$.

$$T_{iter+1} = coolCoef T_{iter} \quad (4.66)$$

$$P(acceptance) = \exp\left(\frac{F(S) - F(S')}{T}\right) \quad (4.67)$$

$$T_0 = \left(\frac{F(S)(1 - \beta)}{\ln \gamma}\right) \quad (4.68)$$

The values for the parameters used in *SA-ALNS* procedure for the selected objective functions are given as follows. These values are chosen by analyzing the preliminary experimentation results.

- $\beta = 10$
- $\gamma_{Obj_1} = 0.95, \gamma_{Obj_{2,2}} = 0.9, \gamma_{ObjRawlsian} = 0.8$
- $coolCoef_{Obj_1} = 0.97, coolCoef_{Obj_{2,2}} = 0.99, coolCoef_{ObjRawlsian} = 0.98$
- $tilim = 3600$
- $initTilim = 600$
- $feasSeqModelTilim = 60$
- $destroyProb = 0.2$
- $feasSeqModelProbMultip = 0.25$
- $scoreUpdateInterval = 50$
- $scoreSmooth = 0.33$
- $scoreG = 4$
- $scoreI = 2$
- $scoreW = 1$

Finally, the algorithmic steps of the *SA-ALNS* heuristic is given in Figure 4.12.

4.7. Experimental Results

In this section we analyze the performance of the *ResponseModel* with the three selected objective functions (Obj_1 , $Obj_{2,2}$, and $ObjRawlsian$) using the proposed *FSGH*

```

Initialize parameters, generate initial solution  $S$ , set  $iter := 1$ 
repeat
    if  $iter \% scoreUpdateInterval == 0$  then
        Calculate interval scores
        Update scores by smoothing
        Clear interval scores
    end if
    Choose a move or destroy heuristic using roulette wheel and apply on  $S$ 
    if Destroy heuristic applied then
        Choose a repair heuristic using roulette wheel and apply
    end if
    Apply NodeEliminationImprove
    Apply VehicleWOTaskImprove
    Apply SwapVehicleListsImprove
    if  $F(S') < F(S)$  or  $Random(0, 1) < exp(\frac{F(S)-F(S')}{T})$  then
        Set  $S := S'$ 
        Apply GreedyMakespanReductionImprove
    end if
    Update destroy and repair neighborhood scores
    Set  $iter := iter + 1$ ,  $T := \alpha T$ 
until  $elapsedTime > tlim$ 

```

Figure 4.12. Pseudocode of the *SA-ALNS* heuristic.

and *SA-ALNS* heuristics, and compare them to the CPLEX solver package. For this purpose, a set of test problems with different sizes are generated. The heuristics are implemented using C# programming language.

4.7.1. Test Instances

To test the numerical performance, 16 test problems with different sizes are generated. The first six of them are generated randomly based on the distance matrix of Turkey. The details on instance generation are given in Appendix A.2.1. These

instances are named “PT01” to “PT06”, and contain 3 or 4 PFs, 15 or 20 TFs, and 3, 4 or 5 vehicles. Instances that are named “PT07” to “PT12”, are the same with the first six except the number of vehicles are doubled in them. Finally, the last four problems are generated based on the coordinates of the benchmark instances given by Solomon (1987). These are referred as “PS13” to “PS16” and the details are provided in Appendix A.2.2.

4.7.2. Results and Discussion

As mentioned in Section 4.6, the planning horizon is an output of the heuristic methods that we propose. In this way the task of selecting a planning horizon, which is hard to estimate, is eliminated. Note that when solving the model with an off-the-shelf solver such an estimate is required beforehand. Selecting a small value could eliminate many feasible solutions, whereas a high value will increase the number of decision variables dramatically, thus make it harder to find even a feasible solution. In this section, we first run the proposed heuristics and obtain the planning horizon, then run the *ResponseModel* using CPLEX for comparison with the given planning horizon.

The experiments are conducted for the given test instances by using IBM ILOG CPLEX 12.8. In all models, X_{vnmt} variables have the highest branching priority. Since we deal with an operational problem run times are limited to one hour as a stopping condition. Finally, the number of threads that the solver can utilize is set to 8. All experiments are carried out on a PC with 3.30 GHz CPU and 16 GB RAM, running under 64-bit Windows 7 operating system.

As the first step of the analysis, we analyze the performance of the *FSGH* and the results are given in Table 4.2. In Table 4.2, the first column indicates the instance name and the subsequent three columns state the number of PFs, TFs, and vehicles, respectively. Then, for each of the alternative objective, the planning horizon (T) obtained by the heuristic is given. The next column provides the percentage difference of the solver upper bound compared to the upper bound obtained by the heuristic. Therefore a positive value in this column indicates that the heuristic performs better

for that instance. Finally, the last two columns for an objective provide the optimality gaps of the heuristic and the solver with respect to the lower bound obtained by the solver. Note that CPLEX may fail to find an upper and/or lower bound for an instance with the given planning horizon. In such a case, the corresponding cells in Table 4.2 are left with a dash. Finally, the cases where the heuristic outperforms the solver are italicized in Table 4.2.

Table 4.2. Numerical performance comparison for *FSGH* (One hour time limit).

				<i>Obj₁</i>				<i>Obj_{2.2}</i>				<i>ObjRawlsian</i>			
	#PF	#TF	#V	T	UB	Opt. Gap %		T	UB	Opt. Gap %		T	UB	Opt. Gap %	
					Diff %	FSGH	Solver		Diff %	FSGH	Solver		Diff %	FSGH	Solver
PT01	3	15	3	30	-20.68	100.0	100.0	39	-26.71	93.4	90.9	32	-40.63	78.3	63.5
PT02	3	15	4	26	-21.83	100.0	100.0	36	<i>21.83</i>	90.8	92.5	29	-4.17	70.9	69.6
PT03	4	15	4	25	-64.89	100.0	100.0	27	-64.84	93.4	81.2	21	-42.86	76.2	58.3
PT04	4	15	5	23	-41.23	100.0	100.0	40	-54.24	92.4	83.4	29	-40.00	80.0	66.7
PT05	4	20	4	28	-50.17	100.0	100.0	32	-28.77	95.6	93.8	24	-20.83	79.2	73.7
PT06	4	20	5	30	-37.87	100.0	100.0	38	-52.75	96.0	91.5	25	-36.00	80.0	68.8
PT07	3	15	6	30	-3.22	100.0	100.0	41	-16.02	90.1	88.2	27	-43.55	75.1	55.9
PT08	3	15	8	24	<i>5.06</i>	100.0	100.0	31	<i>13.01</i>	90.8	91.8	23	-38.09	70.2	51.9
PT09	4	15	8	20	-47.45	100.0	100.0	25	-72.50	90.1	63.8	22	-50.03	71.4	42.9
PT10	4	15	10	27	-10.96	100.0	100.0	32	-43.66	90.4	83.0	25	-48.16	68.2	38.7
PT11	4	20	8	28	-	-	-	35	-	-	-	25	-18.06	72.2	66.1
PT12	4	20	10	30	-	-	-	46	-	-	-	35	-	-	-
PS13	3	23	10	91	-	-	-	92	-	-	-	93	-	-	-
PS14	3	23	10	106	-	-	-	109	-	-	-	112	<i>13.58</i>	89.4	90.7
PS15	4	30	10	112	-	-	-	117	-	-	-	126	-	-	-
PS16	5	46	15	137	-	-	-	148	-	-	-	140	-	-	-

Table 4.2 indicates that CPLEX outperforms *FSGH* in most of the cases for all objectives. *FSGH* yields a better result in one instance for *Obj₁* and *ObjRawlsian*, and in two instances for *Obj_{2.2}* among the instances where CPLEX finds a solution. However it can be concluded that the solver becomes unreliable for the larger cases, especially as the planning horizon becomes larger. Moreover better lower bounding schemes are required to discuss the optimality of the solutions since the optimality gap values are high even for the smallest cases, especially for *Obj₁*.

As the next step, the performance of the *SA-ALNS* is analyzed and the results are given in Table 4.3 where the results are provided for the average of 5 different

replications. Table 4.3 is structured similar to Table 4.2 except for the “Solver Fail %” columns. These columns state the percentage of the replications (out of five) where the solver fails to find a feasible solution. Therefore the remaining columns in Table 4.3 provide the comparison between *SA-ALNS* and CPLEX for the replications where the solver finds a feasible solution. Note that, since *SA-ALNS* may yield different T values for its replications, the solver needs to be re-run for each T value. As before, the cases where the heuristic outperforms the solver, and the instances where the solver fails the find a feasible solution in all replications are italicized in Table 4.3.

The first observation in Table 4.3 is that CPLEX solver can be unreliable even for small instances. There are 7 instances for *Obj_{2.2}* and *ObjRawlsian*, and there are 11 instances for *Obj₁* out of 16 such that there is at least one replication the solver fails to find a solution. Also *SA-ALNS* performs better than *FSGH* by resulting in more cases where the solver is outperformed, and the upper bound differences are smaller for the cases where CPLEX outperforms. From Table 4.3, one can conclude that *SA-ALNS* performs better than the solver for *Obj₁*. Although the solver is able to find better solutions for *Obj_{2.2}* and *ObjRawlsian*, it is not always reliable and its performance drops radically as the instance size and the number of time periods increase. It should also be mentioned that the planning horizon must be determined somehow to run the solver on its own.

As a result of these analyses, one can conclude that the *SA-ALNS* is a better way to deal with the *ResponseModel* compared to *FSGH*. Moreover, although its performance may be surpassed by the solver, especially for the smaller instances, *SA-ALNS* finds a feasible solution in all of our test cases without requiring to explicitly define the planning horizon. However, better moves and lower bounding schemes are still required as a future study.

Table 4.3. Average performance comparison for *SA-ALNS* (One hour time limit).

