DISASTER MITIGATION AND HUMANITARIAN RELIEF LOGISTICS

by

Alper Döyen

B.S., Industrial Engineering, Dokuz Eylül University, 2001

M.S., Industrial Engineering, Selçuk University, 2004

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ABSTRACT

DISASTER MITIGATION AND HUMANITARIAN RELIEF LOGISTICS

In this thesis we are interested in two distinct problems within the disaster management context. These problems are modeled by two-stage stochastic integer programming since stochasticity is inherent in natural disasters. First, we consider a humanitarian relief logistics model which can be used as a pre-disaster planning tool that also considers post-disaster decisions to give an effective response aftermath an earthquake. In this model, decisions are made for location of pre- and post-disaster rescue centers, the amount of relief items to be stocked at the pre-disaster rescue centers, the amount of relief item flows at each echelon, and the amount of relief item shortage. The objective is to minimize the total cost of facility location, inventory holding, transportation and shortage. Since the building and transportation network retrofitting decisions affect the pre-disaster planning of post-disaster response decisions, we propose an integrated model that includes these retrofitting decisions as well. The total mitigation budget is allocated among these mitigation alternatives. The amount of relief item demand is a decision variable that is determined according to the post-disaster damage of buildings. The objective function is defined as the minimization of the total cost of retrofitting, transportation and shortage of relief item demand. The deterministic equivalents of both models are formulated as mixed-integer linear programming models (MILP) and solved by Lagrangean heuristic methods. Results on randomly generated test instances show that the proposed solution methods for both models exhibit good performance under different parameter settings. Also, the value of stochastic solution for both models are high, which validates the incorporation of the uncertainty in the proposed models. In addition, for the integrated model, various analyses are carried out to clearly understand the model behaviour.

ÖZET

AFET ZARARLARINI AZALTMA VE İNSANİ YARDIM MALZEMELERİ LOJİSTİĞİ

Bu tezde afet yönetimi kapsamında ortaya çıkan iki ayrı problem ele alınmıştır. Rastsallık doğal afetlerin tabiatında var olduğundan dolayı bu problemler iki kademeli rastsal tamsayılı programlama ile modellenmiştir. İlk olarak bir insani ihtiyaç malzemeleri lojistiği modeli ele almaktayız. Bu model, depremden sonra etkin bir tepki verebilme amacıyla deprem sonrası kararlarını da ele alan bir afet öncesi planlama aracıdır. Modelde, deprem öncesi ve sonrası kurtarma merkezleri yerleri, deprem öncesi kurulacak kurtarma merkezlerinde depolanacak olan yardım malzemeleri miktarları, her bir kademedeki yardım malzemeleri akış miktarı ve karşılanamayan yardım malzemeleri miktarı kararları verilmektedir. Modelin amacı; toplam tesis yerleşimi, envanter tutma, ulaştırma ve malzeme eksikliği maliyetlerini en küçüklemektir. Bina ve yol güçlendirme kararlarının deprem öncesi planlanması, deprem sonrası tepki kararlarını etkilediği için bu güçlendirme kararlarını da içeren bütünleşik bir model daha önermekteyiz. Toplam deprem etkileri azaltma bütçesi bu güçlendirme seçenekleri arasında dağıtılmaktadır. Yardım malzemeleri talebi, deprem sonrası oluşan bina hasar durumlarına göre belirlenen bir karar değişkenidir. Amaç fonksiyonu; toplam güçlendirme, yardım malzemeleri taşıma ve karşılanamayan talep maliyetlerinin en küçüklenmesi olarak tanımlanmıştır. Her iki modelin belirlenimci eş değerleri, karışık tamsayılı doğrusal programlama modelleri olarak formüle edilmiş ve Lagrange gevşetmesi temelli sezgisel yöntemlerle çözülmüştür. Rastgele oluşturulmuş test örnekleri ile elde edilen sonuçlar göstermiştir ki önerilen çözüm yöntemleri farklı parametre düzenlerinde iyi performans gösterebilmektedir. Her iki model için rastsal çözüm değerinin yüksek olması da, önerilen modellerin belirsizliği içermesini doğrulamaktadır. İlaveten, bütünleşik model üzerinde model davranışını anlayabilmek adına çeşitli analizler yapılmıştır.

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a	unit penalty cost of relief item shortage
a_l	Unit penalty cost for shortage of relief item l
B	Total mitigation budget
$b^c_{km_k}$	Binary parameter which is equal to one if building m_k in district k is at seismic code level c
B_{opt}	Optimal total mitigation cost
B_R	Remaining budget for building retrofitting
B_U	Remaining budget for infrastructure retrofitting
C	Set of seismic code levels
c^s_{ijl}	Unit transportation cost of relief item l sent from RRC at site i to LRC at site j under scenario s
c^s_{jkl}	Unit transportation cost of relief item l sent from LRC at site j to demand point k under scenario s
c^s_{jk}	Unit transportation cost of relief item demand sent from RC at site j to district k under scenario s
C_{km_k}	Set of possible seismic code levels to retrofit building m_k in district k
D	Set of damage levels for buildings
d^s_{kl}	Amount of relief item l demanded at point k under scenario s
d^s_k	Parameter that represents amount of relief item demanded in district k under scenario s
D^s_k	Variable that represents amount of relief item demanded in district k under scenario s
f_B	A fraction value that is multiplied by B_{opt}
f_i	Fixed cost of operating an RRC at site i
g^s_j	Fixed cost of operating an LRC at site j under scenario s
h_{il}	Expected holding cost for one unit of item l stored in RRC i
H_{il}	Amount of relief item l stored in RRC at site i
I	Set of potential sites for regional rescue centers (RRC) in TSLP

J	Set of potential sites for local rescue centers (LRC) in TSLP (or set of rescue centers in IRRP)
K	Set of demand points in TSLP (or districts in IRRP)
L	Set of relief item types
M_k	Set of buildings in district k
N_{1ks}	The highest possible relief item demand amount in district k under scenario s
N_2	The highest $\tilde{t}_{jk}^s$ value
p^s	Probability of occurrence of scenario s
q_j^s	Capacity of an LRC located at site j under scenario s
$r_{km_k}^{cc'}$	Mitigation cost of building m_k in district k to bring it from seismic code level c to c' where $c' \geq c$
$R_{km_k}^{c'}$	Binary variable which is equal to one if building m_k in district k is mitigated to seismic code level c'
S	Set of scenarios
t_{ij}^s	Transportation time from RRC at site i to LRC at site j under scenario s
T_{jkl}^s	Binary variable that defines assignment of demand of item l at demand point k under scenario s to LRC at site j
T_{jk}^s	Transportation time between RC at site j and district k under scenario s
$\tilde{t}_{jk}^s$	Transportation time from RC at site j to district k under scenario s unless link (j,k) is not vulnerable
$t_{\max}$	Maximum allowable transportation time between an LRC and an RRC in TSLP (or maximum allowable transportation time between a RC and a district in IRRP)
U_i	Binary location variable of RRC at site i
u_{jk}	Cost of mitigating link (j,k)
U_{jk}	Binary variable indicating whether link (j,k) is mitigated or not
V_{ijl}^s	Amount of relief item l sent from RRC at site i to LRC at site j under scenario s
v_{jk}^s	Binary parameter which is equal to one if link (j,k) is vulnerable under scenario s unless it is mitigated

v_l	Unit volume of relief item l
W_{kl}^s	Amount of shortage of relief item l at demand point k under scenario s
W_k^s	Amount of shortage in district k under scenario s
X_{jkl}^s	Amount of relief item l sent from LRC at site j to demand point k under scenario s
X_{jk}^s	Amount of relief item sent from RC at site j to district k under scenario s
Y_{ij}^s	Binary variable that defines location of LRC at site j and assignment of this LRC to RRC located at site j
Z_{jk}^s	Binary variable indicating whether district k is assigned to RC at site j under scenario s or not
α_{km_k}	Population of building m_k in district k
β	Transportation cost of a unit of relief item
γ_{kd}^{cs}	Probability that a building in district k which is at seismic code level c has damage level d under scenario s
κ^k	Seismicity index for each district at site k
λ_d	Multiplier for relief item demand for damage level d
λ_{jkls}	Lagrangean multipliers used in relaxing TSLP
μ^s	Intensity coefficient for each scenario
μ_{ks}	Lagrangean multipliers used in relaxing IRRP
θ	Lagrangean multipliers used in relaxing IRRP
θ_{jls}	Lagrangean multipliers used in relaxing TSLP
ρ_{jks}	Lagrangean multipliers used for relaxing LR_2 in LHM2
σ_{jks}	Lagrangean multipliers used for relaxing $FSP2'$ in LHM2

LIST OF ACRONYMS/ABBREVIATIONS

EEV	Expected reference scenario solution
EVPI	Expected value of perfect information
DU	Discrete uniform distribution
FSP	A subproblem used in feasible solution generation
IRRP	The integrated retrofit response model
LB	Lower bound
LH	Lagrangean heuristic
LHM	Lagrangean heuristic method
LHS	Improved solution of LH by applying LS
LR_1	Lagrangean relaxation first sub problem
LR_2	Lagrangean relaxation second sub problem
LRC	Local Rescue Centers
LS	Local search
MILP	Mixed integer linear programming
PD	Percent deviation
RC	Rescue Centers
RRC	Regional Rescue Centers
SP	Stochastic programming solution
TSLP	The two-echelon stochastic facility location problem
UB	Upper bound
VSS	Value of stochastic solution
WS	Wait-and-see solution

1. INTRODUCTION

The World Health Organization defines a disaster as any occurrence that causes damage, destruction, ecological disruption, loss of human life, human suffering, deterioration of health and health services on a scale sufficient to warrant an extraordinary response from outside the affected community or area [1]. Natural disasters can be devastating in terms of human injuries and economic damages. For example, the two earthquakes that occurred in the Marmara region of Turkey in 1999 caused over 20000 casualties and resulted in the collapse of more than 110000 buildings [2]. The total cost of damage from these two earthquakes is estimated to range between 9 and 13 billion dollars [3]. And in the recent Van, Erciş earthquakes, 644 people died and 35000 houses collapsed [4].

It is obvious that earthquake disaster is a serious and intractable problem that threatens the ability of a nation to protect human lives and property losses. The extent of the casualties and economic damage calls for finding efficient solutions to important problems with the aim of enhancing the capability of reducing the impacts of such events and providing a quick and efficient response by rapidly supplying relief items such as emergency food, water, and medicine to those areas that are severely affected [5]. The main motivation for this thesis is to reduce the number of casualties and to protect national properties (e.g. national infrastructure etc.) by solving disaster related problems in an efficient manner. Developing mathematical models for disaster-related problems and solving them by using operations research techniques have received increasing interest due to their efficiency in tackling these problems.

Traditionally the comprehensive emergency management is commonly described in terms of four phases: Mitigation, preparedness, response and recovery. Mitigation is the set of activities that help to reduce the impact of a disaster. Preparedness activities prepare the community and all organizations to a quick and efficient response when a disaster occurs. The objective of disaster response in the humanitarian relief chain is to rapidly provide relief (emergency food, water, medicine, shelter and supplies) to areas affected by large scale emergencies so as to minimize human suffering and death [5]. After a disaster, delivery of adequate relief demands to suffering people is critical due to scarce time. If not well organized, transportation will be time-consuming, which is unacceptable in case of an emergency and also expensive. Therefore, pre-positioning critical relief supplies in strategic locations and effective distribution of the relief items are crucial subjects. The aim of the recovery phase is to restore the affected area to its previous state. It differs from the response phase in its focus; recovery efforts are concerned with issues and decisions that must be made after immediate needs are addressed.

Making plans for any of the four phases is necessary to cope with an earthquake disaster. Therefore, the governmental and civil organizations should dedicate their time and resources for an efficient disaster management. However, it is well-known that in general there is a limited budget allocated for disaster management, in particular in developing countries. This thesis presents mathematical models for minimizing human losses in a disaster by allocating the total budget efficiently among the decisions taken before and after the disaster occurrence. Mathematical models are developed for efficient integration of mitigation, preparedness and response activities. The whole analysis focuses on the strategic level planning of those activities by guiding the budget allocation properly in order to maximize the satisfaction of relief demands with minimum total cost.

Earthquakes, one of the severe natural disasters, involve several uncertainties due to their epicenter, occurrence time and impact. Therefore, it is almost impossible to determine the exact damage and relief requirements before the event. Moreover, the duration between a disaster occurrence and subsequent response actions must be short to save human lives. These two phenomena make pre-disaster response planning a very difficult task. Pre-positioning critical relief items in strategic locations and effective distribution of the relief items after a disaster are considered to be useful tools to cope with the problem [6, 7]. One objective of this thesis is to develop a mathematical optimization model to help decision makers on locating emergency facilities, stocking relief items and distributing these items to demand points efficiently in a humanitarian relief chain responding to disasters. Although research on facility location problems is extensive in terms of theory and applications, sufficient attention has not been paid to the domain of disaster relief. Facility location decisions affect the performance and efficiency of relief operations, since the number and locations of the distribution centers and the amount of relief item stocks held there directly affect the response time and costs incurred through the relief chain. There are fundamental differences between classical facility location-transportation and emergency facility location-relief logistics issues in terms of their strategic goals, customer demand characteristics and environmental factors. The dominating characteristics that bring additional complexity and unique challenges in case of a disaster are as follows:

- unpredictability of demand, in terms of timing, location, type and impact,
- suddenly occurring demand and short lead times for a wide variety of supplies,
- high cost of unsatisfied demand (i.e. loss of lives)

Although earth scientists have extensively analyzed earthquake risk in various regions to predict the probability distribution of earthquake scenarios, it is almost impossible to know the timing and the intensity of any earthquake with certainty. Hence, it is very difficult to determine the impact, resource needs and damage of the infrastructure deterministically in advance. Thus, the facility location and relief logistics planning problem should be treated as a stochastic problem. Stochasticity arises from uncertainty due to magnitude of the earthquake which dictates the amount of relief demand and damage on the transportation network. We assume that the selection of optimal emergency facility locations, relief stocks and distribution policy can be guided with a two stage stochastic programming model.

We develop a two-echelon stochastic facility location model for humanitarian relief logistics problem, which is formulated as a two-stage stochastic program. This approach is chosen because of the flexibility it offers in modeling the uncertainty related with a set of possible earthquake disaster scenarios. Our model can be used as a pre-disaster planning tool that helps a decision-maker to give efficient decisions considering the post-disaster problem. Decisions related to the post-disaster phase are scenario-dependent and they function as the recourse variables while taking the pre-disaster decisions. Thus, the pre- and post-disaster related decisions constitute, respectively, the first and second stage variables in our model, where the aim is to minimize the total facility location, inventory holding, transportation and shortage costs by determining the locations of pre- and post-disaster rescue centers, the amount of relief items to be stocked and the flow amounts of these items at each echelon.

There is a flow of items from the pre-disaster located facilities to post-disaster located facilities, thus they constitute the first and second echelon facilities, respectively. Then, in our model location decisions are given for both the first and second echelon facilities.

The majority of the existing stochastic facility location models in the context of humanitarian relief logistics involve a single echelon network (e.g., [7–9]). They are generally defined in terms of a two-stage stochastic programming model with recourse, where the location and size of the facilities to be established constitute the first-stage decision variables and the efficient allocation of the available relief items to the demand points constitute the second-stage variables. Although there exist studies dealing with a two-echelon model (e.g., [11]) or a multi-echelon model (e.g., [10]), none of them are concerned with location decisions at both of the echelons in contrast to some deterministic models such as [12] having this structure.