					Obj ₁						Obj _{2,2}						ObjRawlsian					
					Solve		UB	Opt. Gap %		T	Solve		UB	Opt. Gap %		T	Solve		UB	Opt. Gap %		
								SA-ALNS	Solver					SA-ALNS	Solver					SA-ALNS	Solver	SA-ALNS
#PF	#TF	#V	T	Fail %	Diff %	SA-ALNS	Solver	Diff %	SA-ALNS	Solver	Fail %	Diff %	SA-ALNS	Solver	Fail %	Diff %	SA-ALNS	Solver				
PT01	3	15	3	24.2	40	3.54	100.0	100.0	100.0	42.6	0	7.66	90.7	91.2	28.0	20	11.25	68.2	71.4			
PT02	3	15	4	25.2	40	28.46	100.0	100.0	100.0	41.8	0	35.55	88.7	91.5	33.6	0	-1.96	72.1	71.2			
PT03	4	15	4	17.0	40	-11.72	100.0	100.0	100.0	36.0	0	-14.37	87.3	85.1	23.8	0	-18.02	70.9	63.9			
PT04	4	15	5	15.6	0	-2.07	100.0	100.0	100.0	32.0	0	-18.99	87.4	84.1	21.0	0	-30.25	67.9	53.9			
PT05	4	20	4	18.0	60	-8.98	100.0	100.0	100.0	30.4	0	-5.76	93.3	92.8	21.0	0	-10.86	74.7	71.5			
PT06	4	20	5	22.0	0	-32.00	100.0	100.0	100.0	32.2	20	-24.47	93.7	91.5	24.0	0	-9.62	71.7	68.2			
PT07	3	15	6	19.6	40	39.79	100.0	100.0	100.0	38.8	0	20.43	85.2	87.7	32.6	0	-12.02	68.8	63.1			
PT08	3	15	8	21.0	0	54.08	100.0	100.0	100.0	42.2	0	-0.65	90.6	90.3	28.8	0	-5.74	72.2	69.8			
PT09	4	15	8	16.4	0	31.55	100.0	100.0	100.0	28.4	0	-30.04	84.2	76.5	19.0	0	-37.25	58.5	32.9			
PT10	4	15	10	17.6	0	30.20	100.0	100.0	100.0	31.8	0	-38.42	87.0	77.1	22.2	0	-33.42	53.8	28.9			
PT11	4	20	8	17.6	40	-4.82	100.0	100.0	100.0	32.2	40	-26.96	91.0	87.3	23.4	40	-23.69	62.5	50.8			
PT12	4	20	10	22.0	60	-38.99	100.0	100.0	100.0	34.2	100	-	-	-	26.0	60	3.73	64.7	65.7			
PS13	3	23	10	76.4	100	-	-	-	100.2	100.2	100	-	-	-	86.4	100	-	-	-			
PS14	3	23	10	95.4	80	7.98	100.0	100.0	100.0	108.8	80	-24.11	97.9	97.2	100.4	60	22.49	88.4	90.5			
PS15	4	30	10	101.2	100	-	-	-	122.8	122.8	100	-	-	-	104.2	100	-	-	-			
PS16	5	46	15	130.0	100	-	-	-	135.8	135.8	100	-	-	-	128.6	100	-	-	-			

5. BENEFITS OF RELATING DISASTER PREPAREDNESS AND RESPONSE APPROACHES

In this chapter we continue our numerical analysis with joint consideration of the preparedness and response stage actions. First the effect of SCWs, which are included in *CLFDIP* to facilitate better fairness in the response stage, is analyzed. Then, we conclude the chapter by analyzing the effect of restricting the *ResponseModel* decisions using the information gained from the preparedness stage, thus combining the efforts in these two disaster management stages. For these analyses, we use the output of the *CLFDIP* model as input to the *ResponseModel*. Since *ResponseModel* assumes a single item type, the three- and four-city instances given in Section 3.5.1 are regenerated and solved for four-scenario case with single item. Then the TF locations are refined for the first scenario realization by minimizing the total weighted distance as explained in Section 3.2.2. Finally the number of vehicles is set as 10 in all instances.

5.1. The Effect of Service Coverage Windows

In Section 3.1 we claim that the SCWs make sure that there are facilities close enough to cover the service requirements for each TF, thus help us to improve effectiveness and equity in the response stage. To test this claim, the problem set is solved again by *CLFDIP*, but the SCW constraints 3.6 are replaced with regular demand satisfaction constraints given in Equation 5.1.

$$\sum_{j \in J} F_{jil}^s \geq \sum_{m \in M_s} d_{ml}^s X_{im}^s \quad s \in S, i \in I, l \in L \quad (5.1)$$

ResponseModel is run for 5 replications with each selected objective for the cases *withSCW* and *withoutSCW*, and their performances are compared in a structure similar to the objective function selection in Section 4.5. Apart from the 11 performance metrics that are mentioned before, the realized planning horizon is also used for com-

parison. However, since the TF compositions are different for the *withSCW* and the *withoutSCW* settings, the performance metrics are calculated with respect to each affected person. The fill rate P_{it} in a TF location i at time t is also assumed to be the satisfaction rate of each individual assigned to that TF location.

Figures 5.1, 5.2, and 5.3 compare the cases *withSCW* and *withoutSCW* for the three selected objective functions (Obj_1 , $Obj_{2,2}$, and $Obj_{Rawlsian}$) respectively. As mentioned before, a smaller performance metric represents a better performance, and one can observe from Figures 5.1, 5.2, and 5.3 that both efficiency, effectiveness and equality measures are worsened for most of the cases if the SCWs are eliminated. The only exception for $Obj_{2,2}$ is that the Gini index is improved by 2.98%. Similarly, the exclusion of SCWs results in improvements of 0.69% for Gini index, and 1.40% for α -fairness with $\alpha = 3$. Note that the improvement in fairness, effectiveness and efficiency are obtained with the expense of a 15.05% cost increase on average. Therefore we can conclude that the expectation to improve effectiveness and equity under SCWs is validated in this manner.

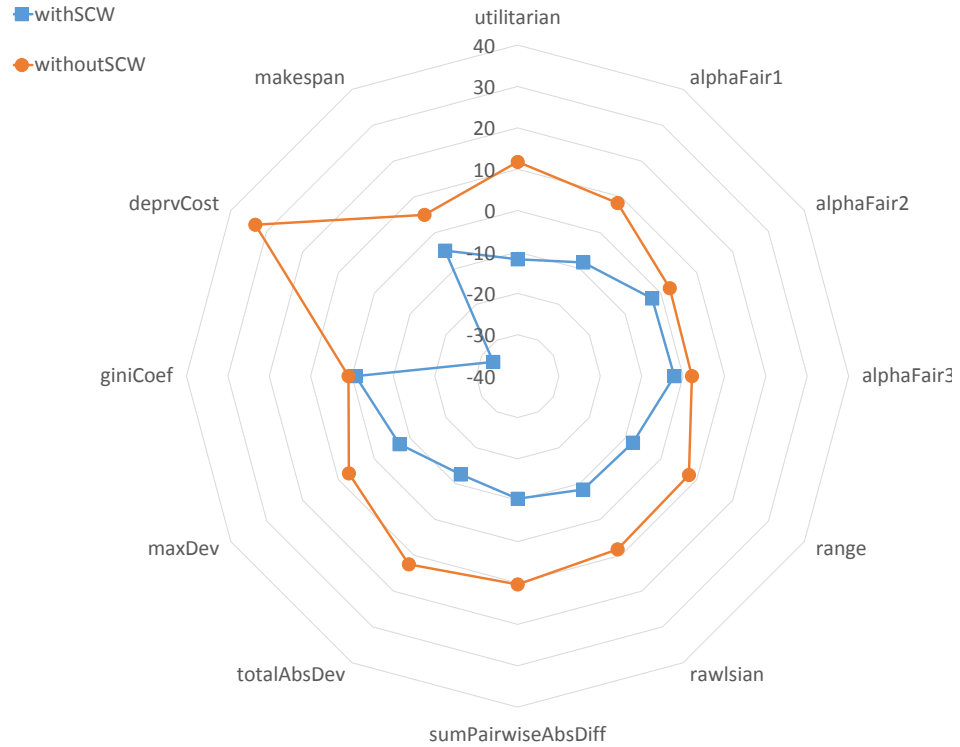


Figure 5.1. Comparison of Obj_1 for the *withSCW* and *withoutSCW* cases.

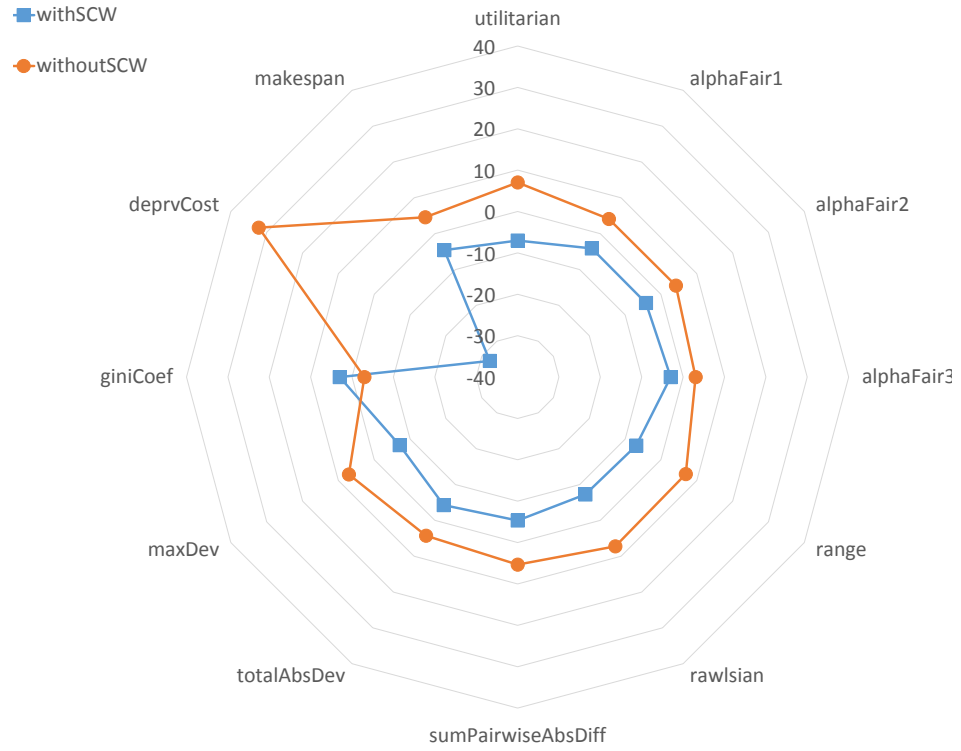


Figure 5.2. Comparison of $Obj_{2.2}$ for the *withSCW* and *withoutSCW* cases.

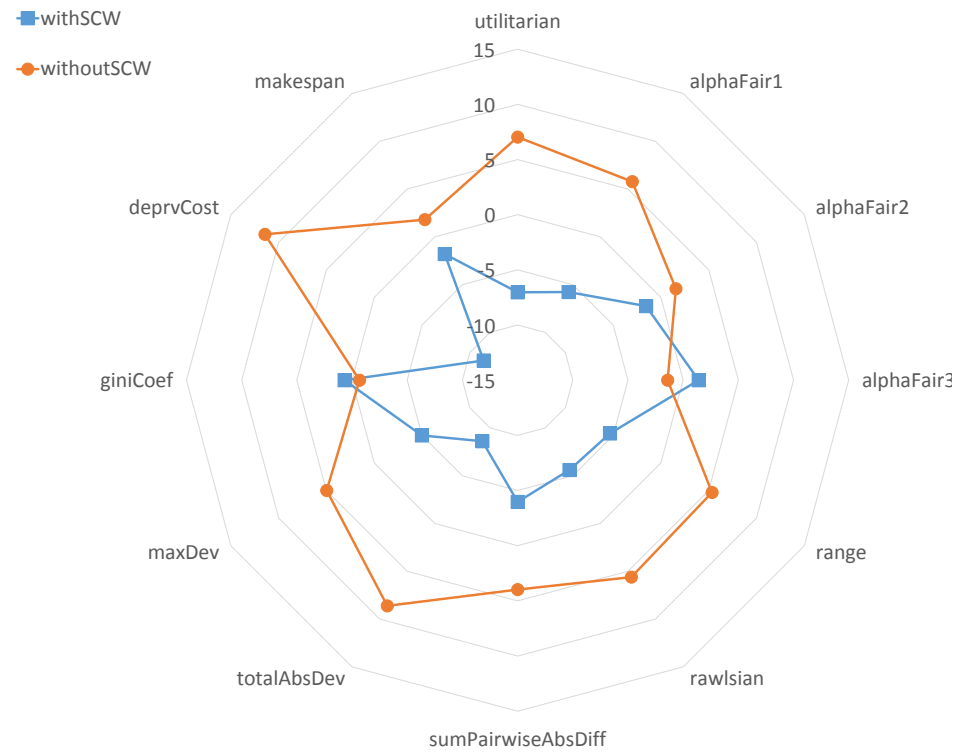


Figure 5.3. Comparison of $Obj_{Rawlsian}$ for the *withSCW* and *withoutSCW* cases.