As an immediate consequence of the pre- and post-disaster facility location decisions, the two-stage stochastic model involves binary variables in both stages. In addition, there exist binary valued, scenario-dependent second echelon facility-demand point assignment variables in the model. Thus, unlike the existing humanitarian logistics models [7–9], the proposed model may have a huge number of binary variables. For a metropolitan city like İstanbul, Turkey with about 13 million inhabitants living in 39 municipal districts, the model could include thousands of binary allocation variables, which makes it very hard to be solved exactly by a general-purpose mixed-integer linear programming (MILP) solver.

Therefore, one may resort to solution methods that are based on decomposing the original stochastic integer problem into smaller subproblems and solving them separately. Stage-wise (primal), scenario-wise (dual) decompositions as well as the well-known Lagrangean relaxation are the most common techniques in the literature. Only a few of the algorithms are applicable when there are mixed-integer variables at both of the first and second stage problems, which is the case for the problems considered in this thesis.

Although decomposition-based methods are widely used to solve different types of two-stage integer stochastic models, to the best of our knowledge, only [7,13,14] applied a decomposition method for a humanitarian logistics problem. Their problem involves binary first-stage and continuous second stage variables and they solve it by a variant of the L-shaped algorithm. In this study, we devise a solution approach based on the well-known Lagrangean relaxation, to cope with the mixed-integer variables in both stages. Our Lagrangean relaxation based solution method enables the decomposition of the overall problem into two subproblems, where the second subproblem further decomposes with respect to each demand point, relief item and scenario triplet.

In addition to the efficient humanitarian logistics decisions, planners need to carry out pre-disaster mitigation efforts to scale down the devastating effects of huge earthquakes. Implementing an efficient mitigation policy is fundamental in disaster management since it prevents the negative effects of the event in advance. Moreover, mitigation arises as the most cost effective component of a disaster management program. A post-disaster response requires to satisfy the relief item needs (such as shelter, food, medicine, clothes) as much as and as soon as possible. However, the amount and location of relief demands and also the post-event condition of transportation infrastructure both depend on the earthquake intensity, which is indeed a function of pre-event resilience of structures. Thus, a pre-disaster planning is needed for effective response activities. This kind of a planning should also take into account the natural uncertainty due to the disaster.

Building and/or transportation infrastructure retrofitting, i.e., strengthening the structure to a higher resistance level, is one of the mitigation options. The pre-disaster status (resilience) of buildings affect the post-disaster damage levels which determine the amount of relief item needs. Additionally, the infrastructure vulnerability due to an earthquake will affect the connectivity of network which is the key factor in effective distribution (transportation) of relief goods (people), respectively. Therefore, retrofitting decisions taken before an earthquake to reinforce the structures (buildings and transportation networks) are highly relevant on the efficiency of post-disaster response. This phenomenon emphasizes the need for considering the pre- and post-disaster decisions together in a systems view. As [15] mentions, a separation of pre- and post-disaster objectives may lead to suboptimal solutions to the overall problem of managing catastrophic events.

In this thesis, we provide a decision making tool for disaster management planners, that takes into consideration mitigation and response related decisions in an integrated manner. We propose an optimization model that conducts a system level analysis regarding the interrelations between pre- and post-disaster decisions. The proposed model helps to give retrofitting decisions for both buildings and transportation links as well as the post-disaster response related decisions in order to minimize the total system cost.

To the best of our knowledge, this is the first model where mitigation decisions are combined with response related decisions. The earlier studies on optimization of mitigation decisions account for either building retrofit [17–19] or transportation infrastructure retrofit [20–24]. In contrast, our model includes both types of the retrofitting decisions. Moreover, past studies evaluate the savings for reconstruction costs in the aftermath of a disaster as the benefit of building retrofit decisions. Different from those works, our model considers a trade off between the retrofit expenditures for buildings and the amount of emerged post-disaster relief item demand. Hence, the amount of relief item demand is a variable affected by the realized intensity scenario and the pre-disaster condition of buildings, which is determined by retrofit decisions. On the other hand, retrofitting links increases post-disaster functionality of the network and decreases the travel times (costs). A non-retrofitted bridge could be so damaged that transportation time on the link becomes higher than a threshold limit that restricts the assignment of a rescue center to a demand point located on the other side of the link. In our model, the network disruptions cause both an increase in the travel times (costs) and a decrease in the connectivity of the network. Thus, response efficiency increases and the total system cost decreases by retrofitting the bridges.

Another contribution of the model is handling of retrofitting decisions for each single building rather than a specific area of buildings. The latter uses continuous retrofitting decision variables and cannot specify which building is mitigated and how much. Hence, modelling each single building retrofit separately results in more accurate decisions at the cost of a much harder model. In our model, the retrofitting decision for a building is a binary variable indicating whether it is retrofitted to a specific seismic code level or not.

We are aware of only one optimization model [25] in which retrofitting decisions are considered for single buildings where mitigation decisions are given for the 15 buildings at Stanford University. In the case of modelling a metropolitan city like İstanbul, Turkey with 800000 buildings approximately, the model could include millions of binary variables, which makes it very hard to be solved monolithic by a MILP solver. Therefore, we propose a Lagrangean relaxation approach to solve the model effectively and efficiently.

The integrated model is formulated as a two-stage stochastic programming model. Similar to the first model, uncertainty with respect to earthquake intensity is modelled by using discrete probability scenarios. The model aims to minimize the total retrofitting costs, relief item transportation costs and penalty cost of shortage in the system. The pre-disaster building and bridge retrofit decisions are the first-stage variables, besides the post-disaster demand point-rescue center assignments, transportation times, amount of relief demand, relief flow and amount of shortage are scenario-dependent second-stage variables which function as recourse variables to regard uncertainty while taking the pre-disaster decisions.

In the next chapter, the four phases of disaster management and their functionalities are stated to position our study in the overall disaster management framework and also clarify the contribution of the intended study. Since the developed models in the thesis are stochastic integer programs, a brief information on stochastic programming problems is given. In Chapter 3, the related literature is reviewed under three categories: (i) mathematical models for emergency facility location and relief logistics, (ii) mathematical models for the disaster risk mitigation problem, and (iii) methods for the solution of stochastic integer programming problems. In Chapter 4, the proposed humanitarian relief logistics model and its solution methodology are explained in detail. Chapter 5 introduces a formulation for the integration of mitigation and response phases. In addition, three different solution methods based on Lagrangean relaxation are given in order to solve the model. Computational results on randomly generated instances for all solution procedures are reported in Chapter 6. Finally, Chapter 7 concludes the thesis.

2. DISASTER MANAGEMENT AND STOCHASTIC PROGRAMMING

2.1. General Overview of Disaster Management Issues

Up to a few decades ago, disasters were regarded as exceptional events without taking into account the social and economic implications and causes of these events [26]. Following our much-improved understanding of the natural processes that underlie hazardous events, a more technocratic paradigm came into existence -"the only way to deal with disasters was by public policy application of geophysical and engineering knowledge" [26]. Today's disaster management is based on scientific disciplines and involves the following phases: mitigation, preparedness, response, and recovery.

As it is a fact that substandard building stocks are more vulnerable to earthquakes. In 1999 Turkey earthquakes, the number of deaths would have been dramatically less if the building regulations were taken into account properly. Although there are regulations, substandard buildings are highly common in Turkey and it is stated that thirty percent of the buildings could collapse completely in an inevitable earthquake in İstanbul causing a terrible disaster.

Mitigation efforts attempt to prevent hazards from developing into disasters, or to reduce the effects of disasters when they occur. The mitigation phase differs from the other phases because it focuses on long-term measures for reducing or eliminating risk. Mitigative measures can be classified as structural and non-structural. Structural measures use technological solutions, like retrofitting. Non-structural measures include legislation, land-use planning and earthquake insurance. Mitigation is the most cost-efficient method for reducing the impact of hazards. For buildings already at risk, one mitigation option is *retrofitting* that is reinforcing the structure to make it earthquake-resistant. *Relocation* of some important buildings to safer areas and *rebuilding* of substandard houses by considering the new regulations are other structural mitigation options.

Retrofitting buildings may have important benefits. Table 2.1 shows the potential benefits and methods to quantify these benefits indicated by [27].

Table 2.1. Retrofitting Buildings to Prevent Damage.

Potential Benefits (avoided cost)	**Methods to quantify benefits**
Damage to property	Value of damaged property
Loss of household possessions	Compare damage to goods with and without retrofitted buildings
Injury and Illnesses	Medical expenses Lost in wages through time spent out of work
Reduction in economic activity (for commercial buildings)	Loss in earnings, eg from estimated drop in number of customers
Clean-up	Estimate the cost of labour and material for cleanup
Emergency services costs	Necessary provision of equipment and people Incident specific costs (staffing, fuels, materials)
Avoid loss of life	Value of a Statistical Life (VOSL)
Greater sense of security	(very difficult to quantify)

Following a disaster, the first 72 hours is very critical in terms of saving lives of injured people, thus it is very important having a good disaster preparedness plan to improve the effectiveness, efficiency and impact of response to a disaster. The preparedness mechanisms and strategies that increase the efficiency and effectiveness of an emergency response are listed as follows [28]:

- Preparations for emergency reception centers and shelters.
- Preparations for storing or making arrangements for rapid acquisition of emergency relief supplies and equipment,
- Measures to activate special installations, such as emergency or mobile hospital facilities
- Procedures for activating distribution systems,
- Evacuation procedures

- An assessment process and information priorities for an emergency response
- Define normal aid delivery routes to anticipated disaster areas and affected populations,
- Specify transportation modes (road, railway, air) and issues such as availability and cost

The preparedness phase continues for an uncertain time since it ends with a disaster occurrence. After that, the execution and adaption of these plans belong to the response phase. Response is the employment of resources and emergency procedures as guided by plans to preserve lives, property, environment, and the social, economic, or political structure of the community [29]. Emergency response operations require effective transport of humanitarian aid, personnel and equipment to the disaster site to be successful so regarding that the following actions should be considered:

- Determining the distribution paths and amounts of relief demand at each district due to actual situation
- Locating local rescue centers
- Providing the mobilization of the necessary emergency services and first responders in the disaster area
- Satisfying the relief demand

The decisions taken by the proposed models in this thesis are relevant to mitigation, preparedness and response phases. Recovery phase, which involves decisions on rebuilding or repairing the damaged properties, lies outside the scope of this thesis. One of the main opportunities of this phase is to enhance the infrastructures and conditions of the affected area by using fundamental mitigation techniques [30].

2.2. Overview of Stochastic Programming

Stochastic programming was set up independently in 1955 by Beale [32] and Dantzig [33]. A few years later, Charnes and Cooper [34] introduced chance constrained programming. Stochastic linear programs can be defined as linear programs in which some problem data may be considered uncertain, and recourse programs are those in which some decisions or recourse actions can be taken after uncertainty is disclosed [55].

The basic idea behind the two stage stochastic linear programming is the concept of recourse, which is the ability to take corrective action after a random event has taken place. Stochastic programs with recourse provide an effective modeling paradigm for sequential decision problems with uncertain or noisy data, when uncertainty can be modeled by a discrete set of scenarios [35].

In two-stage stochastic programming the first stage variables are those that have to be decided before the realization of the uncertain parameters. Subsequently, once the random events have presented themselves, further design or operational policy improvements can be made by selecting, at a certain cost, the values of the second-stage or recourse variables [37]. The objective is to find assignment of the variables that minimize the sum of the first stage costs and the expected value of second stage costs. The concept of recourse has been applied to linear, integer and non-linear stochastic programming problems [36].

The general representation of a two-stage stochastic linear programming problem is given as follows [38]:

$$\min \ z = \mathbf{c}^T\mathbf{x} + E_{\boldsymbol{\xi}}\left[\min \mathbf{q}(\omega)^T\mathbf{y}(\omega)\right] \tag{2.1}$$

$$\text{s.t.}$$

$$\mathbf{A}\mathbf{x} = \mathbf{b} \tag{2.2}$$

$$\mathbf{T}(\omega)\mathbf{x} + \mathbf{W}\mathbf{y}(\omega) = \mathbf{h}(\omega) \tag{2.3}$$

$$\mathbf{x} \geq 0, \mathbf{y} \geq 0 \tag{2.4}$$

Let us consider, the event parameter is element of set Ω with the range of values ω=1, 2, .., $|\Omega|$ and there are associated random vector realizations $\boldsymbol{\xi}(\omega)$ and probabilities

$p(\omega)$ such that:

$$\sum_{\omega \in \Omega} p(\omega) = 1 \tag{2.5}$$

Let $\Xi \in \Re^N$ be the set of all random vectors $\boldsymbol{\xi}(\omega)$, then it is often called the *set of scenarios.* If the probability distribution of the random parameter vectors is discrete, the uncertainty defines a random structure in the form of an event tree, which represents the possible sequence of realizations (scenarios). When the event tree is explicitly given, the model is referred as a *scenario-based recourse problem.* The $\mathbf{x}$ and $\mathbf{y}(\omega)$ are called the first and second stage decision variables, respectively.

The first stage decisions $\mathbf{x}$ are represented by an $n_1 \times 1$ vector. The related vectors and matrices $\mathbf{c}$, $\mathbf{b}$ and $\mathbf{A}$ are of sizes $n_1 \times 1$, $m_1 \times 1$, $m_1 \times n_1$, respectively.

In the second stage, a number of random events $w \in \Omega$ may realize. The functional forms, such as $\mathbf{y}(\omega)$, are used to show explicit dependence on an underlying outcome ω. For a given realization ω, the second-stage problem data $\mathbf{q}(\omega)$, $\mathbf{h}(\omega)$, and $\mathbf{T}(\omega)$ become known, where $\mathbf{q}(\omega)$ is $n_2 \times 1$, $\mathbf{h}(\omega)$ is $m_2 \times 1$ and $\mathbf{T}(\omega)$ is $m_2 \times n_1$. Each component of $\mathbf{q}$, $\mathbf{h}$, and $\mathbf{T}$ is thus a possible random variable. Let $\mathbf{T}_i(\omega)$ be the i^{th} row of $\mathbf{T}(\omega)$, then $\boldsymbol{\xi}$ is a random vector that represents the realized earthquake scenario where $\boldsymbol{\xi}^T(\omega)$=($\mathbf{q}(\omega)^T$, $\mathbf{h}(\omega)^T$, $\mathbf{T}_1(\omega)$,...,$\mathbf{T}_{m_2}(\omega)$) The second stage decision $\mathbf{y}(\omega)$ or $\mathbf{y}(\omega, x)$ can be taken after the actual value of $\boldsymbol{\xi}$ becomes known.

The objective function of the two stage stochastic linear program consists of two parts called a deterministic term $\mathbf{c}^T x$ and the expectation of the second stage objective $\mathbf{q}(\omega)^T \mathbf{y}(\omega)$ taken over all realizations of the random event ω. For each ω, the value $\mathbf{y}(\omega)$ is the solution of a linear program. For a given realization ω, let the second-stage value function be:

$$Q(\mathbf{x}, \boldsymbol{\xi}(\omega)) = \min_y \left\{ \mathbf{q}(\omega)^T \mathbf{y} : \mathbf{W}\mathbf{y} = \mathbf{h}(\omega) - \mathbf{T}(\omega)\mathbf{x}, \quad \mathbf{y} \geq 0 \right\} \tag{2.6}$$

where $\boldsymbol{\xi}(\omega)$ is the probability distribution function of ω.