For a further analysis, we calculate the average percentage of fill rates within the time windows defined in the preparedness stage. Table 5.1 provides the calculations of the selected objectives for the *withSCW* and *withoutSCW* cases. As expected, the average fill rates for the network design under SCWs are higher than the cases with regular demand satisfaction constraints, especially for the smallest window. However, the preparedness stage model designs the network by just considering the flow amount and distances between the nodes, and ignores operational constraints such as vehicles (i.e. assumes there exists unlimited vehicles with abundant capacities). Therefore the time windows that are defined by the decision maker may not be satisfied due to vehicular constraints.

Table 5.1. Comparison of the fill rates within the predefined time windows.

	<i>withSCW</i>			<i>withoutSCW</i>		
	<i>SCW</i> ₁ Fill %	<i>SCW</i> ₂ Fill %	<i>SCW</i> ₃ Fill %	<i>SCW</i> ₁ Fill %	<i>SCW</i> ₂ Fill %	<i>SCW</i> ₃ %
<i>Obj</i> ₁	66.2	68.5	71.9	33.2	52.7	60.3
<i>Obj</i> _{2.2}	61.1	61.0	63.8	31.9	51.3	57.5
<i>ObjRawlsian</i>	65.3	62.2	66.6	29.9	52.9	60.7

5.2. The Effect of Utilizing Preparedness Plans in Disaster Response

Since the performance of the *SA-ALNS* is not dominating the solver, we try to reduce feasible the solution space for the *ResponseModel*. For that reason, we utilize the flow distribution information that is obtained from the preparedness stage model. Similar to Section 5.1 we refine the solutions in a post processing step to minimize total weighted distance of flows for this analysis. In this way, we can decide on which PFs will be serving which TFs using the output of the preparedness stage model. We call this model *ResponseModel.DedicatedV*, where each vehicle can only visit the TFs that are assigned to the PF that the vehicle is initialized. Therefore we define the set I_v , which provides the list of TFs that vehicle v is allowed to visit. The mathematical model *ResponseModel.DedicatedV* is the same as *ResponseModel*, except the X_{vnmt} variables that are disallowed by the I_v set are eliminated. Also the destroy, move, repair heuristics and improvement steps of the *SA-ALNS* are adapted accordingly.

Table 5.2 summarizes the *SA-ALNS* and solver comparison for the selected objective functions as the average of 5 replications. In Table 5.2, the first five columns indicate objective and problem characteristics, columns 6 to 10 present the results for *ResponseModel*, and the rest provides the same analysis for *ResponseModel_DedicatedV*. The “-r1” suffix in the problem names indicate we assume the first scenario is realized among the four scenarios. As before, the cases where the heuristic outperforms the solver, and the instances where the solver fails to find a feasible solution in all replications are italicized in Table 5.2.

In terms of the performance of *SA-ALNS* in *ResponseModel*, observations similar to the ones in Section 4.7.2 can be made for Table 5.2 as well. Although CPLEX can find better upper bounds, it fails to find a feasible solution in most of the cases. Apart from that, the realized planning horizons tend to reduce for *ResponseModel_DedicatedV*. Moreover, *ResponseModel_DedicatedV* performs relatively better against the solver, such that there are more instances where the solver is outperformed among the ones a feasible solution is found.

Next, we compare *ResponseModel* and *ResponseModel_DedicatedV* with respect to the performance measures as before. Figures 5.4, 5.5, and 5.6 provide the comparison for the selected objective functions. Since a smaller performance metric represents a better performance, one can conclude from Figure 5.6 that both efficiency, effectiveness and equality measures are improved for *ObjRawlsian* when the flow distribution decisions are utilized in the response stage model. On the other hand, the Gini index and α -fairness with $\alpha = 1$ and $\alpha = 2$ are worsened for *Obj₁* (5.14%, 0.25% and 0.58%, respectively). Similarly, Gini index is worsened by 1.77% for *Obj_{2.2}*. However these are relatively small deviations and the improvements in other measures are more significant. Note that any feasible solution to *ResponseModel_DedicatedV* is also a solution to the *ResponseModel*, therefore the optimum solution of the *ResponseModel_DedicatedV* can not be better than the other. Thus we can conclude that using the flow distribution decisions that are obtained in the preparedness phase to restrict the vehicles to a subset of nodes results in better performance for the *SA-ALNS* heuristic by reducing the problem complexity and the search space to discover.

Table 5.2. *SA-ALNS* and *CPLEX* comparison for *ResponseModel* and *ResponseModel_DedicatedV* (One hour time limit).

					ResponseModel						ResponseModel_DedicatedV					
	#PF	#TF	#V	T	Solver Fail %	UB Diff %	Opt. Gap %		T	Solver Fail %	UB Diff %	Opt. Gap %				
							SA-ALNS	Solver				SA-ALNS	Solver			
Obj ₁	P3-1-s4-r1	3	23	10	33.0	0	-70.48	100.0	100.0	26.6	20	-11.46	100.0	100.0		
	P3-2-s4-r1	3	15	10	39.2	0	-9.45	100.0	100.0	23.8	0	23.91	96.2	96.9		
	P3-3-s4-r1	3	15	10	56.6	100	-	-	-	51.6	100	-	-	-		
	P3-4-s4-r1	3	18	10	52.4	0	-46.43	100.0	100.0	31.6	60	65.19	100.0	100.0		
	P4-1-s4-r1	3	40	10	65.4	100	-	-	-	39.8	100	-	-	-		
	P4-2-s4-r1	4	21	10	48.8	100	-	-	-	31.4	80	26.61	100.0	100.0		
	P4-3-s4-r1	4	41	10	74.4	100	-	-	-	54.6	100	-	-	-		
	P4-4-s4-r1	5	56	10	119.6	100	-	-	-	113.0	100	-	-	-		
Obj _{2.2}	P3-1-s4-r1	3	23	10	59.4	100	-	-	-	36.2	0	-15.28	92.4	91.0		
	P3-2-s4-r1	3	15	10	67.2	40	-43.00	91.2	84.0	49.4	0	-8.30	67.7	63.9		
	P3-3-s4-r1	3	15	10	79.2	100	-	-	-	78.8	100	-	-	-		
	P3-4-s4-r1	3	18	10	85.6	40	-47.93	95.5	92.8	54.0	0	37.52	93.2	95.0		
	P4-1-s4-r1	3	40	10	80.2	100	-	-	-	60.6	100	-	-	-		
	P4-2-s4-r1	4	21	10	86.2	100	-	-	-	64.2	80	107.42	85.7	93.1		
	P4-3-s4-r1	4	41	10	94.6	100	-	-	-	86.8	100	-	-	-		
	P4-4-s4-r1	5	56	10	129.6	100	-	-	-	150.0	100	-	-	-		
ObjRawlsian	P3-1-s4-r1	3	23	10	47.0	80	-40.89	81.8	69.2	31.8	0	23.41	68.3	74.1		
	P3-2-s4-r1	3	15	10	46.8	0	2.11	70.8	69.9	29.8	0	-16.58	17.2	0.7		
	P3-3-s4-r1	3	15	10	62.0	100	-	-	-	44.2	100	-	-	-		
	P3-4-s4-r1	3	18	10	68.2	0	-5.28	81.2	78.6	37.0	60	44.50	71.2	80.0		
	P4-1-s4-r1	3	40	10	59.6	100	-	-	-	45.6	100	-	-	-		
	P4-2-s4-r1	4	21	10	64.4	100	-	-	-	45.0	60	-3.97	55.5	52.6		
	P4-3-s4-r1	4	41	10	76.4	100	-	-	-	64.8	100	-	-	-		
	P4-4-s4-r1	5	56	10	95.8	100	-	-	-	125.8	100	-	-	-		

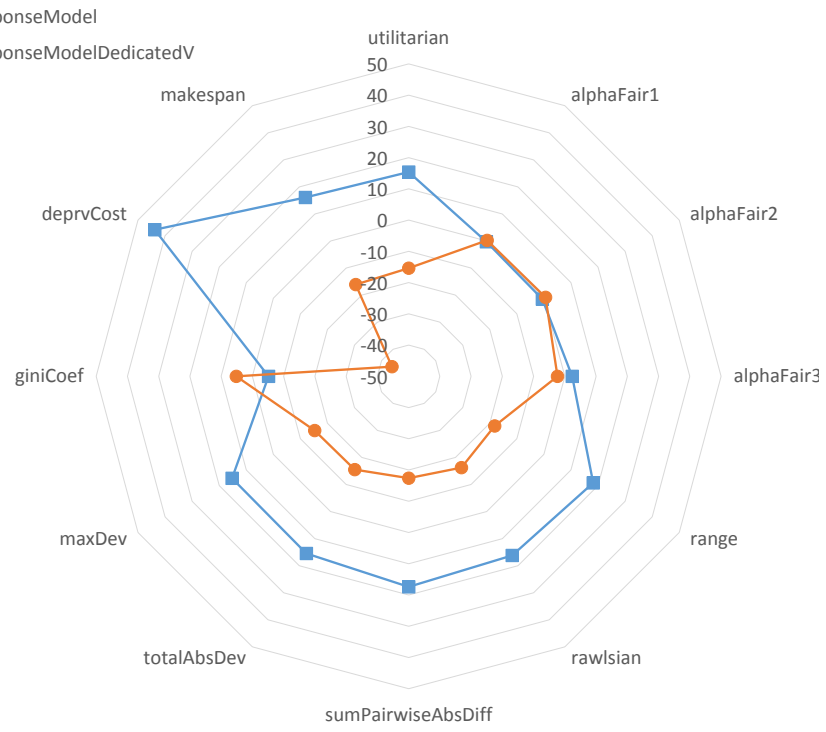


Figure 5.4. Performance comparison of Obj_1 for *ResponseModel* and *ResponseModelDedicatedV*.

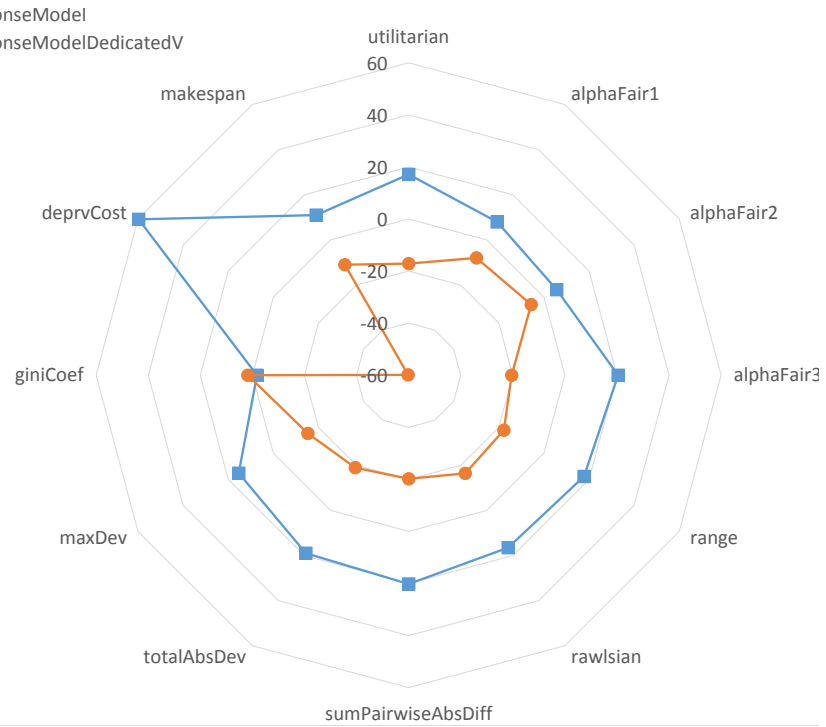


Figure 5.5. Performance comparison of $Obj_{2.2}$ for *ResponseModel* and *ResponseModelDedicatedV*.

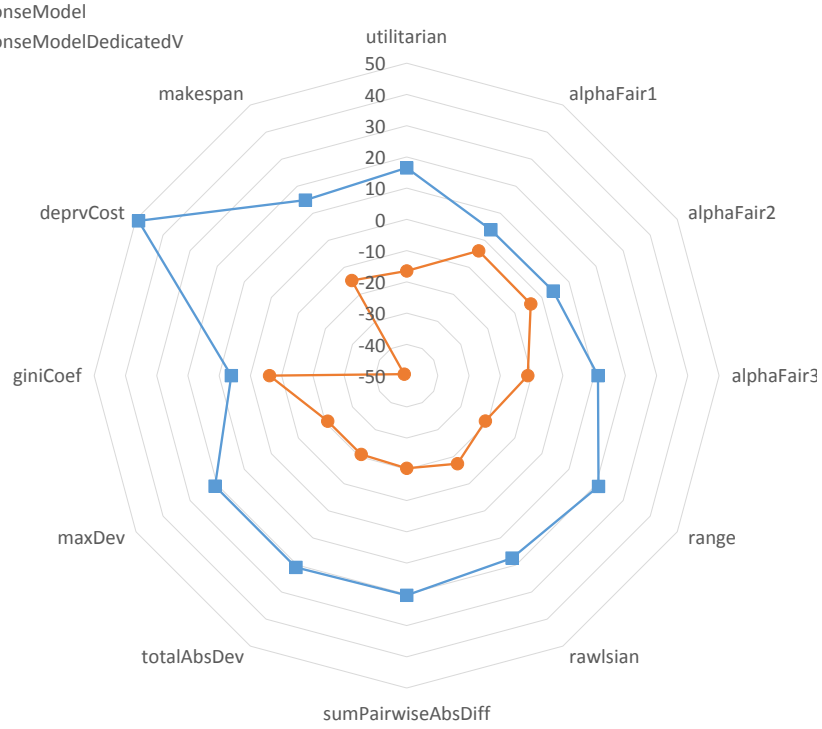


Figure 5.6. Performance comparison of *ObjRawlsian* for *ResponseModel* and *ResponseModelDedicatedV*.

Finally, we conclude the numerical analyses by comparing the selected objectives using *SA-ALNS* heuristic for the *ResponseModelDedicatedV* problem, which yields the best results among others. Figure 5.7 provide the comparison on the radar chart, which indicate the best performances are observed by different objectives. Among the 12 performance metrics, *Obj₁* performed the best in three (utilitarian, deprivation cost, and makespan), *Obj_{2,2}* yields the best results in three (α -fairness with $\alpha = 1, 2, 3$), and *ObjRawlsian* provides the best results in the remaining six (range, rawlsian, sum of pairwise absolute differences, total absolute deviation, maximum deviation, gini coefficient). Since *Obj₁* has an increasing penalty for fill rate differences, it tries to push the observed planning horizon as small as possible, thus improves utility and reduces the deprivation cost as well. *Obj_{2,2}* definition contains both equality and effectiveness terms, which in turn mimics the α -fairness which is an inequity averse aggregation function. On the other hand *ObjRawlsian* focuses only on the equality and performs the best for the equality measures among others.

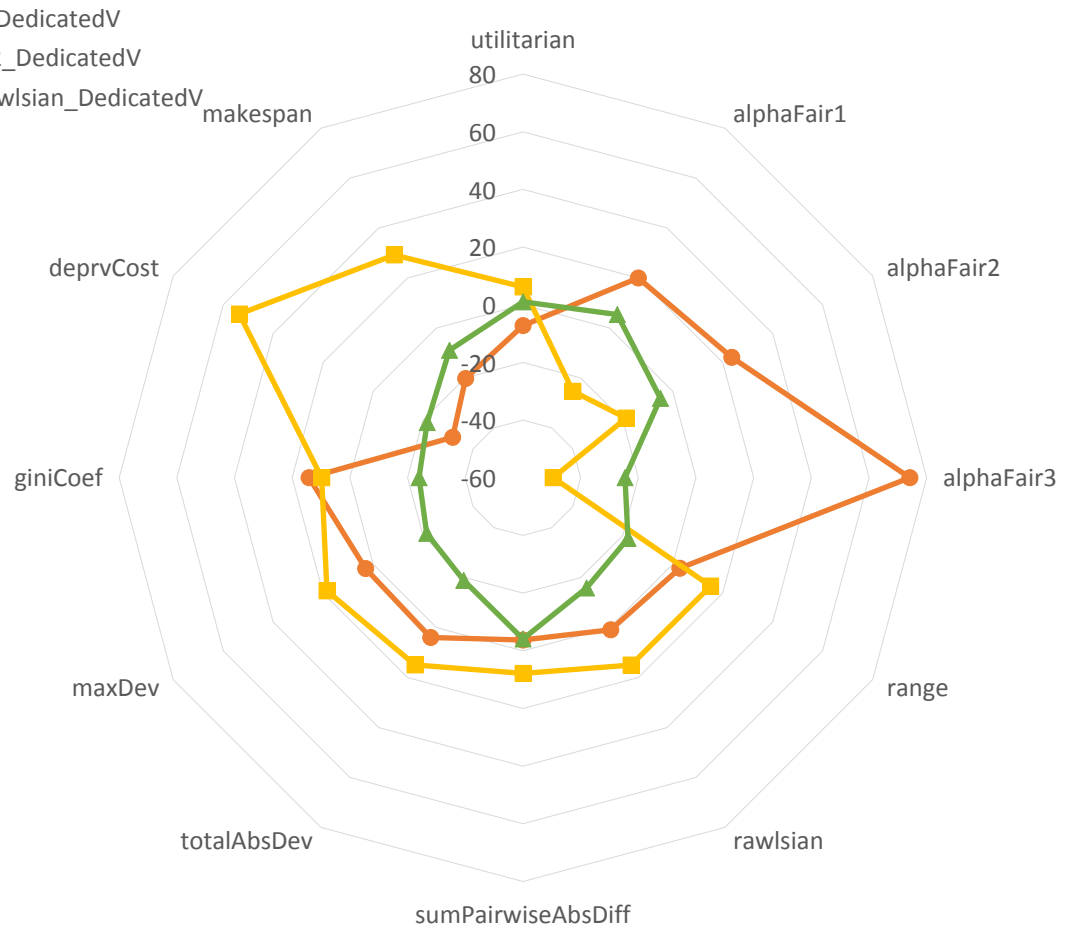


Figure 5.7. Comparison of the selected objectives using *SA-ALNS* for *ResponseModel_DedicatedV*.

6. CONCLUSIONS AND FUTURE RESEARCH

Humanitarian logistics activities are crucial in easing the suffering of the affected population that suddenly became a part of a unfortunate situation. Therefore relief operations, which exhibit interrelated and challenging network optimization problems, should be planned meticulously. Cost efficiency should not be the sole objective of such public operations where human lives are at stake, fairness should be taken into account as much as effectiveness and efficiency.

In this respect, a robust preparedness stage model (*CLFDIP*) is proposed that enables a fair and effective response aftermath a disaster occurrence. The model integrates the selection of distribution and storage center locations, their capacities and inventory levels, with the demand point clustering decisions. After the model assumptions and parameters are validated by subject experts, the model is built as a mixed integer linear program. Since solvers fail to solve large instances, an exact solution method based on logic-based Benders decomposition is proposed, which yields very good results within a reasonable time frame for instances with realistic sizes.

The response stage model (*ResponseModel*) is built upon the same relief network structure, where alternative objective functions are used to seek a trade-off among fairness, effectiveness and efficiency. The main decisions are the route of the vehicles on the network, the amount of items they pick up at PFs, the amount of items that are carried on vehicles on arcs, and the amount of items used to satisfy the demand of beneficiaries at each time segment. Using this information, satisfaction rates are calculated, which are in turn used in the proposed objective functions. The best performing three of them are selected among nine using a set of performance measures that can be categorized as efficiency, effectiveness and fairness metrics. Then a feasible solution generation heuristic (*FSGH*) and a heuristic based on adaptive large neighborhood search running within a simulated annealing framework (*SA-ALNS*) are proposed. Although the performance of *SA-ALNS* does not dominate the solver's entirely, it turns out to be a robust solution method since it can find a feasible solution for all test

instances unlike the solver package.

Finally, the importance of considering preparedness and response stage decisions together is discussed. First, the improvement in effectiveness and fairness designing a relief network while considering the response stage is demonstrated. Moreover, we observe that the *SA-ALNS* heuristic performs better by restricting the vehicles on a subset of nodes as planned in the preparedness model.

The main contributions of the dissertation are given in Section 6.1, and Section 6.2 state the possible future research directions.