The expected second-stage value function is defined as:

$$Q'\mathbf{x} = E_{\boldsymbol{\xi}} Q(\mathbf{x}, \boldsymbol{\xi}(\omega)) \tag{2.7}$$

Then the stochastic linear program is equivalent to the deterministic program:

$$\begin{aligned} \min \ \ z = \mathbf{c}^T\mathbf{x} + Q'(\mathbf{x}) \qquad (2.8)\\ \text{s.t.} \\ \mathbf{A}\mathbf{x} = \mathbf{b}, \\ \mathbf{x} \geq 0 \end{aligned}$$

Stochastic programs seek to minimize the cost of the first stage decision plus the expected cost of the second stage recourse decision. The objective function given in Equation 2.8 minimizes the first stage direct cost, $\mathbf{c}^T\mathbf{x}$, plus the expected recourse cost Q', over all possible scenarios while satisfying the first stage constraints, $\mathbf{A}\mathbf{x} = \mathbf{b}$. The recourse cost Q' depends both on $\mathbf{x}$ which is the first stage decision and on the random event occurred ω.

Most of the real world stochastic problems need integer solutions and in many practical situations, the integrality restrictions dictate that the variables are binary [38]. Stochastic integer programs require that some variables, in either the first stage or the second stage, are integer. Formally, a two stage stochastic integer program is written as below:

$$\begin{aligned} &\min_{x \in X} \ z = \mathbf{c}^T\mathbf{x} + E_{\boldsymbol{\xi}} \left[\min \left\{ \mathbf{q}(\omega)^T\mathbf{y} : \mathbf{W}\mathbf{y} = \mathbf{h}(\omega) - \mathbf{T}(\omega)\mathbf{x}, \ \mathbf{y} \in Y \right\} \right] \\ &\text{s.t.} \\ &\mathbf{A}\mathbf{x} = \mathbf{b}, \qquad (2.9) \end{aligned}$$

where the definitions of $\mathbf{c}$, $\mathbf{b}$, $\boldsymbol{\xi}$, $\mathbf{A}$, $\mathbf{W}$, $\mathbf{T}$ and $\mathbf{h}$ are as before. However, X and/or Y

contain(s) some integrality or binary restrictions on $\mathbf{x}$ and/or $\mathbf{y}$.

The deterministic program can be written in its *extensive form (EF)* as follows:

$$\min \; z = \mathbf{c}^T\mathbf{x} + p(1)\mathbf{q}(1)\mathbf{y}(1) + \ldots + p(\Omega)\mathbf{q}(\Omega)\mathbf{y}(\Omega) \tag{2.10}$$

s.t.

$$\mathbf{A}\mathbf{x} = \mathbf{b}, \tag{2.11}$$

$$\mathbf{T}(1)\mathbf{x} + \mathbf{W}\mathbf{y}(1) = \mathbf{h}(1), \tag{2.12}$$

$$\vdots \tag{2.13}$$

$$\mathbf{T}(\boldsymbol{\Omega})\mathbf{x} + \mathbf{W}\mathbf{y}(\Omega) = \mathbf{h}(\Omega), \tag{2.14}$$

$$\mathbf{x} \geq 0, \mathbf{y}(1), \ldots, \mathbf{y}(\Omega) \geq 0. \tag{2.15}$$

Note that, it may become a very large scale linear problem regarding the number of scenarios and second stage variables in particular. The proposed models in this thesis are large two-stage stochastic integer programs with recourse. Since solving this type of problems is not easy, some special solution approaches are developed to solve them. In Section 3.3, we present a brief review of these solution methods.

3. LITERATURE SURVEY

Tüfekçi and Wallace [15] suggest that emergency response efforts consist of two stages; pre-event and post-event response. Pre-event tasks include predicting and analyzing potential dangers and developing necessary action plans for mitigation. Post-event response starts while the disaster is still in progress. At this stage, the challenge is locating, allocating, coordinating and managing available resources. Authors also suggest that an effective emergency response plan should integrate both of these stages within its objective, separating pre and post-loss objectives may lead to suboptimal solutions to the overall problem. Generally, comprehensive emergency management is commonly described in terms of four programmatic phases: mitigation, preparedness, response and recovery [29, 39]. The four-phase approach covers all of the actions in the classification of [15], while providing a more focused view of emergency management actions.

Another classification for disaster management and homeland security studies was proposed by [40]. Authors used a two-dimensional framework in examining the related OR work. One dimension shows the areas specified by US Department of Homeland Security and the other dimension is used to present the classical four phases of the disaster life cycle. They divided the emergency preparedness and response topic into (i) early work, (ii) location and resource allocation (these are mostly set covering, maximal covering location models or analytical queuing models), (iii) evacuation models and (iv) disaster planning and response.

There are also a few literature surveys focused only on disaster response. Simpson and Hancock [41] analyzed the evolution of the field in the last fifty years. Caunhye *et al.* [42] categorized the optimization models in emergency logistics into three parts: facility location, relief distribution and casualty transportation and some other operations (e.g., traffic control after an earthquake, relief inventory modeling).

The first model proposed in this thesis is a humanitarian relief logistics model which includes facility location decisions, thus in the first section we mention the related noteworthy studies. The second section reviews the optimization based studies that may consider infrastructure retrofitting as well as the residence retrofitting. Since all of the models are modelled as a two-stage stochastic program, in the last section we emphasize on the solution methods briefly.

3.1. Emergency Facility Location and Relief Logistics

The early studies on emergency facility location generally consist of covering and p-median type models. Location set covering problem is an earlier statement of the emergency facility location problem by Toregas *et al.* [43]. The problem aims to locate the least number of facilities that are required to cover all demand points.

The need of covering all demand points sometimes may be infeasible or too expensive. Recognizing this disadvantage, Church and Revelle [44] developed the maximal covering location problem which does not require the full coverage of all demand points, instead provides a maximal coverage of the total demand. Schilling *et al.* [45] generalized the maximal covering location model to locate emergency fire-fighting servers and depots. In their model two different types of servers need to be located simultaneously and the demand point is regarded as covered only if both servers are located within a specified distance. Eaton *et al.* [46] and Hogan and Revelle [47] developed maximal covering models for emergency services that have a secondary backup coverage objective. The models ensure that a second (backup) facility could be available to service a demand area in the case where the first facility is unavailable.

The p-median problem was first introduced by Hakimi [48]. The p-median facility location model considers the value of the average (total) distance between the demand points and the facilities. It is defined as determining the location of p facilities so as to minimize the average (total) distance between the demand points and the facilities. Since its first formulation, the p-median model has been enhanced and applied to a wide range of emergency facility location problems. Şahin *et al.* [49] formulate several mathematical problems to address the location-allocation aspects of blood services of Turkish Red Crescent (TRC) Society. Blood services of TRC has a hierarchical organization structure. The main decisions are (1) location of regional blood centers (RBC), (2) assignment of blood centers to RBCs, (3) determination of service areas for blood centers, (4) location and number of supporting facilities like blood stations to increase the service level, (5) the fleet size of mobile units. They decompose the entire problem into three subproblems. The first subproblem is formulated as a pq-median location model that minimizes the total of population-weighted average distances between the RBCs and blood centers and also between the demand points and their assigned blood centers. The model gives the locations of q RBCs to provide services to p blood centers that will serve demand points. The second subproblem is formulated as a set covering model that locates the supporting facilities like the blood stations. The model minimizes the number of additional blood stations to be located within at most m kms of demand points. The third subproblem is an integer program that aims a homogeneous distribution of mobile units among the service regions so as to maximize the total of regional population-weighted fleet sizes. All mathematical models are solved using CPLEX 6.

Research on emergency service covering models has also been extended to incorporate the stochastic characteristics of emergency situations. Schilling [50] extends the maximal covering problem by incorporating scenarios to maximize the covered demands over all possible scenarios. Individual scenarios are respectively used to identify a range of good location decisions. Carson and Batta [51] propose a p-median model to find the dynamic ambulance positioning strategy for a campus emergency service. The model uses scenarios to represent the demand conditions at different times. The ambulances are located in different scenarios in order to minimize the average response time to the service calls. Mirchandani and Odoni [52] extend Hakimi's early results on network median problems to include random length arcs with known discrete probability distributions. The authors prove that Hakimi's result on the existence of an optimal solution which locates facilities only at the nodes of the network can be generalized to stochastic networks. Serra and Marianov [53] implement a p-median problem and introduce the concept of regret and min-max objectives when locating a fire station for emergency services in Barcelona.

In emergency logistics literature, distribution of relief equipments is generally considered as a multi-commodity network flow with a multi-modal and/or multi-period setting. Haghani and Oh [1] propose a model and two solution methods for disaster relief logistics problem. They formulate a multi-commodity, multi modal network flow problem with time windows as a large scale mixed integer programming model on a time-space network with the objective of minimizing the sum of the vehicular flow costs, commodity flow costs, supply/demand carry-over costs and transfer costs over all time periods. The first solution algorithm utilizes a Lagrangian relaxation approach and the second one employs an iterative fix-and-run process.

Barbarosoğlu and Arda [55], propose a scenario-based, two-stage stochastic programming model for multi-commodity, multi-modal transportation planning in disaster response. Uncertainty is related with uncertain supply and demand of relief and also vulnerability of the transportation system which leads to random arc capacities. A finite sample of scenarios is represented by capacity, supply and demand triplet. The model is validated by using actual data of Marmara earthquake in August 1999 for İstanbul Avcılar site.

Özdamar *et al.* [56] examine the dispatching of multiple commodities from supply centers to distribution centers which are close to disaster area. Their multi period, multi-commodity network flow model integrates with the vehicle routing problem. Model determines pick up and delivery schedules for vehicles with the objective of minimizing the amount of unsatisfied demand over time. The solution method they propose is a Lagrangean relaxation algorithm on capacity constraints and a greedy heuristic. The model can be run repetitively at given time intervals with the changing demand, supply amounts and fleet sizes.

Fiedrich *et al.* [57] point out that the efficient transportation and allocation of resources (e.g. rescue teams, working machines) to disaster areas are very crucial on the first days of the disaster so they develop an optimization model to allocate rescue resources effectively. They make an extensive classification for fatality types, each of which has a different reason, and aim to minimize the totality of these fatalities. They model the problem similar to parallel machine scheduling problem and use Simulated Annealing and Tabu Search as the solution methods.

Barbarosoğlu *et al.* [54], examine the tactical and operational scheduling of helicopter activities in disaster relief operation. They handle the problem as a hierarchical problem where tactical decisions are made on the top level, and the operational routing and loading decisions are made on the base level. Different MIP models are formulated for the tactical and operational problems. The whole problem is solved with an iterative coordination heuristic between the two problems.

Distributing relief items from strategically located rescue centers should enhance the efficiency of relief item distribution in terms of economic terms, transportation speed and demand satisfaction. Due to this fact, interest in facility location models for humanitarian relief logistics has increased in recent years.

Tzeng *et al.* [11] use fuzzy multi-objective programming to minimize the total cost as well as the total travel time, and also maximize the minimum satisfaction, where satisfaction is defined for each relief item at a demand point in each period as the ratio of the transported amount to its demand. They target to minimize the unfair distribution of relief items by maximizing the minimum satisfaction value.

Jia *et al.* [58] analyze the characteristics of large scale emergency facilities and propose a general model that is suitable for covering, p-median or p-center type problems related with different disaster types. In another study [59], the same authors propose three different heuristics to solve their model: a genetic algorithm (GA), a location-allocation heuristic (LocAlloc) and a Lagrangean relaxation (LR) heuristic. While for small values of p GA provides the best results, its performance decreases as p gets larger such that it generates the worst solutions. The other two heuristics perform more or less the same although the LR heuristic yields slightly better solutions in general.

Balcik and Beamon [60] develop a maximal-covering type model to determine the number and locations of the distribution centers in the relief network and the amount of relief supplies to be stocked at each distribution center.

Gormez *et al.* [12] propose a deterministic two-echelon facility location model for the case of İstanbul. They decide on the locations of the first echelon (permanent) and second echelon (temporary) facilities (PF and TF) and the assignments at each echelon. The objective is to minimize the number of PFs and the average-weighted distance between PFs and TFs. They solved several types of models with little modifications on the objective function or constraints and resulted that PF locations are more or less the same, that is they are quite robust under different circumstances.

Two-stage stochastic programming has been successfully applied for humanitarian relief logistics problems, which involve locating facilities. For further reading, a comprehensive literature survey on facility location under uncertainty is given in [70].

Chang *et al.* [10] first group the disaster rescue areas and classify their level of emergency to minimize the expected shipping distance by a stochastic program. Then, the facility set up decisions for local rescue centers and the transportation plans of rescue equipment are determined by another two-stage stochastic program. In their model, setup decisions are given only for the (local) rescue centers in the last echelon.

Günneç and Salman [8] propose a two-stage, multi-criteria stochastic programming model in a goal programming setting. They set up goals on the total expected transportation time, the expected maximum reach time for each commodity, the average risk of the locations where the facilities are located, the total expected shortage and the total cost of facility location and inventory holding.

Mete and Zabinsky [9] devise a two-stage stochastic programming model that includes the selection of active warehouses, determining the inventory levels in these warehouses, optimal distribution amounts from warehouses to demand points and shortage of relief items. The solution provided by two stage stochastic programming is used for a detailed loading and routing plan for emergency vehicles.

Rawls and Turnquist [61] extend their previous work [7] by adding some constraints which ensures the satisfaction of relief demands is above a confidence level and the average shipment distance from facilities to demand points is below a threshold level. The effect of the introduction of the new constraints is investigated on a case study similar to the one in [7].

Solving large-sized humanitarian relief logistics problems that include facility location decisions is not an easy task unless a decomposition-type method is employed. Rawls and Turnquist [7] examine a facility location model which incorporates scenario-related capacity on transportation links and additional costs for unused relief inventory. They solved the model by a heuristic method which utilizes the L-shaped method and Lagrangean relaxation. Noyan [14] introduces a risk averse measure on the model of Rawls and Turnquist [7] and solves it by two decomposition algorithms based on the L-shaped method. In another study, Li *et al.* [13] develop a model where location and capacities of shelters are decided to receive both evacuee flows from affected areas and resource flows from distribution centers. They use the L-shaped method to solve a real world problem.

The model proposed in this thesis considers location decisions of rescue centers at two distinct echelons. Thus, the model includes binary variables in the second stage as well, which is not the case for recently mentioned two-stage stochastic models. Then, the number of binary variables increases by the number of scenarios which is not the case in other studies. The model involves mixed-integer variables in both of the stages and we solved it by a Lagrangean relaxation based solution method efficiently.

3.2. Disaster Risk Mitigation Models

Although there is an abundant literature on disaster mitigation studies for buildings, very few of them use optimization to make retrofitting decisions. The literature on the usage of mathematical models for the mitigation phase can be considered in two parts: studies that consider retrofit decisions of buildings to decrease reconstruction costs and studies that focus on pre-disaster transportation link investments to get a better disaster response. To the best of our knowledge, our model is the first attempt that includes both infrastructure and building retrofitting.

Until recent years, most of the building mitigation studies have compared a set of predefined alternatives by using the net present value (NPV) or benefit-cost analysis, and selected the best alternative as the mitigation decision. Probably, the study of Shah *et al.* [25] is one of the first attempts that use a mathematical model to give optimal mitigation decisions. They propose an integer programming model to maximize the NPV of mitigation investment on 15 buildings of Stanford University by using a single earthquake scenario.

Dodo [16] gives three alternative optimization formulations for different situations. The decisions are about which building groups have to be mitigated and how much. Each building group is defined by its census tract location, structural type, occupancy type and seismic design level. The amount of square footage of a building group that is retrofitted from one design level to an upper one in a time period is a continuous decision variable. Other variables are the amount of reconstructed building groups and the amount of building groups at the end of each period. The higher design level results in a lower damage level for buildings, which means lower expected post-earthquake reconstruction costs. They tested their models on a small size case study for Los Angeles.