6.1. Main Contributions

We can first discuss the contributions regarding the disaster preparedness models. *CLFDIP* aims is to design a humanitarian relief network that has built-in features for a feasible, effective, and fair post-disaster distribution plan by means of a model that is easy to understand, implement, and solve. The following features summarize the novel contributions of *CLFDIP*:

- Service adequacy and fairness are the main drivers of the model, whereas cost is secondary. Fairness is considered in the following two aspects:
 - (i) In the beneficiary's access to TF, by incorporating the closest assignment property and limiting the maximum distance between the demand point (beneficiary) and the TF to which it is assigned.
 - (ii) In the delivery of relief items from PFs to TFs, by ensuring that every TF location has close enough PF locations to meet the service requirements set by humanitarian experts.
- Service adequacy is achieved through the model robustness approach, which guarantees any feasible solution to satisfy all demands under all disaster scenarios. Furthermore, in this manner, the model does not rely on arbitrary or hard-to-estimate parameters such as disaster scenario probabilities or shortage penalty costs.

- The grouping (clustering) of individual demand points (e.g. buildings) to TFs with the closest assignment property is treated as an integral part of the problem. While closest assignment property defines a more realistic setting, integration of clustering decisions improves the quality of the solutions.
- A demand covering scheme called “service coverage windows” is proposed to model item urgency in a more accurate, intuitive, and direct manner.
- An exact solution technique, logic-based Benders decomposition, is proposed to solve large problem instances.

The *ResponseModel* aims to distribute the prepositioned goods after a disaster in an efficient, effective, and equitable manner. The following features summarize the contributions of the *ResponseModel*:

- The satisfaction ratios at each TF point at each time segment is used as the key to define linear objective functions. Although these functions may not have a direct meaning, they act as proxy measures to capture efficiency, effectiveness and fairness simultaneously to different extends. These objectives along with the ones adapted from the literature are compared in terms of these measures.
- Demand satisfaction is guaranteed by the model assumptions, since we consider a robust relief network is designed in the preparedness stage. Therefore efficiency is defined as the time horizon required to fulfill all demands, effectiveness is defined by the total unsatisfied demand ratio throughout the planning horizon, and fairness is related with the differences among the fill rates of TFs.
- Although there are some limitations (e.g. different items are bundled into a single item, there are sufficient items to cover the whole demand), a Rich-VRP problem is modeled where multiple-depots and heterogeneous fleet of vehicles with multiple use exist, routes are open, split deliveries are allowed, and vehicles do not have any assigned nodes. Also, we assume demand arrivals can occur any time throughout the planning horizon.
- Matheuristics that are based on a simplified mathematical model and ALNS algorithm are proposed. New destroy and repair heuristics along with moves are proposed that also utilize the simplified model.

6.2. Possible Future Research Directions

The first future research direction is to further improve the response stage heuristics by defining new destroy/repair heuristics and moves. Also, better lower bounding schemes are required to be able to measure the solution quality more accurately.

Focusing on the limitations of the models is another research direction. *CLFDIP* provides a robust network, which may be costly to build. We can therefore study an extension where the objective is to minimize unattended demand points while imposing a budget constraint. This model extension will also require a new exact solution method, since the model structure will be changed. In the *ResponseModel*, it is assumed a single item exists, and there are enough goods present in the warehouses. Considering multiple item types, and/or assuming insufficient initial supply amounts is another possible future study. Apart from these, the *ResponseModel* can be run in a rolling horizon fashion.

Finally, different nonlinear objective structures can be utilized for a more direct definition of equity in the response stage model. Adapting the heuristic methods accordingly, and analyzing their performances in the utilitarian-egalitarian range is another future research direction.

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APPENDIX A: DATA GENERATION

A.1. Data Generation Scheme for Disaster Preparedness

A.1.1. Random Data Generation Scheme

In this section, we explain in detail the steps of data generation scheme developed to allow numerical experimentation on instances with different sizes and characteristics for *CLFDIP*. While the data generation scheme is built as realistically as possible, it should be noted that the aim is not to represent reality in every aspect, but rather to obtain self-consistent random problem instances. For this purpose, the features of the problem are parametrized. In this way the data generation scheme will be driven by the user through setting these parameters to produce instances of required properties.

We define the “map” as the general collection of all demand points, TF locations, and PF locations. It is a rectangular grid represented by a number of “cells”. Each cell can be:

- *Empty Cell*: They do not contain any demand points or candidate TF locations, however there can be some candidate PF locations.
- *Sparse Cell*: They contain few demand locations and a set of candidate PF locations exist.
- *Moderate Cell*: They are crowded areas with moderately dense population, therefore public facilities such as schools or sports centers are located in these areas.
- *Dense Cell*: They are residential areas that contain high-rise buildings which make the population denser compared to the others. However, this is not a restrictive definition since what “sparse” or “dense” means in these cells is defined by the decision maker. Similarly, public facilities such as schools or sports centers are also located in these areas.

Each cell is further divided as a grid into “points”; where a point can be a demand point, a TF candidate location, a PF candidate location, or empty. The size of a cell and the number of grid points in a cell are determined by the decision maker. In order to generate a map, decision maker basically inputs the size of a city in terms of number of rows and columns of cells, the number of grid points in a cell, and the other required parameters. In the generated map, the type of each cell, and the type of points in the cell are determined randomly following uniform distribution, with the probabilities supplied by the decision maker. Also, amount of population in each demand point is generated by a uniform random distribution within the limits that decision maker provides. After building all of the cells and the points of those cells, a map of a hypothetical city of the desired size is generated. Moreover, decision maker can generate a map that contains multiple cities. In this case, cities are generated and combined in a single map with a user defined clearance between them. The generated map determines the I , J , and M sets, and δ_{im} parameter used in the model. The related input values that are required to find the sets mentioned above for an instance are given below:

- *# Cities*: The number of cities.
- *# Rows*: The number of cells in each column of cities.
- *# Columns*: The number of cells in each row of cities.
- *Clearance*: Minimum number of Empty Cells between two cities. The default value is 3 for each city.
- *Resolution of a Cell*: The number of points in each row and each column within a cell. The default value is 10.
- *Length of a Cell*: The length of a side of each cell in unit distance. The default value is 1.
- *Seed*: The seed value used to initialize the random number stream.
- *Sparse Cell Probability*: For each cell in a city, the probability of its being a Sparse Cell. The default value is 0.1.
- *Sparse Cell PF Probability*: In each Sparse Cell, the probability of having a PF candidate location in each point. The default value is 0.02.
- *Sparse Cell Demand Point Probability Limits*: In each PF Cell, the lower and

upper limits of the probability of having a demand location in each point. The default values are 0.05-0.3.

- *# Persons per Sparse Cell Demand Point*: For each demand point in a Sparse Cell, the lower and upper limits of the number of potentially affected people. The defaults value are 20-60.
- *Dense Cell Probability*: For each cell in a city, the probability of its being a Dense Cell. The default value is 0.2.
- *Dense Cell TF Point Probability*: In each Dense Cell, the probability of having a TF candidate location in each point. The default value is 0.01.
- *Dense Cell Demand Point Probability*: In each Dense Cell, the probability of having a demand point in each possible point. The default value is 0.65.
- *# Persons per Dense Cell Demand Point*: For each demand point in a Dense Cell, the lower and upper limits of the number of potentially affected people. The default values are 80-200.
- *Moderate Cell Probability*: For each cell in a city, the probability of its being a Moderate Cell. The default value is 0.5.
- *Moderate Cell TF Point Probability*: In each Moderate Cell, the probability of having a TF candidate location in each point. The default value is 0.02.
- *Moderate Cell Demand Point Probability*: In each Moderate Cell, the probability of having a demand point in each possible point. The default value is 0.65.
- *# Persons per Moderate Cell Demand Point*: For each demand point in a Moderate Cell, the lower and upper limits of the number of potentially affected people. The default values are 20-60.
- *Empty Cell PF Probability*: In each Empty Cell, the probability of having a PF candidate location in each point. The default value is 0.001.

Apart from the input parameters that are used to generate a map, decision maker provides the following sets and parameters necessary for the model:

- *K*: The number of service coverage windows. The default value is 3.
- *T*: The number of PF size options. The default value is 2.
- *L*: The number of item types. The default value is 3.

- r_{kl} : Proportion of demand for item l to be satisfied within service coverage window k . The default values corresponding to each item type and service window are as follows: 0.33;0.66;1 for the first item type, 0.5;0.8;1 for the second item type and 0.2;0.5;1 for the last item type.
- *Coverage Distance Limits*: The maximum distances defined for each service coverage window. J_i^k parameters are determined using these limits. The default values are 5;15;30 unit distances, where each value corresponds to a SCW.
- u_l : Capacity consumption of item l . The default values are 0.15;0.032;2 where each value corresponds to an item.
- h_l : Acquisition, expected inventory holding and wastage costs cost of item l . The default values are 0.1;5;2 where each value corresponds to an item.
- *Clustering Distance Limit*: The maximum distance that affected people can travel in order to obtain relief item from their assigned TF location. I_m sets are constructed using this information. The default value is 3 unit distances.

The number of disaster scenarios S is determined by the user, and for each scenario the cell which is the point source of the disaster (i.e. the epicenter of the earthquake) is randomly selected. Also, the earthquake severity in each scenario is determined randomly, following a uniform distribution within the specified limits. It should be noted that the earthquake severity term used in this context does not have a direct physical seismic counterpart; it is used to derive a hypothetical probability of being affected by the earthquake as a consequence of the physical intensity of the disaster. The amount of demand that is generated due to each disaster scenario is proportional to the severity, and the “observed severity” in each cell reduces linearly as the rectilinear distance to the epicenter increases. In each cell, each demand point generates demand according to the observed severity in the cell. In this way, M_s and d_{ml}^s parameters are determined. The related input values are given below:

- *# Scenarios*: Number of disaster scenarios to produce.
- *Earthquake Severity Limits*: The upper and lower limits of the probability of each demand point to be affected in the epicenter of the earthquake. The default limits are 0.3-0.7.

- *# Impact Levels:* The maximum rectilinear distance of a cell from the epicenter to be affected by the earthquake. The default value is 15 cells.
- *# Items required per person:* The number of items needed by an affected person for each item type. The value can be less than one for shared items. The default values are 1;10;0.1 where each value corresponds to an item.

The TF capacity parameters K_i^T are selected randomly among the possible values provided by the user. On the other hand, K_t^P parameters are generated relative to the population in the instance. A base capacity requirement per candidate PF location is obtained considering the case where the half of the population is affected and all PF locations are opened. Using the capacity scaling factor, this requirement is scaled up or down to create different levels of capacity tightness in the problem. Then the actual PF size levels are determined by multiplying this scaled base capacity value by the PF size multipliers. The relevant parameters are stated below:

- *TF Size Options:* The size options for the TF candidate locations. The default values are 3000;7000 where each value corresponds to a different size option.
- *Capacity Scaling Factor:* The multiplier to scale base PF capacity. The default value is 3.
- *PF Size Multipliers:* The multiplier values that represents relative size differences of each PF size. The default values are 0.5;1.5 where each value corresponds to a different size.