Later, Dodo *et al.* [17] consider one of the models proposed by [16]: The objective is to minimize the total of retrofit and expected reconstruction costs under a limited mitigation budget. They use a more realistic case study and propose two solution methods to solve the model: A Dantzig-Wolfe decomposition and a greedy heuristic algorithm.

The study of Dodo *et al.* [17] is extended in [18] with a multi-objective model by considering the variability in reconstruction costs along with the expected value of total costs. The reconstruction costs exceeding an allowable threshold level are penalized to minimize risk. After proving the equivalence of multi and single-period formulations, a real case problem is modeled by the single period formulation and solved by a Dantzig-Wolfe solution method.

Vaziri *et al.* [19] modified models given by [17] and [18] for developing countries where economic resources are more constrained, the resulting damage is more widespread and death tolls are much higher than a well-developed country. Since economic resources are limited for developing countries, some damaged buildings cannot be reconstructed immediately after an earthquake. Therefore, the model they propose allows for reconstruction in a later period when more funds are available. The model also allows to change the structural type and original code level during their reconstruction. Moreover, since death tolls can be extremely high in Iran, an objective term related with minimizing the chance of extremely high deaths is included in the model. This approach is the same with the risk-return trade-off used in [18] with the only difference that it focuses on the risk of high life loss rather than high economic loss.

The retrofitting decisions of infrastructure systems can be given by a prioritization approach [62, 63] using some factors but these factors do not consider the interrelations between individual components and the expected overall network performance. However, an optimization approach that captures how investments would alter the performance of the post-disaster network can be posed to provide a systems level analysis [23].

In [20] a multi-objective integer programming model is presented. The two objectives are minimizing the total travel time between the origin-destination pairs and maximizing the total population of covered centers (multiplying this term with -1 turns it to a minimization objective). The model is formulated as an integer program and the objective function is minimized by seeking non inferior paths such that the total bridge retrofitting costs on the selected paths are subject to a budget constraint. A case study is given where retrofitting a link is an obligation to be able to use that link. The model is deterministic since it does not consider the uncertainty related with the intensity of an earthquake.

Sanchez-Silva *et al.* [21] propose a non-linear optimization model that aims to maximize the accessibility of a transportation network. The accessibility of a centroid is measured by a decreasing function of expected cost of traveling from every other centroid to that centroid. The expected cost of traveling is calculated by using a continuous time Markov chain where the failure and repair rates of links are the main parameters. The model decides on the optimal failure and repair rates under a limited budget. Then the model could find an optimal assignment of resources such that the accessibility of a centroid or the total network is maximized. However, the strong assumption in their model that only one link can fail at a time is not justifiable for disaster management context.

Liu *et al.* [22] formulates a two-stage stochastic programming model that helps to determine optimal retrofit decisions of transportation links to minimize mean-risk objective of the system cost. Retrofit decisions are the first stage variables that are taken before earthquake happens. If a link is retrofitted before the earthquake, then it is not damaged, else it could be damaged due to the pre-retrofit state of this link. The cost of the second stage, including the repair cost term and weighted flow cost term which depends on the travel time, depends on the first-stage retrofit decisions and particular realizations of link damages. In order to solve large instances of the problem in an efficient manner, a generalized Benders decomposition algorithm is proposed.

A similar two-stage stochastic programming model with the objective of minimizing traveling costs is proposed in [23]. The retrofit decisions taken under a limited budget increase link survival probabilities, and if there does not exist a path connecting an origin and a destination, then a large penalty cost is incurred. An approximate solution procedure is developed, its solution quality is proved by showing that the optimal solution obtained by the method is a local optimum. The authors investigate the effects of the parameters and solution quality on a real case transportation network of İstanbul highways.

Günneç and Salman [24] assess the functionality and performance of a network in the aftermath of a disaster by a number of performance measures. They consider multiple disaster scenarios and the vulnerability probability of each link differs for each scenario. They propose a new dependency model for link failures and a polynomial-time algorithm when the number of paths connecting an origin-destination pair is fixed. This polynomial-time algorithm is applied in İstanbul data for dependent link failures and different dependency structures are compared. For the independent link failures case, authors use a Monte Carlo sampling algorithm.

3.3. Stochastic Integer Programming Methods

The solution methods for stochastic integer problems can be classified as decomposition methods (decomposition by time stages or by scenarios), Lagrangean relaxation, enumeration methods, convex approximation methods, sampling based methods and some other cutting plane or branch-and-bound methods. In this section, we present a limited overview of the most relevant solution methods, in particular decomposition methods.

Decomposition methods for stochastic problems can be classified into two groups: primal methods that work with subproblems assigned to time stages (e.g., the L-shaped method), and dual methods that work with subproblems assigned to scenarios (e.g., dual decomposition method). Decomposition idea for stochastic programs started with the L-Shaped method. Firstly, Van Slyke and Wets [64] proposed the method, then various extensions of the method have been suggested.

One of the earliest solution methods was a cutting plane algorithm proposed by Wollmer [65]. This algorithm works for integer first-stage and continuous second-stage variables. Laporte and Louveaux [66] extended Wollmer's approach and the classical L-Shaped algorithm. They have proposed the Integer L-Shaped Algorithm which can be applied for binary first-stage and arbitrarily second-stage variables. In addition, second-stage problem must be an easily solvable problem. In general, the expected value function of such a problem is non-convex, therefore it cannot be described using linear cuts as in the continuous case. However, due to the fact that the first-stage variables are binary, it is possible to construct a valid set of linear optimality cuts. The method has been successfully used in solving two-stage stochastic problems of the following issues: routing [67, 68], stochastic location [69], reverse logistics [71].

Unfortunately, the Integer L-Shaped Algorithm is not applicable if first-stage variables are continuous. Carøe and Tind [72] improved the algorithm to handle arbitrary first-stage variables and pure integer second-stage variables. By using the generalized duality theory, the method applies non-linear integer programming dual functions (feasibility and optimality cuts) to approximate the second-stage value function. However, it has to be assured that the nonlinear master problems can be solved by a finite method.

An enumerative algorithm is presented in [73]. It applies to two-stage stochastic models with continuous first-stage, pure integer second-stage and integer right-hand side parameters of the second-stage problem. Using structural properties of the expected value function, a finite subset of the feasible set containing an optimal solution is constructed. This set may be very large, and it needs solving integer subproblems to enumerate this set which makes the approach computationally extensive.

Scenario decomposition approach of [74] has led to many studies. For the general case of mixed-integer first and second stage variables, Carøe and Schultz [75] develop a scenario-based decomposition approach. This approach is in a sense dual to the L-shaped algorithms discussed above. The copies of the first-stage variables are introduced for each scenario considered in the model, and then non-anticipativity conditions, which equate the first-stage variables, are added. Lagrangean relaxation with respect to the non-anticipativity conditions results in a Lagrangean dual problem that can be decomposed in terms of scenarios and subsequently solved by subgradient methods. The subproblems may be difficult to solve since they include integer variables. This approach is used as a bounding procedure with a branch-and-bound framework to find an optimal solution.

In [76], the authors propose a hybrid algorithm which performs an evolutionary heuristic algorithm in the first stage problem and mathematical programming in the second stage problem. The algorithm is based on a stage-wise (primal) decomposition. The performance of the algorithm is compared with the dual decomposition of [75] and the monolithic solution (without using any decomposition based algorithm) of the problem in CPLEX. The have found similar results for their algorithm and the one proposed in [75], both of the two algorithms are significantly better than the monolithic CPLEX solution.

A branch-and-bound algorithm is introduced in [37] by exploiting the structure of the value function of the second-stage integer problem. The algorithm applies for problems with integer recourse and discrete distributions. The performance of the algorithm is compared with the algorithms proposed in [73,75] and also with the monolithic solution of the model by CPLEX and BARON solvers. This algorithm outperforms the other methods.

In [77], the authors state that solution methods based on L-shaped decomposition use a master problem whose linear programming relaxation is not stronger than the linear-programming relaxation of the original model. Consequently, these decompositions will suffer if the original model formulation has a poor continuous relaxation. In contrast, Branch and Price solves a column-oriented reformulation of a model, also by a form of decomposition, but that reformulation normally has a tighter relaxation than the original model [78]. Thus, a branch-and-price algorithm is proposed for solving a class of problems (including stochastic facility location problem) that are amenable to column-oriented formulations.

Apart from these, Lagrangean relaxation is also successfully employed to solve a two-stage stochastic program within the context of electricity distribution [79]. In addition, the models in this thesis involve mixed-integer variables in both of the stages. Therefore, we adopt to apply Lagrangean relaxation for the solution of the two-stage stochastic programming models.

For reviewing further studies on integer stochastic programming studies, one should refer to the survey papers. Birge [80] reviews the stochastic programming models and methods, but the survey does only include the algorithms on stochastic linear programming models. Sahinidis's paper [36] entails more different issues like stochastic non-linear, robust stochastic, probabilistic programming, fuzzy mathematical programming and integer stochastic programming models and methods. Moreover, there are some papers which merely consider stochastic integer programming models and methods. Haneveld *et al.* [81] generally focus on stochastic programs with mixed-integer recourse, they present the structural properties of the methods to solve these problems. The study of [82] is an extensive literature survey about theory, general purpose solution methods and specific applications of stochastic integer programs. Schultz [83] presents an extensive discussion on stochastic integer programming and it is the newest review, as far as we know. Sherali and Zhu [84] have reviewed some recent advances in solving two-stage stochastic integer programs and have provided some insights and results that exhibit certain interconnections between the methods.

Stochastic integer programming has been applied in logistics and facility location problems for several times. A class of Capacitated Facility Location Problems with uncertain customer demands is solved in [69]. The first stage variables are binary variables associated with opening a facility in a potential facility site or not. The second stage variables associated with the delivered quantities are continuous. The problem is solved with the integer L-Shaped method. They have solved problems in different settings (up to 10 potential facility locations and 40 customers). Computational results validate the efficiency and robustness of the algorithm.

Listeş [71] presents a generic stochastic model for re-manufacturing type of systems in reverse logistics. The model has binary first-stage and continuous second-stage variables which represent the delivered quantities from plants to markets in a specific scenario. The scenarios differ by the discrete values of demand and returns. They use a decomposition approach based on the L-shaped algorithm. They show that the algorithm performs well.

Another study related with the product recovery network design is given in [85]. They consider a real problem which involves two kinds of uncertainty in its nature: supply uncertainty and demand uncertainty. Different decisions are associated with these uncertainties, so they propose a three-stage stochastic integer programming model. In the first and second stages, the binary decisions are associated with the initial location of facilities and locating additional facilities. The allocation decisions which are defined as continuous variables are given in the third stage. The model is formulated in GAMS and solved by the solver CPLEX. The three-stage model, which has 214 integer and 92000 continuous variables, requires 28 hours of computation. However, a decomposition based approach may be effective to solve this type of a model.

Santoso *et al.* [86] propose a stochastic programming model and solution algorithm for facility location and distribution decisions in a realistic-sized supply chain network configuration. They claim that existing approaches to solve these problems are generally for deterministic environments or can handle a modest number of scenarios. To handle a large number scenarios they embed a sampling strategy called the sampling average approximation into an accelerated L-Shape type decomposition algorithm. They show the performance of their algorithm on two real supply chain networks.

A stochastic location model for a supply chain network which considers the risk of being out of inventory is presented in [87]. The model optimizes location, inventory and allocation decisions under random parameters described by discrete scenarios. The constraints which satisfy the assignment of retailers to only one distribution center are relaxed in a Lagrangean manner. The resulting Lagrangean subproblem is a non-linear integer program but to solve it efficiently they use a polynomial algorithm due to [88]. They present extensive experimental results which validate the remarkable performance of their algorithm.

Owen and Daskin [89] provide an extensive review on strategic facility location. The reviewed studies are mostly on emergency type facility location problems, especially stochastic, robust, dynamic and hierarchical emergency location problems.

4. A TWO-ECHELON EMERGENCY FACILITIES LOCATION PROBLEM

None of the stochastic facility location studies in humanitarian relief logistics context presents a two-echelon relief logistics network, where facility location decisions are given in both of the echelons. However, it is very common in real world cases that locating large sized depots that distribute relief items to smaller sized temporary emergency facilities (e.g., [12]).

The proposed model in this thesis includes two kinds of emergency facilities: Regional Rescue Centers (RRCs) and Local Rescue Centers (LRCs). The relief items stored in RRCs, which are located before the disaster, are distributed to the demand points through the LRCs that are established after the disaster. A representation of the considered humanitarian relief logistics network is given in Figure 4.1.

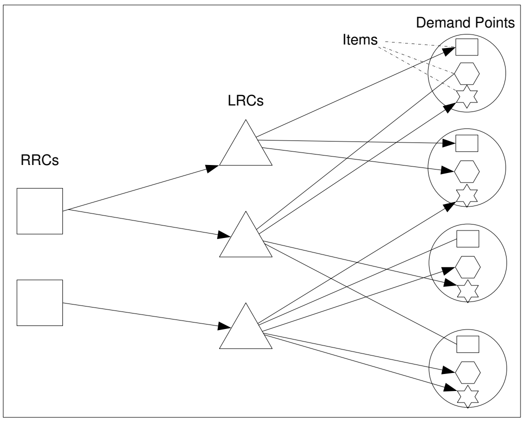

Figure 4.1. The humanitarian relief logistics network.

RRCs are large facilities in which all types of relief items and medical equipments are stocked. RRCs are considered uncapacitated since it is assumed that a continuous relief item supply from non-devastated regions to these facilities is secured after the earthquake.

LRCs, on the other hand, are existing capacitated facilities (e.g., schools, sport centers, stadiums) or prefabricated buildings (or shelter tents), which can be set up as emergency facilities after an earthquake hits. They are established to satisfy the demand of the relief items in disaster areas. Thus, their locations as well as relief items flowing through them to demand points are related with the amount and site of the needs that occur in an earthquake scenario.

Notice that, strategic location decisions of both RRCs and LRCs are given in the pre-disaster planning stage for effective post-disaster response. LRCs improve the quick response and reduce the high risks of an earthquake especially in metropolitan areas. Moreover, it is pointed out in [12] that according to the response agency representatives it is not practical to establish a large number of facilities that remain idle until a disaster occurs. Instead, utilizing some existing public facilities could be a better alternative for disaster response purposes.

Each LRC is assigned to a single RRC, which implies single-sourcing of LRCs. Besides, each type of relief item at a demand point is received from a single LRC. In case of an earthquake, having an efficient and simple response plan is important. Thus single-sourcing is advisable because it reduces the complexity of the network management for the planners. Moreover, an LRC can be assigned to an RRC when it is reachable within a pre-determined travel time. The intensity and location of an earthquake disaster is not known exactly, so a scenario-based modeling is used to include uncertainty. In this setting, discrete scenarios are defined from a set of possible ones where each scenario is associated with uncertain relief item demand at each location and uncertain transportation time/cost between nodes due to road destructions. Each unit of shortage is penalized with a very high cost in the model.

We formulate this two-echelon (or three-tier) multi-commodity stochastic facility location model as a two-stage stochastic program with recourse. The uncertainty related to a disaster is captured by using a number of possible earthquake intensity scenarios. The locations of RRCs and the amount of items stored in each open RRC are the first stage decisions while the LRC locations, LRC-demand point assignments, flow amounts at both of the echelons and amount of shortage are the second stage (recourse) decisions. The latter are used to compensate for the poor decisions that might have been taken in the first stage before it is known which disaster scenario is realized. The objective is to minimize the total costs of locating RRCs and LRCs, holding and shortage costs of relief item as well as the transportation costs at each echelon.