Fixed cost parameter, c_{jt} , is determined such that there is a balance between the two terms in the objective function of *CLFDIP*, fixed cost of PFs and inventory holding cost. Similar to PF capacity calculation, a base cost per candidate PF is calculated by assuming the items required to serve the half of the population will be hold. This base value is adjusted by using the cost scaling factor, and PF fixed cost multipliers are used to produce the cost values with respect to capacity levels. Finally, the c_{jt} parameters are differentiated based on PF location j by assuming that the fixed cost of a warehouse within a crowded area will be higher. The base price determines the actual cost of a PF location within a cell with average crowdedness, and the rest are

deviated around it depending on their percentage difference from average crowdedness within the limits given by PF fixed cost location effect parameter. The related input parameters and their default values are given below:

- *Cost Scaling Factor*: The multiplier to scale base PF cost. The default value is 3.
- *PF Fixed Cost Multipliers*: The multiplier values that represents relative cost differences of each PF size. The default values are 1;1.5 where each value corresponds to a different size.
- *PF Fixed Cost Location Effect*: The maximum percentage deviation from the base price of a PF with respect to the crowdedness of the PF Cell. The default value is 0.2.

In order to validate our data generation scheme, we consulted a subject expert in Boğaziçi University Kandilli Observatory and Earthquake Research Institute (KOERI). It is agreed that the data generation scheme is a valid abstraction of the problem, and the number of scenarios does not need to be high since we model the worst case, i.e. each scenario corresponds to a disaster epicenter, and the highest disaster severity anticipated for each epicenter is used. In addition, it should be noted that the number of disaster scenarios considered in the JICA report (JICA, 2002) is four for İstanbul, which is one of the biggest metropolitan cities in the world.

As opposed to our point source assumption for a disaster, another approach could be using line source where the rupture would be modeled to occur on multiple consecutive cells instead of a single cell. Furthermore, the effect of the disaster with respect to the distance to the source could be modeled more realistically instead of assuming linear decay. Also, the current data generation scheme assumes either day time or night time population, whereas it is possible to consider both. All these features can be incorporated into the data generation scheme if required.

The data generation scheme is built as a software with visual user interface. It takes the necessary inputs, and provides the user the sets and parameters required in

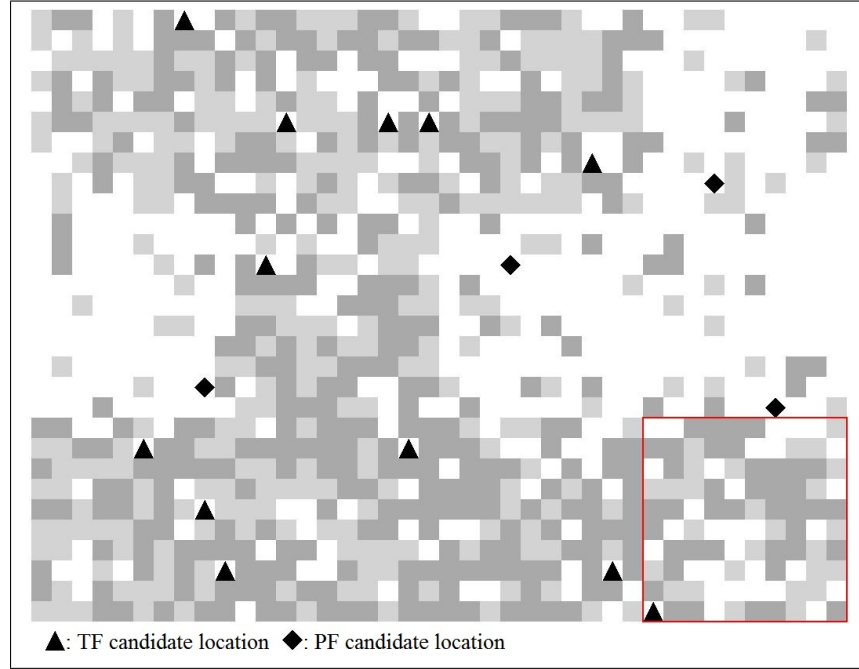


Figure A.1. An example of a generated map.

CLFDIP model along with a visualization of the generated map. An example of a small map is given in Figure A.1 for a small single city instance. In Figure A.1 gray points are residential areas where dark grays are affected by a disaster scenario, black triangles represent candidate TF locations and black diamonds indicate PF locations. The cell which is the disaster epicenter is shown by a square around it.

A.1.2. An example based on İstanbul Anatolian Side

In this section, the details of the example on the İstanbul Anatolian side are presented. We base our case on the report by Japan International Cooperation Agency (JICA, 2002), and the facility locations provided by Disaster Coordination Center (abbreviated as AKOM) of İstanbul Metropolitan Municipality and used by Görmez *et al.* (2011). The warehouse candidate locations and the neighborhoods within each district are specified by AKOM, and the warehouse locations in the Anatolian side are used as PF candidate points directly. For our candidate TF locations, JICA report and the neighborhoods specified by AKOM are used. In the JICA report, the number of school buildings that are planned to be used as temporary housing in each district are given, thus they are used as the number of TFs in each district. Then, the required

number of TF locations are randomly selected among the neighborhood coordinates in the corresponding district. In this way, 18 potential PFs (J) and 104 TF locations (I) are determined.

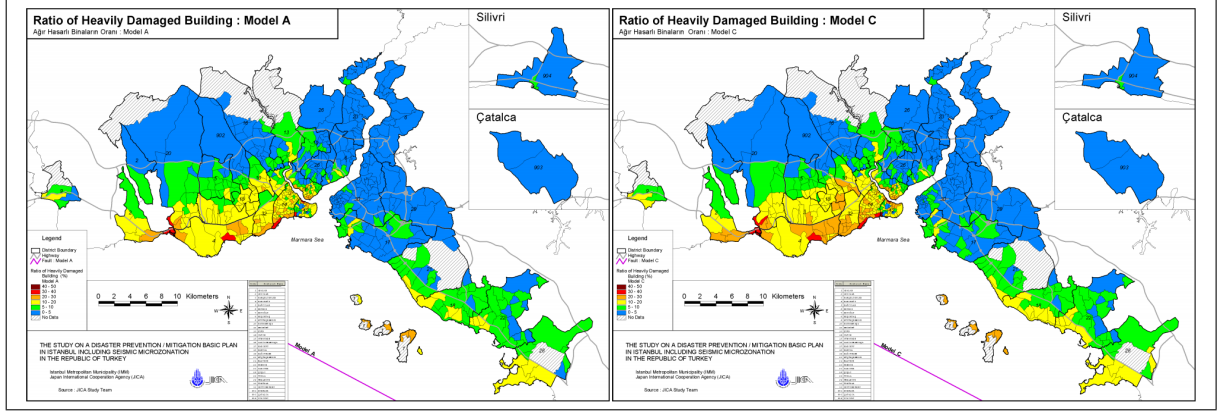


Figure A.2. Expected building damage for the two scenarios (JICA, 2002).

In the next step, the demand points are determined. There are four disaster models presented in the JICA report, however, the damage estimation is provided for two of them (Models A and C) since the other two are similar. Figure A.2 provides the two models presented in the JICA report. The number of buildings that are heavily damaged in each district are provided in the report, and they are selected as the number of demand points in each scenario. Since the two model has similar characteristics, we assume that 90% of the buildings in the first scenario will also be affected in the other scenario. Thus for each district, required number of demand points are randomly generated within the convex hull of the coordinates determined by the neighborhoods. In the end, 15140 unique demand points (M_s) are generated, while 12270 of them are in the first scenario, and 13930 of them are in the second scenario. The demand values (d_{ml}^s) are generated considering the population density information in the JICA report. The average number of people living in each building in each district is given, then we generate a random demand around these to determine the demand amounts.

The rest of the parameters are determined with a similar approach to the data generation scheme given in Section A.1.1. TF capacities are determined such that they are proportional to the given available floor areas in the JICA report. The maximum

distance a beneficiary may walk is limited to 3500 meters. Similar to the data generation scheme, there are three service coverage windows, and the distance limits for these are 15000, 25000, and 50000 meters, respectively. Euclidean distance is used in the calculations. Figure A.3 provides the resulting PF and TF candidate locations (triangles and diamonds, respectively) on the map.

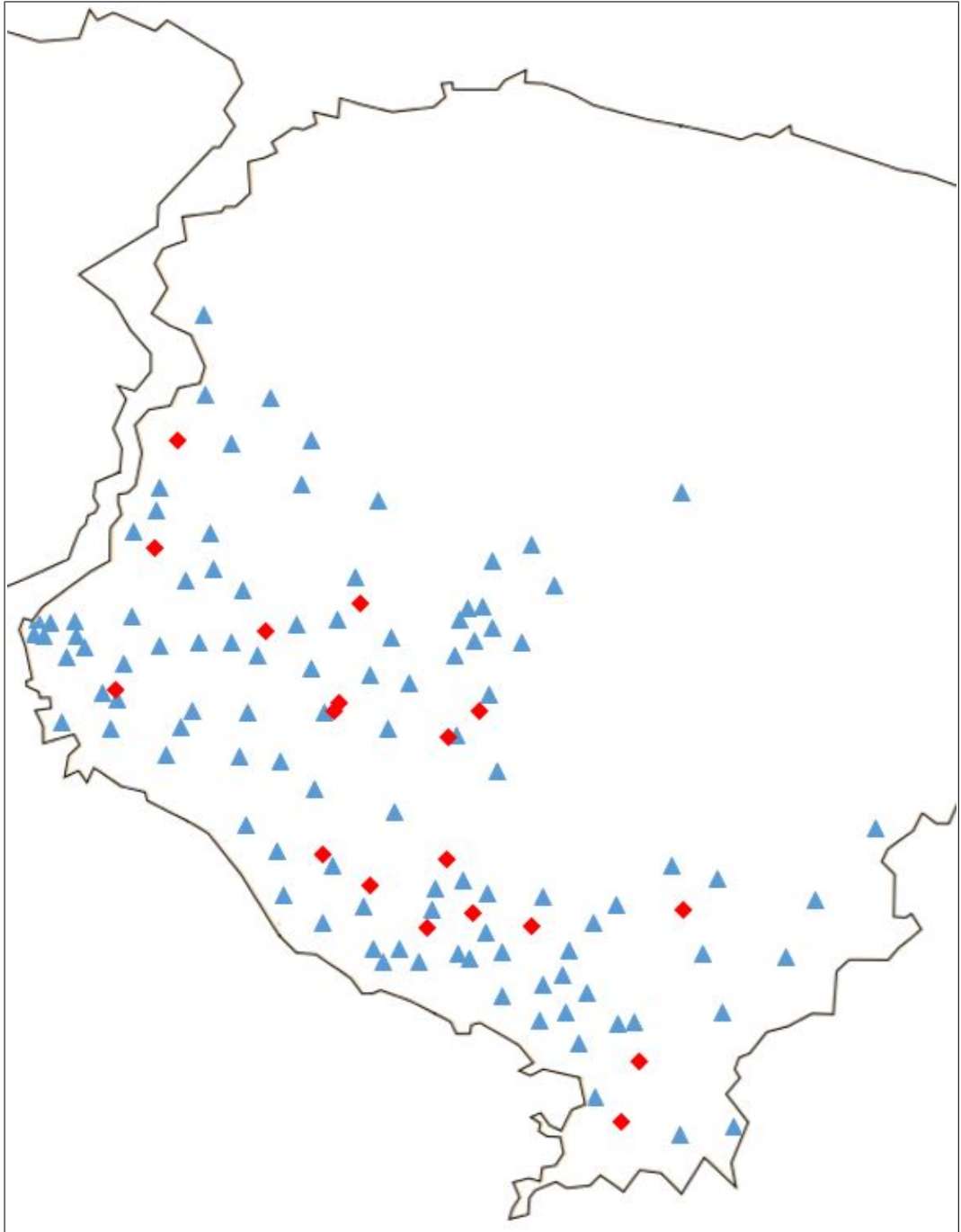


Figure A.3. Candidate PF and TF locations in the İstanbul Anatolian Side case.