Modeling the problem as a two-echelon facility location problem makes the problem very complicated and hard to solve. This is due to that, one cannot separate the binary location variables as the first stage variables and the continuous transportation variables as the recourse variables since the decision for setting up LRCs is dependent on the realized earthquake. Then it turns out a stochastic problem with binary and continuous variables at each stage.

In Section 4.1, we first define the parameters and decision variables, then present the deterministic equivalent of our two-echelon stochastic facility location problem (TSLP), which is an MILP.

4.1. Proposed stochastic facility location model

The parameters and decision variables used in the mathematical model are given in Table 4.1-4.3.

Table 4.1. Parameters used in the TSLP.

I	set of potential sites for regional rescue centers (RRC)
J	set of potential sites for local rescue centers (LRC)
K	set of demand points
L	set of relief item types
S	set of scenarios
f_i	fixed cost of operating an RRC at site i
g_j^s	fixed cost of operating an LRC at site j under scenario s
c_{ijl}^s	unit transportation cost of relief item l sent from RRC at site i to LRC at site j under scenario s
c_{jkl}^s	unit transportation cost of relief item l sent from LRC at site j to demand point k under scenario s

Table 4.2. Parameters used in the TSLP (cont'd.).

a_l	unit penalty cost for shortage of relief item l
p^s	probability of occurrence of scenario s
v_l	unit volume of relief item l
q_j^s	capacity of an LRC located at site j under scenario s
d_{kl}^s	amount of relief item l demanded at point k under scenario s
t_{ij}^s	transportation time from RRC at site i to LRC at site j under scenario s
$t_{\max}$	maximum allowable transportation time between an LRC and an RRC

Table 4.3. Decision variables used in the TSLP.

H_{il}	amount of relief item l stored in RRC at site i
V_{ijl}^s	amount of relief item l sent from RRC at site i to LRC at site j under scenario s
X_{jkl}^s	amount of relief item l sent from LRC at site j to demand point k under scenario s
U_i	$\begin{cases} 1 & \text{if an RRC is located at site } i \\ 0 & \text{otherwise} \end{cases}$
Y_{ij}^s	$\begin{cases} 1 & \text{if an LRC is set up at site } j \text{ and served from RRC} \\ & \text{at site } i \text{ under scenario } s \\ 0 & \text{otherwise} \end{cases}$
T_{jkl}^s	$\begin{cases} 1 & \text{if the demand of item } l \text{ at demand point } k \text{ under} \\ & \text{scenario } s \text{ is assigned to LRC at site } j \\ 0 & \text{otherwise} \end{cases}$
W_{kl}^s	shortage amount of relief item l at demand point k under scenario s

With the help of the defined parameters and variables, the mathematical model of TSLP can be expressed as follows.

$$\begin{aligned} \text{TSLP} : \min \sum_i f_i U_i + \sum_i \sum_l h_{il} H_{il} + \sum_i \sum_j \sum_s p^s g_j^s Y_{ij}^s + \sum_k \sum_l \sum_s p^s a_l W_{kl}^s \\ + \sum_i \sum_j \sum_l \sum_s p^s c_{ijl}^s V_{ijl}^s + \sum_j \sum_k \sum_l \sum_s p^s c_{jkl}^s X_{jkl}^s \quad (4.1) \end{aligned}$$

subject to

$$Y_{ij}^s \leq U_i \qquad i \in I, j \in J, s \in S \tag{4.2}$$

$$\sum_i Y_{ij}^s \leq 1 \qquad j \in J, s \in S \tag{4.3}$$

$$t_{ij}^s Y_{ij}^s \leq t_{\max} \qquad i \in I, j \in J, s \in S \tag{4.4}$$

$$\sum_l V_{ijl}^s v_l \leq q_j^s Y_{ij}^s \qquad i \in I, j \in J, s \in S \tag{4.5}$$

$$\sum_j V_{ijl}^s \leq H_{il} \qquad i \in I, l \in L, s \in S \tag{4.6}$$

$$\sum_k X_{jkl}^s = \sum_i V_{ijl}^s \qquad j \in J, l \in L, s \in S \tag{4.7}$$

$$T_{jkl}^s \leq \sum_i Y_{ij}^s \qquad j \in J, k \in K, l \in L, s \in S \tag{4.8}$$

$$\sum_j T_{jkl}^s \leq 1 \qquad k \in K, l \in L, s \in S \tag{4.9}$$

$$X_{jkl}^s \leq d_{kl}^s T_{jkl}^s \qquad j \in J, k \in K, l \in L, s \in S \tag{4.10}$$

$$\sum_j X_{jkl}^s + W_{kl}^s = d_{kl}^s \qquad k \in K, l \in L, s \in S \tag{4.11}$$

$$U_i, Y_{ij}^s, T_{jkl}^s \in \{0, 1\} \qquad i \in I, j \in J, k \in K, l \in L, s \in S \tag{4.12}$$

$$H_{il}, V_{ijl}^s, X_{jkl}^s, W_{kl}^s \geq 0 \qquad i \in I, j \in J, k \in K, l \in L, s \in S \tag{4.13}$$

The objective function (4.1) aims to minimize the total costs associated with establishing LRCs and RRCs, relief item transportation at each echelon, inventory holding at RRCs and penalty for shortage. Constraints (4.2) guarantee that an RRC must be located at site i to set up and assign an LRC at site j to this RRC. Constraints (4.3) state that if an LRC is set up at site j in scenario s, then it can be assigned to only one RRC. Constraints (4.4) limit the maximum transportation time allowed between an LRC and an RRC. Constraints (4.5) ensure that to have a distribution from RRC at site i to an LRC at site j in scenario s the LRC must be set up and assigned to RRC. Moreover, the distributed volume of items is no more than the capacity of LRC at site j in scenario s. Constraints (4.6) imply that the amount of relief item l stored in RRC i must satisfy the distributed amount in all scenarios. Constraints (4.7) are the flow balance equations that make the outflow from an LRC equal to the inflow to that LRC. Constraints (4.8) guarantee that the demand of relief l at demand point k cannot be satisfied from LRC at site j if it is not located there and assigned to RRC at site i. Constraints (4.9) ensure that the demand for item type l at demand point k in scenario s must be satisfied by at most one LRC. Constraints (4.10) state that to have a flow for item l to demand point k in scenario s through LRC at site j, demand point k must be assigned to this LRC, and also the flow cannot exceed d^s_{kl}. Constraints (4.11) show that the shortage of relief item l at demand point k under scenario s is the difference between demand and the total amount of relief item l sent from all of the LRC facilities. Constraints (4.12) and (4.13) define the binary and non-negativity restrictions on decision variables, respectively.

4.2. Lagrangean Relaxation Based Solution Methodology

Notice that the second echelon problem of TSLP (establishing LRCs and assigning them to demand points) is a single-source capacitated facility location problem, which belongs to the class of NP-Hard problems. Therefore, the TSLP is an NP-Hard problem as well. Hence, for large instances general-purpose MILP solvers are not likely to find a good solution within a reasonable amount of computation time.

As a result, we propose a heuristic based on Lagrangean relaxation (which is successfully applied in the literature for other two-echelon facility location problems [91–93]. The solution given by the Lagrangean heuristic (LH) is further improved by a local search algorithm. We explain the details of the proposed LH below.

4.2.1. Calculation of the Best Lower Bound

Since TSLP has a two-echelon network structure with flow conservation and assignment constraints that establish the link between the two echelons, we relax these constraints to obtain two subproblems. We define $\boldsymbol{\theta}$ and $\boldsymbol{\lambda}$ as the Lagrange multiplier vectors associated with constraint sets (4.7) and (4.8), respectively. When these two constraints are relaxed, we obtain two subproblems called LR_1 and LR_2, where

$$\text{LR}_1 : \min \sum_i f_i U_i + \sum_i \sum_j \sum_s \left(p^s g_j^s - \sum_k \sum_l \lambda_{jkls} \right) Y_{ij}^s + \sum_i \sum_j \sum_l \sum_s \left(p^s c_{ijl}^s - \theta_{jls} \right) V_{ijl}^s + \sum_i \sum_l h_{il} H_{il} \quad (4.14)$$

subject to $\left\{ \text{constraints } (4.2) - (4.6), U_i, Y_{ij}^s \in \{0,1\}, H_{il}, V_{ijl}^s \geq 0 \right\}$, and

$$\text{LR}_2 : \min \sum_j \sum_k \sum_l \sum_s \left(p^s c_{jkl}^s + \theta_{jls} \right) X_{jkl}^s + \sum_k \sum_l \sum_s p^s a_l W_{kl}^s + \sum_j \sum_k \sum_l \sum_s \lambda_{jkls} T_{jkl}^s \quad (4.15)$$

subject to $\left\{ \text{constraints } (4.9) - (4.11), T_{jkl}^s \in \{0,1\}, X_{jkl}^s, W_{kl}^s \geq 0 \right\}$.

In realistic cases, the number of demand points is typically much larger than the number of potential rescue center locations. Thus T_{jkl}^s variables constitute a larger proportion of the binary variables in the model. This implies that due to a relatively smaller number of binary variables U_i and Y_{ij}^s, LR_1 can be solved efficiently by a commercial MILP solver like CPLEX. To solve LR_2 we first decompose the problem with respect to k, l, and s. The following algorithm is used to find the optimal solution of each subproblem LR_2^{kls}.

Calculate $\alpha_{jkls} d_{kl}^s + \lambda_{jkls}$ and $\beta_{kls} d_{kl}^s$

$j^* = \arg\min_j = \alpha_{jkls} d_{kl}^s + \lambda_{jkls}$

if $\alpha_{j^*kls} d_{kl}^s + \lambda_{j^*kls} < \beta_{kls} d_{kl}^s$ **then**

  $T_{j^*kl}^s = 1$, $X_{j^*kl}^s = d_{kl}^s$, $W_{kl}^s = 0$, $T_{jkl}^s = X_{jkl}^s = 0$ for all $j \neq j^*$

else

  $T_{jkl}^s = 0$, $X_{jkl}^s = 0$ for all j and $W_{kl}^s := d_{kl}^s$

end if

Figure 4.2. Solution algorithm to solve LR_2^{kls}.

Since there is no capacity constraint associated with the LRCs in the subproblem LR_2^{kls}, the total demand d_{kl}^s should be either satisfied from a single LRC or left unsatisfied due to constraint (4.11). The decision is made by considering the total cost of the two alternatives. The algorithm given in Figure 4.2 computes and compares these cost values to find the optimal assignment, flow and shortage decisions for every d_{kl}^s. For notational convenience, the objective function coefficients of X_{jkl}^s and W_{kl}^s in (4.15) are denoted by $\alpha_{jkls} = p^s c_{jkl}^s + \theta_{jls}$ and $\beta_{kls} = p^s a_l$, respectively. Then, the cost of satisfying d_{kl}^s from an LRC located at j is given as $\alpha_{jkls} d_{kl}^s + \lambda_{jkls}$ and the shortage cost of leaving the demand unsatisfied as $\beta_{kls} d_{kl}^s$. Consequently, if the cost of assigning the demand to LRC j^*, which is the LRC with the minimum cost among all the LRCs, is smaller than the shortage cost, then the assignment variable $T_{j^*kl}^s = 1$ along with $X_{j^*kl}^s = d_{kl}^s$ and $W_{kl}^s = 0$. Otherwise, the amount of shortage becomes equal to d_{kl}^s, i.e., $W_{kl}^s = d_{kl}^s$ along with $T_{jkl}^s = 0$ and $X_{jkl}^s = 0$ for all j. The optimal objective value $z_{\mathrm{LR}_2^{kls}}^*$ of LR_2^{kls} is computed as $\sum_j \alpha_{jkls} X_{jkl}^s + \beta_{kls} W_{kl}^s + \sum_j \lambda_{jkls} T_{jkl}^s$. As a result, the optimal objective value $z_{\mathrm{LR}_2}^*$ of LR_2 is given by summing up $z_{\mathrm{LR}_2^{kls}}^*$ over k, l, and s, i.e., $z_{\mathrm{LR}_2}^* = \sum_k \sum_l \sum_s z_{\mathrm{LR}_2^{kls}}^*$.

As soon as the optimal solutions of subproblems LR_1 and LR_2 are found for given multiplier vectors $\boldsymbol{\theta}$ and $\boldsymbol{\lambda}$, $z_{\mathrm{LR}}(\boldsymbol{\theta}, \boldsymbol{\lambda}) = z_{\mathrm{LR}_1}^* + z_{\mathrm{LR}_2}^*$ becomes a lower bound on the optimal objective value of z^* of TSLP. The best (maximum) lower bound is obtained by solving the Lagrangean dual problem $\max_{\boldsymbol{\theta}, \boldsymbol{\lambda}} z_{\mathrm{LR}}(\boldsymbol{\theta}, \boldsymbol{\lambda})$ by subgradient optimization [94]. It is used at each iteration of LH to update $\boldsymbol{\theta}$ and $\boldsymbol{\lambda}$, which requires an upper bound on z^*.

4.2.2. Calculation of the Best Upper Bound

An upper bound on z^* can be found by generating a feasible solution to TSLP at each iteration of LH by using the solution of LR_1. The idea is fixing the location variables U_i of the RRCs and location variables Y_{ij}^s of LRCs found as a result of solving LR_1 and finding feasible values for the remaining decision variables.

As explained below, first the Algorithm given in Figure 4.3 is employed to generate feasible values for T_{jkl}^s, X_{jkl}^s, and W_{kl}^s, and then a simple procedure is utilized to determine the values of the remaining decision variables V_{ijl}^{s} and H_{il}. When the locations of the opened LRCs (i.e., $Y_{ij}^{s} = 0$ or 1) are given, determining the assignment of each relief item demand d_{kl}^{s} for scenario s to the LRCs is similar to the generalized assignment problem (GAP). The only difference is that in our case there may exist shortage because of capacity limitations at the LRCs. Therefore, we modify the regret-based greedy heuristic of Martello and Toth [95] for the GAP to find feasible values of T_{jkl}^{s}, X_{jkl}^{s} and W_{kl}^{s}.

The assignment of demand d_{kl}^{s} to an open LRC($Y_{ij}^{s} = 1$) is achieved by means of a weight function $f(Y_{ij}^{s}, d_{kl}^{s})$. Depending on whether the remaining capacity $\overline{q}_{j}^{s}$ at an LRC is sufficient or not to accommodate additional relief item demand, we define $f(Y_{ij}^{s}, d_{kl}^{s})$ as a function of $\overline{q}_{j}^{s}$, the demand quantity d_{kl}^{s}, the transportation cost c_{jkl}^{s}, and the penalty cost a_l for unit shortage of the relief item as follows:

$$f(Y_{ij}^{s}, d_{kl}^{s}) = \begin{cases} c_{jkl}^{s} d_{kl}^{s} & \text{if } d_{kl}^{s} v_l \leq \overline{q}_{j}^{s} \\ c_{jkl}^{s} \left(\frac{\max(0, \overline{q}_{j}^{s})}{v_l} \right) + a_l \frac{\left(d_{kl}^{s} v_l - \overline{q}_{j}^{s} \right)}{v_l} & \text{otherwise} \end{cases}$$

Then, for each relief item l demand at point k under scenario s (i.e., d_{kl}^{s}), we find the facility $\widehat{Y}_{i^*j^*s}^{kl}$ with the smallest weight and the facility with the second smallest weight. The difference between the two weight values constitutes a regret measure. As soon as the demand point k^* and the relief item l^* at this demand point giving rise to the maximum regret are obtained, the following cases can be identified.

In the first case, demand $d_{k^*l^*}^{s}$ is satisfied completely from the LRC at site j^* because its remaining capacity is sufficient. As a result, $T_{j^*k^*l^*}^{s} = 1$, $X_{j^*k^*l^*}^{s} = d_{k^*l^*}^{s}$ and shortage $W_{k^*l^*}^{s} = 0$. In the second case, a partial assignment of demand is made to the LRC at site j^*, and hence $T_{j^*k^*l^*}^{s} = 1$ and $X_{j^*k^*l^*}^{s} = \max(\overline{q}_{j^*}^{s}/v_{l^*}, 0)$. The magnitude of the shortage is given as $W_{k^*l^*}^{s} = d_{k^*l^*}^{s} - X_{j^*k^*l^*}^{s}$. In the last case, when there is no remaining capacity at the facility, no assignment is made (i.e., $T_{j^*k^*l^*}^{s} = 0$ and $X_{j^*k^*l^*}^{s} = 0$), and the shortage $W_{k^*l^*}^{s}$ attains its maximum value, which is equal to $d_{k^*l^*}^{s}$.

After the remaining capacity of the LRC at site j^* is updated, the procedure is repeated for another demand point/relief item pair belonging to the same scenario. When all demand point/relief item pairs for the same scenario are considered, it is

Initialization Set $s = 1$

Do While $s \leq |S|$

Step 1: Let $\mathcal{D}^s = \{d^s_{kl}$ for all k,l$\}$, $\mathcal{F}^s = \{Y^s_{ij} : Y^s_{ij} = 1\}$, and $\overline{q}^s_j = q^s_j$.

Step 2: Let

$$\widehat{Y}^{kl}_{i^*j^*s} = \arg\min_{Y^s_{ij}} f(Y^s_{ij}, d^s_{kl}), Y^s_{ij} \in \mathcal{F}^s \quad \text{and} \quad d^s_{kl} \in \mathcal{D}^s$$

$$R^s_{kl} = \min_{Y^s_{ij} \neq \widehat{Y}^{kl}_{i^*j^*s}} \left(f(Y^s_{ij}, d^s_{kl}) - f(\widehat{Y}^{kl}_{i^*j^*s}, d^s_{kl}) \right), Y^s_{ij} \in \mathcal{F}^s \quad \text{and} \quad d^s_{kl} \in \mathcal{D}^s$$

Step 3: Let $(k^*, l^*) = \arg\max_{k \in K, l \in L} R^s_{kl}$. Then,

$$X^s_{j^*k^*l^*} = \begin{cases} d^s_{k^*l^*},\ W^s_{k^*l^*} = 0 & \text{if } d^s_{k^*l^*} v_{l^*} \leq \overline{q}^s_{j^*} \\ \max(\frac{\overline{q}^s_{j^*}}{v_{l^*}}, 0),\ W^s_{k^*l^*} = d^s_{k^*l^*} - X^s_{j^*k^*l^*} & \text{otherwise} \end{cases}$$

$$T^s_{j^*k^*l^*} = \begin{cases} 1, & \text{if } X^s_{j^*k^*l^*} > 0 \\ 0, & \text{otherwise} \end{cases}$$

$$\overline{q}^s_{j^*} = \overline{q}^s_{j^*} - X^s_{j^*k^*l^*} v_{l^*}$$

$$\mathcal{D}^s = \mathcal{D}^s \setminus \{d^s_{k^*l^*}\}$$

Step 3:

if $\mathcal{D}^s = \varnothing$ **then**

a feasible solution is found for scenario s.

else

Go to Step 2

end if

$s \leftarrow s + 1$.

Figure 4.3. Algorithm to find feasible values of T^s_{jkl}, X^s_{jkl}, and W^s_{kl}.

possible to move on to the next scenario. After feasible values are obtained by the algorithm in Figure 4.3 for variables T^s_{jkl}, X^s_{jkl}, and W^s_{kl}, it is a relatively simple task to find feasible values for the other variables of the problem, namely V^s_{ijl} and H_{il}. The outflow of relief item l from LRC at site j under scenario s should be equal to the inflow of that item to the same LRC under the same scenario. Since any open LRC at site j is assigned to a single RRC at site i' under scenario s (i.e., $Y^s_{i'j} = 1$ and $Y^s_{ij} = 0$ for $i \neq i'$), it implies that $V^s_{i'jl} = \sum_k X^s_{jkl}$. Then the value of $H_{i'l}$ is set to the maximum of the outflow of item l at RRC i' over all scenarios due to constraints (4.6). Note that since each relief item demand is assigned to at most one LRC, the values of T^s_{jkl}, X^s_{jkl}, and W^s_{kl} variables are found by respecting the capacities of LRCs as described above, and the values of V^s_{ijl} and H_{il} are generated accordingly, the final solution must be feasible for the overall problem TSLP.

4.2.3. Local Search Algorithm

The solution generated by LH can be improved by performing local search (LS) in the neighborhood of the solution space defined by the location variables. Starting with the best feasible solution found by LH, at each iteration of LS we move from the current solution to the best neighboring solution even if it is worse than the current solution to avoid early stopping. We use three types of moves: 1-*Add*, 1-*Drop*, and 1-*Swap* defined as follows. In the 1-Add move, a new facility is added to the set of open facilities; in the 1-Drop move, an open facility is closed, while in the 1-Swap move the location of a facility is exchanged with another one.

The LS procedure works by first applying a possible move on RRCs to obtain a neighboring solution from the current solution. For this RRC move, we apply all possible moves on LRCs considering each scenario separately (recall that LRCs are established after the earthquake occurs, that is their locations are scenario-dependent). The objective value of the solution obtained by a move on LRCs with the fixed RRC locations is computed via the heuristic algorithm explained in Section 5.2.2. For each scenario, the move with the best (smallest) objective value is chosen as the best LRC move for a given RRC move. After generating all the neighboring solutions by the moves on RRCs and LRCs, we determine the best neighboring solution, which becomes the next current solution. The LS algorithm is terminated when the total running time, i.e., the time needed by LH and subsequent LS reaches the allowed limit.

5. AN INTEGRATED MODEL FOR MITIGATION AND RESPONSE DECISIONS

Mitigation is the most important phase in disaster management since an efficient mitigation policy reduces both the negative effects of a disaster and the related preparedness and response efforts. The damage related with the earthquake intensity is decreased by mitigation. As the damage decreases, the effort and financial resources needed for a successful response also decrease. This unrefutable fact implies that the mitigation and response decisions are non-separable and they must be considered simultaneously as a preparedness plan before the disaster. Therefore, we develop an integrated optimization model that incorporates mitigation and response decisions concurrently. To the best of our knowledge, this is the first attempt for such an integration.

5.1. The model

The integrated model for retrofitting and response related decisions (IRRP) helps to give optimal decisions in the pre-disaster planning stage of a disaster. The model gives two kinds of retrofitting decisions: retrofitting of buildings and retrofitting of transportation infrastructure. The building retrofit affects the post-disaster relief item demand and the infrastructure retrofit affects the transportation time and connectivity of the network after the disaster.

Each building's resistance can be improved by retrofitting it from a lower seismic code level to a higher one. The damage status of a building is determined by the realized earthquake scenario and its pre-disaster condition, i.e, seismic code level before the disaster. With respect to the building population and its damage level, the amount of relief item requirements can approximately be calculated by assuming that retrofitting lowers the relief item demand. As the demand for relief items increases, the need for transportation of relief items increases as well, and consequently higher response cost is incurred. Thus, the linking variable between the mitigation decisions and the humanitarian logistics decisions is the relief demand.

Following an earthquake, the transportation time on a link is likely to increase due to road failures, debris of buildings that close the roads partially, or increased traffic congestion related with closed links. Thus, we assign a different transportation time for each link depending on the earthquake intensity. Moreover, bridges, viaducts and overpasses are the weakest components of a transportation infrastructure. We call a link between two nodes in the network "vulnerable" under a specific scenario if there exists at least one bridge/viaduct or overpass that may not resist under that scenario. Then retrofitting a link, actually means retrofitting all vulnerable structures on that link. If a link is retrofitted, then it is resistant to any earthquake scenario. However, if a link is not retrofitted and additionally vulnerable under a scenario then it cannot be used for that scenario or more severe ones. Link failures are assumed independent since bridges/viaducts are structurally heterogeneous due to their type, design, maintenance levels, load, age, and moreover the geotechnical conditions of a bridge/viaduct vary from one location to another [23]. We also assume that a bridge/viaduct does not belong to more than one link, which means retrofitting a link does not affect another link in any way. In the network structure, we assume that there is a separate direct link between each RC and district pair. These links do not intersect with each other, thus each of them is the unique transportation path between a RC and a district.

The total cost of bridge/viaduct and building retrofit decisions are given under a limited mitigation budget allotted by the government/municipality for pre-disaster retrofit actions. The building mitigation costs are compensated by the government/municipality, and so are the bridge retrofitting and the post disaster response costs. Thus the model stands on a public decision making perspective similar to those used in [17–19].

In USA the Disaster Mitigation Act of 2000 states that to be eligible for Hazard Grant mitigation Program (HMGP) funds, each state and local government must submit a mitigation plan to the Federal Emergency Management Agency (FEMA) describing how it is prioritizing mitigation actions so that its overall mitigation strategy is cost-effective and maximizes overall wealth [17]. In Turkey, funding of residence retrofitting is a bit grueling. In general, residents do not have strong assurance about the effectiveness of retrofitting and they mostly do not believe that consensus for retrofitting can be reached in their building [101, 102]. Although the owner of a property is normally required to pay for any upgrading, he/she has no liability for death or injury caused by earthquakes. They find future property losses small by comparison with the cost of full retrofit.

One of the factors that supports this perception is the low premiums of Turkish catastrophe insurance pool (TCIP). They are by far short of actual risks [104], thus the property owners do not think that it is profitable to retrofit their premises. Instead, they wait for the damage and reimbursement for damages as stated by [100]. It should also be noted that it is not reasonable to use the pool fund retrofit at its current financial status.

Erdik and Durukal [99] state that although building owners cannot visualize the benefit, society in general will greatly benefit from a retrofit campaign by the reduction of the physical, social, and consequential societal losses that will eventually be covered by the public. The use of public funds for retrofit purposes can therefore be justified under a strategy designed to maximize benefits with well prioritized and fairly distributed minimum expenditure. Such a strategy can lead to the concept of minimum retrofit [99]. Issues mentioned above suggest that there is a strong case for government involvement, which is also asserted by [103]. Therefore, in the developed model it is assumed that all type of costs are paid by the state or local municipality.

Besides the mitigation decisions, the response decisions also constitute an important part of the total cost. The assignments of each relief demand type to rescue centers together with transportation and shortage amounts affect response efficiency. A demand type refers to demand emerged at a demand point in a disaster scenario. Each demand type is received from a single rescue center (RC). This setting ensures a more simple and efficient response plan which is very important in disaster management.

We believe that for areas with a very high annual probability of earthquake occurrence planning should be done as if the earthquake occurred in a very short period. Thus, our model setting assumes that earthquake will occur in the near future, which is long enough to carry out planned retrofitting actions. It is remarkable that annual probability of occurrence for İstanbul is approximately 2 %, one of the largest in the world [99].

We formulate the IRRP as a two-stage stochastic program with recourse to minimize the total costs of building and link retrofitting, transportation and shortage. Its deterministic equivalent can be written by assuming a discrete probability distribution of the scenario occurrences. The building and bridge/viaduct retrofit decisions are modelled as the first-stage variables since they are realized before the earthquake. By contrast, the rest of the variables are dependent on the realized earthquake scenario, so these decision variables constitute the second-stage variables and referred to as the recourse variables. Thus, the resulting MILP model includes binary first-stage and mixed-integer second-stage variables.

Below, we first define the parameters and decision variables in Table 5.1-5.4. Then we give the formulation of the IRRP model, and present three different Lagrangean heuristic methods to solve it.

Table 5.1. Parameters used in the IRRP.

J	set of rescue centers
K	set of districts
M_k	set of buildings in district k
C	set of seismic code levels
D	set of damage levels for buildings
S	set of scenarios
$b^c_{km_k}$	$\begin{cases} 1 & \text{if building } m_k \text{ in district } k \text{ is at seismic code level } c \text{ before retrofit} \\ 0 & \text{otherwise} \end{cases}$
C_{km_k}	set of possible seismic code levels to retrofit building m_k in district k, i.e., $c' \in C_{km_k}$ where $c' \geq c$ and c such that $b^c_{km_k} = 1$

Table 5.2. Parameters used in the IRRP (cont'd.).

γ_{kd}^{cs}	probability that a building in district k which is at seismic code level c has damage level d under scenario s
$r_{km_k}^{cc'}$	mitigation cost of building m_k in district k to bring it from seismic code level c to c' where $c' \geq c$
α_{km_k}	population of building m_k in district k
λ_d	multiplier for relief item demand for damage level d
B	total mitigation budget
c_{jk}^{s}	unit transportation cost of relief item demand sent from RC at site j to district k under scenario s
a	unit penalty cost of relief item shortage
p^s	probability of occurrence of scenario s
$\tilde{t}_{jk}^{s}$	transportation time from RC at site j to district k under scenario s unless link (j,k) is not vulnerable
$t_{\max}$	maximum allowable transportation time between an RC and a district
v_{jk}^{s}	$\begin{cases} 1 & \text{if link } (j,k) \text{ is vulnerable under scenario } s \text{ unless it is mitigated} \\ 0 & \text{otherwise} \end{cases}$
u_{jk}	cost of mitigating link (j,k)
N_{1ks}	highest possible relief item demand amount in district k under scenario s
N_2	highest $\tilde{t}_{jk}^{s}$ value

Table 5.3. Decision variables used in the IRRP.

$R_{km_k}^{c'}$	$\begin{cases} 1 & \text{if building } m_k \text{ in district } k \text{ is mitigated to seismic code level } c' \\ & \text{where } c' \text{ where } c' \geq c : b_{km_k}^{c} = 1 \\ 0 & \text{otherwise} \end{cases}$
U_{jk}	$\begin{cases} 1 & \text{if link } (j,k) \text{ is mitigated} \\ 0 & \text{otherwise} \end{cases}$
Z_{jk}^{s}	$\begin{cases} 1 & \text{if district } k \text{ is assigned to RC at site } j \text{ under scenario } s \\ 0 & \text{otherwise} \end{cases}$
X_{jk}^{s}	amount of relief item sent from RC at site j to district k under scenario s

Table 5.4. Decision variables used in the IRRP. (cont'd.).