A.2. Data Generation Scheme for Disaster Response

A.2.1. Based on the Distance Matrix of Turkey

The data generation scheme for the response stage that is based on the distance matrix of Turkey is parameterized and enables the decision maker to generate instances with different characteristics. As parameters, the *seed* value to initialize a random stream, the last possible demand arrival time *lastT*, the *number of PFs*, the *number of TFs*, and the *number of vehicles* are given by the decision maker. We then assign the PFs and TFs to a subset of 81 cities randomly. The distances between these cities determine the arc lengths, using the parameter that determines the *distance in kilometers that correspond to a time bucket*. Since the vehicle fleet is heterogeneous, we provide a set of *vehicle capacities*, which are randomly assigned to the vehicles by the given *vehicle size probabilities*. If the *number of vehicles* is equal to the *number of PFs*, each vehicle starts from a different random PF node at time zero. If there are more vehicles than PFs, the excess vehicles are randomly assigned to PFs. If there are less number of vehicles than PFs, then the vehicles are assigned to PF nodes randomly.

In order to generate the demand amounts, decision maker provides a *total expected number of vehicle runs* parameter, which is multiplied by the total vehicle capacity to obtain the total demand over all TFs. A weight is assigned randomly to each TF between 1 and *maximum base demand multiplier for TFs* parameter, and the total demand is distributed over TF points with respect to these weights. In order to distribute the total demand of a TF over time periods, a random number of arrivals between *min number of arrivals* and *max number of arrivals* are generated.

The last step is to determine the supply amounts of the PF nodes. We multiply the total demand by a random value generated between *min supply demand ratio* and *max supply demand ratio* to obtain the total supply. This total supply is distributed over PF nodes similar to TFs, a weight is assigned randomly to each PF between 1 and *maximum base supply multiplier for PFs* parameter. Then the total supply is assigned to PFs with respect to these weights.

A.2.2. Based on Solomon Instances

The second set of test instances for the response stage is generated based on the coordinates of the benchmark instances given by Solomon (1987) for the vehicle routing problem with time windows. We use the coordinates of the problem “RC101” that has both random and clustered node structures. There are 101 nodes in the instance where the first node is designated as depot and the rest as customers with demands, ready times, due dates and service times. We use subsets of these nodes to generate the instances, namely “PS13”, “PS14”, “PS15” and “PS16”, where the instance characteristics are provided in Tables 4.2 and 4.3. There are 3 PFs and 23 TFs in PS13, and the first node of every four nodes in RC101 is selected as the candidate nodes. The first node is kept as a PF node, and two more are randomly selected to serve as PFs. In this way, the TFs and PFs are determined. Similarly, the second of every four nodes constitute the node list in PS14. The first in every three nodes, and the first in every two nodes are the node sets that are used in PS15 and PS16, respectively.

Then, the demand amounts in RC101 that correspond to the selected nodes are used as cumulative TF demands. PF supply amounts are calculated as $OverallDemand * Rand(0.8, 1.2) / |J|$. The last possible demand arrival time $lastT$ parameter set as the largest due date of TF nodes in RC101 case. Number of vehicles are set as 10 for PS13 and PS14, and it is 15 for the others. The rest of the procedure is the same as the one explained in Section A.2.1

As the last step, supply, demand and capacity values are multiplied by 10 and rounded in order to obtain integer values.

APPENDIX B: OTHER EXPERIMENTAL RESULTS

B.1. Test Results of *CLFDIP_EarlyNotify*

Table B.1. Numerical performance comparison for *CLFDIP_EarlyNotify*.

	regularCplex		bendersCplex		LBBD	
Problem	Gap%	Time	Gap%	Time	Gap%	Time
P2-1-s2	0.00	2373.4	0.00	33.1	0.00	26.2
P2-1-s3	9.32	28800.3	0.00	73.4	0.00	52.2
P2-1-s4	9.32	28800.2	0.00	104.9	0.00	83.0
P2-1-s10	0.00	22475.1	0.00	291.6	0.00	856.8
P2-2-s2	0.00	6177.5	0.00	131.1	0.00	60.2
P2-2-s3	11.90	28800.2	0.00	1628.9	0.00	106.9
P2-2-s4	24.56	28800.3	0.00	3297.4	0.00	114.1
P2-2-s10	29.89	28800.7	0.00	698.0	0.00	347.0
P2-3-s2	17.01	28800.3	0.00	255.7	0.00	100.7
P2-3-s3	23.55	28800.2	0.00	829.1	0.00	186.3
P2-3-s4	48.19	28800.2	0.00	1078.2	0.00	318.1
P2-3-s10	80.09	28800.9	0.00	3209.7	0.00	1771.2
P2-4-s2	13.82	28800.2	8.93	28800.3	0.00	83.4
P2-4-s3	17.25	28800.3	2.98	28800.1	0.00	167.6
P2-4-s4	51.49	28800.3	0.00	10927.4	0.00	394.2
P2-4-s10	86.80	28800.4	0.00	25194.7	0.00	1074.4
P3-1-s2	36.78	28800.2	0.00	4044.4	1.06	28808.5
P3-1-s3	36.40	28800.2	0.00	1946.7	0.00	120.1
P3-1-s4	48.66	28800.3	0.00	14028.5	0.00	183.8
P3-1-s10	78.24	28800.3	0.00	11013.6	0.00	731.8
P3-2-s2	19.59	28800.2	0.00	123.0	0.00	64.9
P3-2-s3	14.60	28800.3	0.00	11111.7	0.00	107.9
P3-2-s4	22.07	28800.3	0.00	2372.8	0.00	171.4
P3-2-s10	72.52	28800.5	0.00	9539.3	0.00	681.7
P3-3-s2	31.47	28798.1	0.00	15678.6	0.00	21805.8
P3-3-s3	18.80	28800.4	10.29	28800.4	5.85	28800.8
P3-3-s4	36.76	28800.3	5.85	28800.4	1.85	28800.4
P3-3-s10	89.44	28800.6	6.98	28803.1	0.00	3450.8
P3-4-s2	30.80	28800.3	11.58	28798.5	7.08	28800.3
P3-4-s3	91.37	28800.5	60.27	28800.7	0.00	4943.1
P3-4-s4	89.45	28800.3	15.25	28800.8	0.00	2433.5
P3-4-s10	91.37	28801.1	81.40	28810.1	0.00	6642.2
P4-1-s2	36.81	28800.3	0.00	1386.6	0.00	228.8
P4-1-s3	74.32	28800.2	0.00	4845.2	0.00	367.6
P4-1-s4	87.75	28800.2	6.70	28800.6	0.00	683.1
P4-1-s10	89.37	28800.7	2.50	28801.2	0.00	8731.0
P4-2-s2	41.45	28800.2	0.00	320.1	0.00	123.7
P4-2-s3	62.09	28800.3	0.00	879.9	0.00	305.2
P4-2-s4	89.08	28800.5	3.28	28800.6	0.00	626.0
P4-2-s10	81.15	13019.1	6.23	28801.4	0.00	2434.9
P4-3-s2	34.95	28800.5	0.00	24533.9	0.00	374.0
P4-3-s3	93.61	28800.2	14.92	28800.9	3.90	28803.8
P4-3-s4	90.35	28800.8	31.18	28800.6	0.00	3058.0
P4-3-s10	90.35	28801.3	21.99	28801.6	0.62	28801.9
P4-4-s2	95.23	28800.7	74.75	28801.7	0.00	13386.5
P4-4-s3	54.62	28800.5	21.19	28800.3	0.00	1121.6
P4-4-s4	94.93	28800.4	34.43	28800.8	0.00	3131.7
P4-4-s10	95.04	28800.3	24.39	28801.4	0.00	4407.2

B.2. Test Results of Objective Selection

Table B.2. Results for the proposed objectives with $\alpha = 0$.

$\alpha = 0$	Obj_1		$Obj_{2.1}$		$Obj_{2.2}$		Obj_3	
Problem	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time
P-3-4-3-16	0.98	15.55	1.00	7.50	0.00	3.34	0.96	0.88
P-3-4-4-16	0.82	10.45	1.00	10.77	0.00	4.30	0.98	1.57
P-3-4-3-20	1.00	477.58	1.00	123.93	0.01	4.81	1.00	8.04
P-3-4-4-20	1.00	6388.59	1.00	111.84	0.01	5.71	1.00	3.65
P-3-6-3-16	1.00	742.58	1.00	486.50	1.00	35.94	1.00	91.86
P-3-6-4-16	73.21	7200.09	18.68	7200.07	0.99	27.58	1.00	343.68
P-3-6-3-20	99.66	7207.17	19.95	7207.06	1.00	78.37	1.00	220.26
P-3-6-4-20	99.99	7207.98	17.01	7205.79	0.99	30.61	1.00	65.66
P-2-6-2-20	1.00	1501.69	1.00	762.99	0.65	63.23	1.00	70.67
P-2-6-3-20	99.64	7200.78	29.48	7210.92	0.84	434.66	1.00	1500.03
P-2-6-2-23	98.54	7206.15	17.69	7202.15	1.00	67.78	1.00	244.77
P-2-6-3-23	99.97	7205.23	20.43	7203.96	1.00	244.38	1.00	570.35
P-2-7-2-20	1.37	7200.21	1.00	1882.13	1.00	30.26	0.99	80.71
P-2-7-3-20	91.43	7206.48	48.67	7205.55	1.00	80.24	5.01	7206.04
P-2-7-2-23	85.28	7204.17	43.77	7203.89	1.00	114.12	1.00	6160.68
P-2-7-3-23	92.70	7205.54	48.38	7205.68	1.00	1392.47	6.57	7205.12
P-2-8-2-20	1.00	1566.48	1.00	792.73	0.76	93.41	1.00	263.90
P-2-8-3-20	31.43	7200.61	37.72	7206.14	1.00	816.03	1.00	773.94
P-2-8-2-23	1.00	647.07	1.00	858.18	0.99	234.96	0.99	413.53
P-2-8-3-23	98.16	7204.04	55.73	7206.66	1.00	609.71	26.20	7207.41

Table B.3. Results for the proposed objectives with $\alpha = 1$.

$\alpha = 1$	<i>Obj₁</i>		<i>Obj_{2.1}</i>		<i>Obj_{2.2}</i>		<i>Obj_{2.3}</i>		<i>Obj₃</i>	
Problem	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time
P-3-4-3-16	0.97	17.99	0.99	20.92	1.00	9.94	0.98	11.45	0.95	0.91
P-3-4-4-16	0.89	14.77	0.96	13.02	0.99	10.96	0.99	9.02	1.00	1.55
P-3-4-3-20	1.00	1518.62	1.00	644.87	1.00	126.17	1.00	137.11	0.99	13.07
P-3-4-4-20	1.00	3572.22	1.00	5961.42	1.00	476.36	1.00	346.97	1.00	9.43
P-3-6-3-16	1.00	815.28	1.00	801.45	1.00	772.01	1.00	591.32	1.00	74.45
P-3-6-4-16	76.96	7201.03	65.58	7201.44	23.76	7201.23	19.03	7200.94	1.00	2555.02
P-3-6-3-20	99.97	7203.15	84.34	7207.01	11.95	7202.11	14.31	7203.11	0.69	238.13
P-3-6-4-20	100.00	7200.46	80.50	7206.59	8.64	7204.96	5.22	7204.72	1.00	207.75
P-2-6-2-20	1.00	1565.06	1.00	1374.99	1.00	645.59	1.00	531.46	1.00	75.82
P-2-6-3-20	99.97	7200.24	83.11	7201.28	28.23	7208.15	23.63	7200.08	1.00	1090.88
P-2-6-2-23	99.40	7201.69	80.55	7200.24	1.00	4229.11	1.00	5462.51	1.00	293.72
P-2-6-3-23	99.98	7205.45	83.78	7210.21	18.33	7205.43	9.10	7201.58	1.00	671.60
P-2-7-2-20	1.00	1676.19	1.00	1341.91	1.00	712.81	1.00	1372.10	0.98	15.37
P-2-7-3-20	93.51	7209.15	90.35	7207.62	51.93	7207.48	43.44	7206.58	24.48	7204.19
P-2-7-2-23	73.89	7206.05	82.55	7204.41	42.28	7205.96	36.19	7204.64	1.00	5988.40
P-2-7-3-23	92.01	7200.22	89.40	7205.45	54.19	7206.49	47.23	7208.60	8.46	7201.47
P-2-8-2-20	1.00	1118.23	1.00	838.94	1.00	1134.59	1.00	901.10	0.97	272.92
P-2-8-3-20	34.67	7200.27	62.41	7204.91	23.93	7200.75	37.19	7204.74	1.00	1343.35
P-2-8-2-23	1.00	840.45	1.00	687.06	1.00	773.43	1.00	778.01	1.00	309.86
P-2-8-3-23	99.56	7204.49	94.01	7202.85	60.82	7204.86	58.49	7205.11	38.18	7207.68

Table B.4. Results for the proposed objectives with $\alpha = 2$.

$\alpha = 2$	<i>Obj₁</i>		<i>Obj_{2.1}</i>		<i>Obj_{2.2}</i>		<i>Obj_{2.3}</i>		<i>Obj₃</i>	
Problem	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time
P-3-4-3-16	1.00	20.51	1.00	18.82	1.00	14.15	1.00	12.89	0.97	0.91
P-3-4-4-16	0.93	14.09	0.97	18.02	1.00	16.77	1.00	9.85	0.99	1.88
P-3-4-3-20	1.00	1254.12	1.00	698.34	1.00	365.37	1.00	147.63	0.99	12.75
P-3-4-4-20	7.30	7200.30	1.00	3692.27	1.00	1444.34	1.00	315.75	1.00	10.51
P-3-6-3-16	1.00	901.15	1.00	924.31	1.00	857.75	1.00	505.75	1.00	63.22
P-3-6-4-16	94.91	7201.50	92.40	7202.35	33.04	7201.16	18.44	7202.02	1.00	1080.08
P-3-6-3-20	99.95	7202.49	97.55	7201.03	44.44	7203.48	18.71	7202.04	1.00	437.32
P-3-6-4-20	100.00	7207.74	98.09	7211.16	43.38	7204.96	5.80	7205.80	1.00	709.38
P-2-6-2-20	1.00	1510.07	1.00	2097.20	1.00	995.31	1.00	768.30	0.99	127.69
P-2-6-3-20	99.98	7200.18	97.60	7208.93	50.68	7205.48	23.53	7200.15	1.00	586.10
P-2-6-2-23	99.93	7203.73	97.98	7200.24	32.41	7200.16	1.22	7200.46	1.00	318.48
P-2-6-3-23	99.99	7200.41	97.95	7205.68	40.92	7209.77	9.58	7207.14	1.00	756.41
P-2-7-2-20	1.00	1199.21	1.00	920.70	1.00	2331.75	1.00	806.71	0.89	11.59
P-2-7-3-20	97.39	7203.58	95.17	7202.54	71.59	7205.03	44.82	7206.73	28.42	7213.22
P-2-7-2-23	88.77	7200.91	88.96	7204.49	56.44	7204.55	37.57	7203.69	6.12	7200.87
P-2-7-3-23	98.49	7200.30	98.58	7200.74	71.70	7205.41	49.80	7207.06	4.63	7204.01
P-2-8-2-20	1.00	1102.05	1.00	1234.39	1.00	1232.90	1.00	782.73	0.98	294.51
P-2-8-3-20	70.64	7200.51	68.89	7200.61	51.24	7204.75	33.36	7200.85	1.00	1986.49
P-2-8-2-23	1.00	674.44	1.00	892.60	1.00	803.06	1.00	653.65	0.99	321.79
P-2-8-3-23	99.82	7200.55	99.10	7200.45	77.50	7205.53	59.49	7204.97	40.79	7210.81

Table B.5. Results for the proposed objectives with $\alpha = 3$.

$\alpha = 3$	<i>Obj₁</i>		<i>Obj_{2.1}</i>		<i>Obj_{2.2}</i>		<i>Obj_{2.3}</i>		<i>Obj₃</i>	
Problem	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time
P-3-4-3-16	0.96	22.81	0.92	23.67	1.00	18.63	1.00	9.81	0.99	1.14
P-3-4-4-16	0.96	13.56	1.00	15.47	1.00	16.97	0.99	11.67	0.99	2.67
P-3-4-3-20	1.00	1181.91	1.00	1317.16	1.00	443.04	1.00	97.89	0.97	11.97
P-3-4-4-20	1.00	3305.03	72.58	7200.85	1.00	2756.56	1.00	284.01	0.94	5.24
P-3-6-3-16	1.00	1117.89	1.00	1069.71	1.00	699.68	1.00	714.72	0.99	183.06
P-3-6-4-16	96.51	7201.18	92.62	7201.35	41.26	7201.50	22.58	7202.50	1.00	1438.72
P-3-6-3-20	100.00	7201.57	99.74	7201.78	54.07	7204.75	13.05	7201.07	1.00	466.91
P-3-6-4-20	100.00	7204.48	99.71	7204.56	50.42	7209.49	4.27	7200.41	1.00	876.60
P-2-6-2-20	1.00	1257.22	1.00	1054.52	1.00	1305.13	1.00	674.72	1.00	268.84
P-2-6-3-20	99.98	7205.18	99.85	7205.00	63.10	7203.62	25.76	7203.78	1.00	1159.60
P-2-6-2-23	99.92	7200.50	99.76	7201.77	47.75	7200.16	1.00	5839.39	1.00	311.11
P-2-6-3-23	99.99	7205.50	99.67	7201.00	51.82	7210.69	9.15	7200.60	1.00	1006.48
P-2-7-2-20	1.00	553.33	1.00	890.79	1.00	1968.54	1.00	1253.74	0.69	10.90
P-2-7-3-20	99.50	7205.62	98.19	7208.52	77.56	7207.18	43.20	7201.75	17.18	7200.16
P-2-7-2-23	90.65	7200.55	93.67	7200.58	61.79	7204.01	36.60	7204.78	1.00	5096.23
P-2-7-3-23	99.69	7200.26	97.38	7201.07	73.33	7200.74	48.44	7206.65	14.76	7207.03
P-2-8-2-20	1.00	1137.69	1.00	1215.66	1.00	1444.47	1.00	846.19	0.99	327.80
P-2-8-3-20	61.32	7203.81	41.95	7200.33	42.70	7203.19	27.25	7203.57	1.00	1037.00
P-2-8-2-23	1.00	671.53	1.00	832.31	1.00	749.22	1.00	1068.65	0.99	297.74
P-2-8-3-23	99.66	7200.85	99.56	7200.63	85.00	7203.89	52.23	7203.25	1.00	5976.53

Table B.6. Results for the objectives in the literature.

	<i>ObjHSB</i>		<i>ObjPcwsPropFair</i>		<i>ObjRange</i>		<i>ObjRawlsian</i>	
Problem	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time	Gap(%)	Time
P-3-4-3-16	0.65	1.96	0.99	5.08	65.89	28.96	0.73	1.57
P-3-4-4-16	0.91	6.46	0.00	5.61	1.00	60.80	0.97	8.23
P-3-4-3-20	0.76	10.40	0.00	7.04	100.00	235.58	0.98	11.64
P-3-4-4-20	0.99	16.01	0.98	9.90	100.00	16.96	1.00	28.09
P-3-6-3-16	1.00	71.29	0.47	23.63	9.20	649.92	0.95	52.22
P-3-6-4-16	1.00	61.03	0.99	20.14	100.00	7200.35	0.96	62.31
P-3-6-3-20	1.00	46.41	1.00	80.59	100.00	1223.77	0.77	130.65
P-3-6-4-20	0.99	42.64	1.00	33.49	100.00	9.59	0.98	59.52
P-2-6-2-20	1.00	105.19	1.00	76.42	0.98	1139.93	0.99	143.47
P-2-6-3-20	1.00	359.32	1.00	300.99	100.00	2438.36	1.00	197.73
P-2-6-2-23	1.00	131.93	1.00	123.65	100.00	164.90	1.00	293.68
P-2-6-3-23	1.00	101.84	1.00	146.44	100.00	80.91	0.22	146.17
P-2-7-2-20	0.99	69.20	1.00	69.77	1.00	1173.51	1.00	115.44
P-2-7-3-20	1.00	551.42	1.00	880.45	100.00	7206.47	17.02	7205.06
P-2-7-2-23	1.00	780.53	1.00	1653.89	100.00	7203.46	13.05	7201.54
P-2-7-3-23	1.00	4994.18	4.58	7201.65	100.00	7204.61	15.22	7203.71
P-2-8-2-20	0.99	280.53	0.97	168.70	0.99	806.30	0.95	298.09
P-2-8-3-20	1.00	2928.66	1.00	2926.18	30.77	7203.84	1.00	5246.10
P-2-8-2-23	1.00	318.62	0.74	367.03	0.82	808.29	0.98	534.29
P-2-8-3-23	10.23	7204.33	1.00	5837.87	100.00	7208.07	26.76	7205.44