D_k^s	amount of relief item demanded in district k under scenario s
T_{jk}^s	transport time between RC at site j and district k under scenario s
W_k^s	amount of shortage in district k under scenario s

Using the parameters and decision variables defined above, the model can be formulated as follows:

$$\text{IRRP:}\quad \min \sum_k \sum_{m_k} \sum_c \sum_{c' \in C_{km_k}} b_{km_k}^c r_{km_k}^{cc'} R_{km_k}^{c'} + \sum_j \sum_k u_{jk} U_{jk} + \sum_j \sum_k \sum_s p^s c_{jk}^s X_{jk}^s + \sum_k \sum_s p^s a W_k^s \tag{5.1}$$

subject to

$$\sum_{c' \in C_{km_k}} R_{km_k}^{c'} = 1 \qquad k \in K, m_k \in M_k \tag{5.2}$$

$$\sum_d \lambda_d \sum_{m_k} \sum_{c' \in C_{km_k}} \gamma_{kd}^{c's} \alpha_{km_k} R_{km_k}^{c'} = D_k^s \qquad k \in K, s \in S \tag{5.3}$$

$$T_{jk}^s = \left[\tilde{t}_{jk}^s v_{jk}^s - v_{jk}^s(t_{\max}+1)\right] U_{jk} + \left[t_{\max} + 1 - \tilde{t}_{jk}^s\right] v_{jk}^s + \tilde{t}_{jk}^s \qquad j \in J, k \in K, s \in S \tag{5.4}$$

$$\sum_k \sum_{m_k} \sum_c \sum_{c' \in C_{km_k}} b_{km_k}^c r_{km_k}^{cc'} R_{km_k}^{c'} + \sum_j \sum_k u_{jk} U_{jk} \leq B \tag{5.5}$$

$$X_{jk}^s \leq N_{1ks} Z_{jk}^s \qquad j \in J, k \in K, s \in S \tag{5.6}$$

$$\sum_j Z_{jk}^s \leq 1 \qquad k \in K, s \in S \tag{5.7}$$

$$\sum_j X_{jk}^s + W_k^s = D_k^s \qquad k \in K, s \in S \tag{5.8}$$

$$N_2 Z_{jk}^s + T_{jk}^s \leq t_{\max} + N_2 \qquad j \in J, k \in K, s \in S \tag{5.9}$$

$$X_{jk}^s, D_k^s, W_k^s, T_{jk}^s \geq 0, \quad U_{jk}, R_{km_k}^c, Z_{jk}^s \in \{0,1\} \quad j \in J, k \in K, s \in S, m_k \in M_k, c \in C_{km_k} \tag{5.10}$$

The objective (5.1) is to minimize the total cost associated with building retrofit, link retrofit, relief item transportation and shortage of relief items. Constraint set (5.2) states that building m_k in district k and at seismic code level c can be retrofitted only to a higher seismic code level or left at code level c (i.e., not retrofitted). Constraint set (5.3) ensures that if disaster scenario s occurs, the amount of relief item demand in district k is equal to a value calculated on the left hand-side of the constraint. Here, the probability of a specific building m_k at seismic code level c' located in district k and having a damage level d under scenario s is found by $\gamma_{kd}^{c's} R_{km_k}^{c'}$. Notice that here value of the $R_{km_k}^{c'}$ variable indicates the code level of building m_k in district k after retrofitting. A building is found at one single code level c after retrofitting, i.e., $R_{km_k}^{c'} = 1$ for one of the c' code levels and $R_{km_k}^{c'} = 0$ for the rest of the code levels. Then, the expected number of people in this building facing a damage level d is $\gamma_{kd}^{c's} R_{km_k}^{c'} \alpha_{km}$ and consequently the amount of relief item demand is calculated by $\lambda_d \gamma_{kd}^{c's} R_{km_k}^{c'} \alpha_{km}$. Summing up for all buildings, code levels and damage types results in total demand D_k^s. Constraint set (5.4) describes the transportation time T_{jk}^s of link (j,k) in scenario s as a function of vulnerability v_{jk}^s of the link in scenario s and the retrofitting decision U_{jk} of the link. Then, T_{jk}^s values are determined as

$$T_{jk}^s = \begin{cases} \tilde{t}_{jk}^s & \text{if } U_{jk} = 0, v_{jk}^s = 0 \\ \tilde{t}_{jk}^s & \text{if } U_{jk} = 1, v_{jk}^s = 0 \\ \tilde{t}_{jk}^s & \text{if } U_{jk} = 1, v_{jk}^s = 1 \\ t_{\max} + 1 & \text{if } U_{jk} = 0, v_{jk}^s = 1 \end{cases}$$

Here, $\tilde{t}_{jk}^s$ represents the estimated transportation time for link (j,k) in disaster scenario s if the link is not disrupted. If the link is disrupted, the transportation time is set to $t_{\max}+1$, which is higher than the threshold level $t_{\max}$ to be able to make an assignment on that link. Constraint set (5.5) limits the total costs of building and bridge/viaduct retrofitting by a pre-determined mitigation budget. Constraint set (5.6) ensures that to have a positive relief item flow from RC at site j to district k under scenario s, district k must be assigned to RC at site j in scenario s. Also value of X_{jk}^s cannot be higher than N_{1ks}, which is the highest possible relief item demand amount in district k under scenario s, i.e., the relief item demand amount when all of the buildings in district k are at their initial seismic code level. Constraint set (5.7) guarantees that the relief item demand in district k under scenario s must be satisfied by at most one RC. Constraint set (5.8) shows that the shortage of relief item demand in district k under scenario s is the difference between demand and the total amount of relief items received from RCs. Constraint set (5.9) implies that district k could only be assigned to RC at site j in scenario s (i.e., $Z^s_{jk} = 1$) when T^s_{jk} does not exceed $t_{\max}$. Here, N_2 can be set to the highest $\tilde{t}^s_{jk}$ value in the problem. Constraint set (5.10) defines the binary and non-negativity restrictions on the decision variables.

IRRP can be reformulated by expressing constraints (5.4) and (5.9) in a different fashion as follows:

$$Z^s_{jk} \leq U_{jk} - v^s_{jk} + 1 \qquad j \in J, k \in K, s \in S \tag{5.11}$$

and

$$N_2 Z^s_{jk} + \tilde{t}^s_{jk} \leq t_{\max} + N_2 \qquad j \in J, k \in K, s \in S \tag{5.12}$$

Constraint set (5.11) ensures that assignment of RC at site j to district k is not possible in scenario s if the link (j,k) is vulnerable (i.e., $v^s_{jk} = 1$) and the link was not retrofitted (i.e., $U_{jk} = 0$), since

$$Z^s_{jk} \leq \begin{cases} 0 & \text{if } U_{jk} = 0, v^s_{jk} = 1 \\ 1 & \text{if } U_{jk} = 0, v^s_{jk} = 0 \\ 1 & \text{if } U_{jk} = 1, v^s_{jk} = 1 \\ 2 & \text{if } U_{jk} = 1, v^s_{jk} = 0 \end{cases}$$

Constraint set (5.12) restricts the assignment on (j,k) link if the estimated transportation time along (j,k) under scenario s, is greater than $t_{\max}$.

This new formulation results in less decision variables since the T^s_{jk} variables are not needed any more. The T_{jk}^s variables are continuous and their number is relatively small with respect to binary variables. Moreover, the number of constraints in the two formulations is same. On the basis of several experiments, we observe that the solutions times of the models do not differ significantly from each other.

However, the new formulation results in tighter LP relaxation bounds. It is important because for some large instances in our experiments, we cannot obtain any bounds on the optimal solution although the MILP solver employed runs for more than 24 hours. In these cases, we use the lower bound provided by the LP relaxation to evaluate the performance of the proposed solution methods.

IRRP is a two-stage stochastic mixed-integer linear program. The binary variables Z_{jk}^s are scenario-dependent variables, so their number increases in the number of scenarios. Moreover, the number of $R_{km_k}^c$ variables are related with the number of buildings which can be in millions for a large city/district. Thus, the deterministic equivalent of IRRP can include millions of variables as well as constraints. A MILP of this size might not be solved with a commercial MILP solver like CPLEX, efficiently. However, one can decompose the problem into smaller subproblems and solve each one by a special-purpose solution algorithm.

We propose three heuristics based on Lagrangean relaxation, which is successfully applied for some other two-stage stochastic mixed-integer linear programs in the literature (e.g., [79, 90]). In each of the Lagrangean heuristics (i.e., LHM1, LHM2 and LHM3) the same constraints are relaxed. Thus, similar subproblems are obtained, in particular, the first subproblem is the same in each of the solution methods and the second subproblem differs due to the modified constraints (5.11) and (5.12) instead of (5.4) and (5.9). LHM1, LHM2, and LHM3 differ by their solution algorithms to solve the second subproblem and to obtain feasible solutions that provide upper bounds. The details of the LHM1, LHM2 and LHM3 are given in Sections 5.2, 5.3 and 5.4, respectively.

5.2. First Lagrangean Heuristic Method

In IRRP the pre-disaster building retrofit decisions are linked with the post-disaster relief item demand by constraint set (5.3). Therefore, constraint set (5.3) can be relaxed to get a subproblem which consists of pure building retrofitting decisions. Moreover, in our preliminary experiments we have observed that the existence of constraints (5.5), which in fact behave like knapsack constraints, make the problem very hard to solve. Thus, we relax constraint sets (5.3) and (5.5) to get easily solvable subproblems with the help of Lagrangean multiplier vectors $\boldsymbol{\mu}$ and $\boldsymbol{\theta}$, respectively. Relaxation of these two constraints leads to two separate subproblems.

5.2.1. Calculation of the Best Lower Bound

The Lagrangean relaxation leads to the following subproblems: LR_1 and LR_2.

$$\mathrm{LR}_1 : \min \sum_{k} \sum_{m_k} \sum_{c' \in C_{km_k}} R^{c'}_{km_k} \left[\sum_{c} b^{c}_{km_k} r^{cc'}_{km_k} (1+\theta) + \sum_{s} \sum_{d} \lambda_d \gamma^{c's}_{kd} \alpha_{km_k} \mu_{ks} \right] - B\theta \tag{5.13}$$

subject to constraints (5.2), and

$$R^{c'}_{km_k} \in \{0,1\} \qquad k \in K, m_k \in M_k, c' \in C_{km_k} \tag{5.14}$$

$$\mathrm{LR}_2 : \min \sum_{j} \sum_{k} \sum_{s} p^s c^s_{jk} X^s_{jk} + \sum_{k} \sum_{s} p^s a W^s_k - \sum_{k} \sum_{s} \mu_{ks} D^s_k + \sum_{j} \sum_{k} U_{jk} u_{jk} (1+\theta) \tag{5.15}$$

subject to constraints (5.4), (5.6), (5.7), (5.8), (5.9), and

$$D_k^s \le \sum_d \lambda_d \sum_{m_k} \sum_c \gamma_{kd}^{cs} \alpha_{km_k} b_{km_k}^c \qquad k \in K, s \in S \tag{5.16}$$

$$Z_{jk}^s, U_{jk} \in \{0,1\} \qquad j \in J, k \in K, s \in S \tag{5.17}$$

$$X_{jk}^s, D_k^s, W_k^s, T_{jk}^s \ge 0 \qquad j \in J, k \in K, s \in S \tag{5.18}$$

Subproblem LR_1 can be solved to optimality by inspection with the algorithm given in Figure 5.1. We decompose LR_1 with respect to k and m_k to obtain subproblems $\mathrm{LR}_1^{km_k}$. In fact, solving each subproblem corresponds to determining the retrofit decision for a single building m_k located in district k with seismic code level c such that $b_{km_k}^c = 1$.

Initialization: Let $z_{\mathrm{LR}_1}^* = 0$

$R_{km_k}^{c'} = 0$, for all $k \in K, m_k \in M_k, c' \in C_{km_k}$

for all $k \in K, m_k \in M_k$ **do**

Let $c^* = \arg\min_{c' \in C_{km_k}} \left[\sum_c b_{km_k}^c r_{km_k}^{cc'} (1+\theta) + \sum_s \sum_d \lambda_d \gamma_{kd}^{c's} \alpha_{km_k} \mu_{ks} \right]$

$R_{km_k}^{c^*} = 1$ and $z_{\mathrm{LR}_1^{km_k}}^* = \left[\sum_c b_{km_k}^c r_{km_k}^{cc^*} (1+\theta) + \sum_s \sum_d \lambda_d \gamma_{kd}^{c^*s} \alpha_{km_k} \mu_{ks} \right]$

$z_{\mathrm{LR}_1}^* = z_{\mathrm{LR}_1}^* + z_{\mathrm{LR}_1^{km_k}}^*$

end for

$z_{\mathrm{LR}_1}^* = z_{\mathrm{LR}_1}^* - B\theta$

Figure 5.1. Solution Algorithm for LR_1 of LHM1.

A building can only be retrofitted to a higher seismic code level c' (c' such that $c' > c$) or can remain non-retrofitted, i.e. c'=c. If a building is retrofitted to seismic code level c', then it implies that $R_{km_k}^{c'} = 1$. For each building (or for each $\mathrm{LR}_1^{km_k}$), we should give a retrofitting decision which results in the minimum total cost. Retrofitting cost for each c' is equal to the objective function coefficient $\left[\sum_c b_{km_k}^c r_{km_k}^{cc'} (1+\theta) + \sum_s \sum_d \lambda_d \gamma_{kd}^{c's} \alpha_{km_k} \mu_{ks} \right]$.

The c' code level that satisfies the minimum cost is indicated by c^* thus the retrofit decision is set to $R_{km_k}^{c^*} = 1$. The minimum cost is assigned to $z_{\mathrm{LR}_1^{km_k}}^*$ as the optimal objective value of subproblem $\mathrm{LR}_1^{km_k}$. The optimal objective value $z_{\mathrm{LR}_1}^*$ of LR_1

is found by summing up the costs of each subproblem $\mathrm{LR}_1^{km_k}$ as $z^*_{\mathrm{LR}_1} = \sum\limits_{k\in K}\sum\limits_{m\in M_k} z^*_{\mathrm{LR}_1^{km_k}}$ and subtracting the term $B\theta$.

Let $|M| = \arg\max\limits_{k} M_k$, then the computational complexity of the algorithm is given by $O(|K||M||C|)$.

Subproblem LR_2 involves the decisions of link retrofitting, relief item amounts, relief item flows from RCs to districts and amount of shortage. Note that we add the redundant constraint (5.16) as a valid inequality to benefit in the solution process of the model. The D_k^s should be lower than the right-hand side value, which is the relief item demand when all of the buildings are at their initial seismic code level (i.e., $b^c_{km_k}$). The number of binary variables U_{jk} and Z^s_{jk} are relatively small in the model since they are not related to buildings as well as the constraints. Moreover, the number of U_{jk} variables is equal to the number of links and does not depend on the scenario. These factors imply that this subproblem can be solved by a general MILP solver efficiently, even for the largest instances. Therefore, we solve LR_2 by CPLEX.

As soon as the optimal solutions of subproblems LR_1 and LR_2 are found for given multiplier vectors $\boldsymbol{\mu}$ and $\boldsymbol{\theta}$, $z_{\mathrm{LR}}(\boldsymbol{\mu},\boldsymbol{\theta}) = z^*_{\mathrm{LR}_1} + z^*_{\mathrm{LR}_2}$ becomes a lower bound on the optimal objective value z^* of IRRP. The best (maximum) lower bound is obtained by solving the Lagrangean dual problem $\max_{\boldsymbol{\mu},\boldsymbol{\theta}} z_{\mathrm{LR}}(\boldsymbol{\mu},\boldsymbol{\theta})$ using subgradient optimization [94]. It is used at each iteration of LHM1 to update $\boldsymbol{\mu}$ and $\boldsymbol{\theta}$, which requires an upper bound on z^*.

5.2.2. Calculation of the Upper Bound in LHM1

An upper bound on z^* can be found by generating a feasible solution to IRRP at each iteration of LHM1 by utilizing the solution of LR_2 in the algorithm given in Figure 5.2.

In this algorithm, we first consider the link retrofit variables U_{jk} found as a result of solving LR_2 and calculate the remaining available budget B_R for the building

Set sum=0 and $R^{c'}_{km_k} = 0$, for all $k \in K, m_k \in M_k, c' \in C_{km_k}$

Set $B_R = B - \sum_j \sum_k u_{jk} U_{jk}$ where values of U_{jk} are determined by LR$_2$

for all $k \in K, m_k \in M_k$ **do**

  Let $c^* = \arg \min_{c' \in C_{km_k}} \left[\sum_c b^c_{km_k} r^{cc'}_{km_k}(1+\theta) + \sum_s \sum_d \lambda_d \gamma^{c's}_{kd} \alpha_{km_k} \mu_{ks} \right]$

  $R^{c^*}_{km_k} = 1$

  Add the $R^{c^*}_{km_k}$ variables with their corresponding k, m_k, c^* indices to set $\mathcal{L}$

end for

Let $p^c_{km_k} = \sum_s \sum_d \lambda_d \gamma^{cs}_{kd} \alpha_{km_k} \mu_{ks}$

Sort the $R^{c^*}_{km_k}$ elements of set $\mathcal{L}$ in non-increasing order with respect to:

$$Q^{c^*}_{km_k} = \frac{r^{cc^*}_{km_k}}{p^c_{km_k} - p^{c^*}_{km_k}} \text{ where } c : b^c_{km_k} = 1$$

for all $R^{c^*}_{km_k} \in \mathcal{L}$ **do**

  if sum+$r^{cc^*}_{km_k} \leq B_R$ **then**

    $R^{c^*}_{km_k} = 1$

    sum=sum+$r^{cc^*}_{km_k}$

  else

    Set $R^{c^*}_{km_k} = 0$

    $R^c_{km_k} = 1$ for $c : b^c_{km_k} = 1$

  end if

end for

Set $D^s_k = \sum_d \lambda_d \sum_{m_k} \sum_{c' \in C_{km_k}} \gamma^{c's}_{kd} \alpha_{km_k} R^{c'}_{km_k}$

$d^s_k = D^s_k$

$B_U = B - \sum_k \sum_{m_k} \sum_c \sum_{c' \in C_{km_k}} r^{cc'}_{km} R^{c'}_{km}$

Solve FSP to find feasible values of $U_{jk}, Z^s_{jk}, T^s_{jk}, X^s_{jk}$ and W^s_k

Figure 5.2. Feasible solution generating algorithm of LHM1.

retrofit decisions when those values of U_{jk} are accepted as link retrofit decisions, i.e., $B_R = B - \sum_j \sum_k u_{jk} U_{jk}$. For each building m_k in district k the retrofitting decisions are determined as in Section 5.2.1. Add all the retrofitting decisions such that $R^{c^*}_{km_k} = 1$ to a set $\mathcal{L}$. However, due to the limiting budget B_R, the set $\mathcal{L}$ may not be a feasible solution for building retrofit decisions. To get a feasible solution, we should select some elements of set $\mathcal{L}$ such that the total retrofitting cost is not higher than B_R. To determine which ones are to be selected, we sort the $R^{c^*}_{km_k}$ variables in $\mathcal{L}$ in non-decreasing order with respect to $Q^{c^*}_{km_k}$ values:

$$Q^{c^*}_{km_k} = \frac{r^{cc^*}_{km_k}}{p^c_{km_k} - p^{c^*}_{km_k}} \tag{5.19}$$

where $p^c_{km_k} = \sum\limits_s \sum\limits_d \lambda_d \gamma^{cs}_{kd} \alpha_{km_k} \mu_{ks}$. It can be considered as a measure of relief item demand when a building is in code level c. Therefore, the denominator indicates a demand reduction measure when the building is retrofitted from code level c (such that $b^c_{km_k} = 1$) to code level c^*.

We begin from the first element of $\mathcal{L}$, and check all the elements one by one whether the remaining retrofit budget is sufficient or not to satisfy the retrofitting cost of an element (i.e., $r^{cc^*}_{km_k}$) from code level c (such that $b^c_{km_k} = 1$) to code level c^*. The retrofitting variables are set accordingly. $R^{c^*}_{km_k} = 1$ means that building m_k located in district k is retrofitted to code level c^*, whereas $R^{c^*}_{km_k} = 0$ implies that retrofitting decision cannot be taken.

After setting the values of $R^{c^*}_{km_k}$ variables, the demand variables D^s_k are determined by constraint set (5.3) of IRRP. The computational complexity up to this point is given by $O\left(|K||M|\left(|C| + \log\left(|K||M|\right)\right)\right)$. The rest of the variables including U_{jk} are determined by solving the following feasible solution generating problem (FSP). Then, we have a solution that satisfies all the constraints of IRRP, i.e., a feasible solution. In FSP, the budget limit for transportation link retrofitting is determined as $B_U = B - \sum\limits_k \sum\limits_{m_k \in M_k} \sum\limits_c \sum\limits_{c' \in C_{km_k}} r^{cc'}_{km} R^{c'}_{km}$ and the values of D^s_k are fixed and used as parameter d^s_k, i.e. $d^s_k = D^s_k$.

$$\text{FSP} : \min \sum_j \sum_k u_{jk} U_{jk} + \sum_j \sum_k \sum_s p^s c^s_{jk} X^s_{jk} + \sum_k \sum_s p^s a W^s_k \tag{5.20}$$

subject to constraints (5.4), (5.6), (5.7), (5.9), and

$$\sum_j \sum_k u_{jk} U_{jk} \leq B_U \tag{5.21}$$

$$\sum_j X^s_{jk} + W^s_k = d^s_k \qquad k \in K, s \in S \tag{5.22}$$

$$Z^s_{jk}, U_{jk} \in \{0, 1\} \qquad j \in J, k \in K, s \in S \tag{5.23}$$

$$X^s_{jk}, W^s_k, T^s_{jk} \geq 0 \qquad j \in J, k \in K, s \in S \tag{5.24}$$

5.3. Second Lagrangean Heuristic Method

In LHM2, again the same constraint sets (constraints (5.3) and (5.5)) are relaxed. However, the second subproblem and the FSP problem used to compute upper bound are solved by Lagrangean heuristics rather than CPLEX.

In the following, we describe all the lower and upper bound calculations in detail.

5.3.1. Calculation of the Best Lower Bound

We relax constraints (5.3) and (5.5) using the Lagrangean multiplier vectors $\boldsymbol{\mu}$ and $\boldsymbol{\theta}$, respectively. The first resulting subproblem is the same as LR_1 given in Section 5.2.1 but the second subproblem differs by the modified constraints (5.11) and (5.12).

$$\begin{aligned} \text{LR}_2 : \min \; & \sum_j \sum_k \sum_s p^s c^s_{jk} X^s_{jk} + \sum_k \sum_s p^s a W^s_k \\ & - \sum_k \sum_s \mu_{ks} D^s_k + \sum_j \sum_k U_{jk} u_{jk} (1 + \theta) \end{aligned} \tag{5.25}$$

subject to constraints (5.6), (5.7), (5.8), (5.11), (5.12), (5.16) and

$$Z_{jk}^s, U_{jk} \in \{0,1\} \qquad j \in J, k \in K, s \in S \tag{5.26}$$

$$X_{jk}^s, D_k^s, W_k^s \geq 0 \qquad j \in J, k \in K, s \in S \tag{5.27}$$

The optimal objective value of LR_1 can be obtained by the algorithm given in Figure 5.1. For LR_2, we find a lower bound by Lagrangean relaxation rather than solving it optimally. The sum of the optimal objective value $z^*_{\mathrm{LR}_1}$ of LR_1 and lower bound $z^{LB}_{\mathrm{LR}_2}$ for LR_2 gives a lower bound for IRRP.

The following procedures are used to obtain lower and upper bounds for LR_2,

<u>5.3.1.1. Calculation of the lower bound for LR_2.</u> Constraints (5.11) in LR_2 are relaxed using the associated multipliers ρ_{jks} for all j, k, s, which results in the following two subproblems: LR_{21} and LR_{22}. The sum of the optimal objective values of the first and second subproblems, i.e., $z^*_{\mathrm{LR}_{21}}$ and $z^*_{\mathrm{LR}_{22}}$ result in a lower bound for LR_2, i.e., $z^{LB}_{\mathrm{LR}_2} = z^*_{\mathrm{LR}_{21}} + z^*_{\mathrm{LR}_{22}}$.

$$\mathrm{LR}_{21} : \min \sum_j \sum_k U_{jk} \left(u_{jk}(1+\theta) - \sum_s \rho_{jks} \right) + \sum_j \sum_k \sum_s \rho_{jks} v_{jk}^s - \sum_j \sum_k \sum_s \rho_{jks} \tag{5.28}$$

subject to $U_{jk} \in \{0,1\}$

$$\mathrm{LR}_{22} : \min \sum_j \sum_k \sum_s p^s c_{jk}^s X_{jk}^s + \sum_k \sum_s p^s a W_k^s - \sum_k \sum_s \mu_{ks} D_k^s + \sum_j \sum_k \sum_s \rho_{jks} Z_{jk}^s \tag{5.29}$$

subject to (5.6), (5.7), (5.8), (5.12), (5.16) and

$$Z_{jk}^s \in \{0,1\} \qquad j \in J, k \in K, s \in S \tag{5.30}$$

$$X_{jk}^s, D_k^s, W_k^s \geq 0 \qquad j \in J, k \in K, s \in S \tag{5.31}$$

LR_{21} and LR_{22} can be solved by the algorithms given in Figure 5.3 and Figure 5.4, respectively. The computational complexities of these algorithms are $O(|J||K|)$ and $O(|K||S||J|)$, respectively.

for all j, k **do**
  Calculate $u_{jk}(1+\theta) - \sum_s \rho_{jks}$,
  if $u_{jk}(1+\theta) - \sum_s \rho_{jks} \leq 0$ **then**
    $U_{jk} = 1$
  else
    $U_{jk} = 0$
  end if
end for
Calculate $z^*_{\text{LR}_{21}}$ using the values of U_{jk}

Figure 5.3. Solution Algorithm for LR_{21}.

5.3.1.2. Calculation of the upper bound for LR_2. We have found feasible values of $X_{jk}^s, Z_{jk}^s, D_k^s$ and W_k^s variables in LR_{22} that satisfies all constraints except (5.11), which are relaxed. To have a feasible solution to problem LR_2 we need to find feasible U_{jk} values that satisfy constraint (5.11). This is done by the algorithm in Figure 5.5 which has a complexity of $O(|J||K||S|)$. Consequently, an upper bound $z^{UB}_{\text{LR}_2}$ can be obtained for LR_2.

5.3.2. Calculation of the Upper Bound in LHM2

A feasible solution for IRRP can be obtained similar to the upper bound generating procedure in LHM1 as outlined in Section 5.2.2. The values of $R^{c'}_{km_k}$ and D_k^s variables as well as d_k^s and B_U parameters are determined in exactly the same way as

Initialization Set $z^*_{\mathrm{LR}_{22}}$=0 and $X^s_{jk},\ Z^s_{jk},\ D^s_k,\ W^s_k = 0, \forall j,k,s$

for all k, s **do**

  if $\mu_{ks} \leq 0$ **then**

    if $\exists\ j' \in J$ such that $\rho_{j'ks} \leq 0$ and $\tilde{t}^s_{j'k} \leq t_{\max}$ **then**

      Let $j^* = \arg\min_{j'} \rho_{j'ks}$

      $Z^s_{j^*k} = 1$ and $Z^s_{jk} = 0,\ \ \forall j \neq j^*$

      $z^*_{\mathrm{LR}_{22}} = z^*_{\mathrm{LR}_{22}} + \rho_{j^*ks}$

    end if

  else

    Let $D^{max}_{ks} = \sum_d \lambda_d \sum_{m_k} \sum_c \gamma^{cs}_{kd} \alpha_{km_k} b^c_{km_k}$ and $A = D^{max}_{ks}\mu_{ks}$

    if $\exists\ j' \in J$ such that $\tilde{t}^s_{j'k} \leq t_{\max}$ and $p^s c^s_{j'k} D^{max}_{ks} + \rho_{j'ks} \leq A$ **then**

      Let $j^* = \arg\min_{j'} p^s c^s_{j'k} D^{max}_{ks} + \rho_{j'ks}$

      $D^s_k = D^{max}_{ks}$, $Z^s_{j^*k} = 1$, $X^s_{j^*k} = D^{max}_{ks}$, $W^s_k = 0$ and

      $z^*_{\mathrm{LR}_{22}} = z^*_{\mathrm{LR}_{22}} + p^s c^s_{j^*k} X^s_{j^*k} - \mu_{ks} D^s_k + \rho_{j^*ks}$

    end if

    if $\nexists\ j \in J$ such that $\tilde{t}^s_{jk} \leq t_{\max}$ and $p^s c^s_{jk} D^{max}_{ks} + \rho_{jks} \leq A$ **then**

      if $p^s a D^{max}_{ks} \leq A$ **then**

        $D^s_k = D^{max}_{ks}$, $W^s_k = D^{max}_{ks}$ and $X^s_{jk} = 0,\ \ Z^s_{jk} = 0\ \forall j$

        $z^*_{\mathrm{LR}_{22}} = z^*_{\mathrm{LR}_{22}} + D^s_k(p^s a - \mu_{ks})$

      end if

    end if

  end if

end for

Figure 5.4. Solution Algorithm for LR_{22}.

Initialization Set $U_{jk} = 0, \forall j,k$

for all j,k,s **do**

  if $Z_{jk}(s) = 1$ and $v_{jk}(s) = 1$ **then**

    $U_{jk} = 1$

  else

    $U_{jk} = 0$

  end if

end for

Figure 5.5. Finding feasible U_{jk} variables.

explained there. Then, we solve the following model FSP2 (similar to FSP in LHM1) to obtain feasible values for the rest of the variables (i.e., $U_{jk}, X_{jk}^s, Z_{jk}^s$ and W_k^s).

$$\text{FSP2} \quad : \quad \min \sum_j \sum_k u_{jk} U_{jk} \; + \; \sum_j \sum_k \sum_s p^s c_{jk}^s X_{jk}^s \; + \; \sum_k \sum_s p^s a W_k^s \quad (5.32)$$

subject to constraints (5.6), (5.7), (5.11), (5.12), (5.21), (5.22), and

$$Z_{jk}^s, U_{jk} \in \{0,1\} \qquad j \in J, k \in K, s \in S \qquad (5.33)$$

$$X_{jk}^s, W_k^s \geq 0 \qquad j \in J, k \in K, s \in S \qquad (5.34)$$

Instead of solving FSP2, we can solve the following equivalent maximization model where the objective function is obtained by multiplying the objective function (5.32) by (-1).

$$\text{FSP2}' \; : \; \max \sum_j \sum_k -u_{jk} U_{jk} + \sum_j \sum_k \sum_s -p^s c_{jk}^s X_{jk}^s + \sum_k \sum_s -p^s a W_k^s \quad (5.35)$$

subject to constraints (5.6), (5.7), (5.11), (5.12), (5.21), (5.22), (5.33) and (5.34)

The main refinement here is solving FSP2$'$ with a LH instead of CPLEX which was the case in Section 5.2.2. Notice that a feasible solution is a lower bound for FSP2$'$ and we seek for the best lower bound. The upper and lower bound generating algorithms of the FSP2$'$ are given in subsections 5.3.2.1 and 5.3.2.2, respectively.

5.3.2.1. Calculation of upper bound for FSP2$'$. Constraints (5.11) in FSP2$'$ are relaxed using multipliers $\sigma_{jks} \geq 0, \forall j, k, s$ which results in the following two subproblems: FSP2$'_1$ and FSP2$'_2$. The sum of the optimal objective value $z^*_{\text{FSP2}'_1}$ of FSP2$'_1$ and $z^*_{\text{FSP2}'_2}$

of FSP$2_2'$ results in an upper bound for FSP$2'$, i.e. $z^{UB}_{\text{FSP}'} = z^*_{\text{FSP}2_1'} + z^*_{\text{FSP}2_2'}$

$$\text{FSP}2_1' : \max \sum_j \sum_k U_{jk} \left(-u_{jk} + \sum_s \sigma_{jks} \right) - \sum_j \sum_k \sum_s \sigma_{jks} v^s_{jk} + \sum_j \sum_k \sum_s \sigma_{jks} \tag{5.36}$$

subject to constraints (5.21) and

$$U_{jk} \in \{0,1\}$$

$$\text{FSP}2_2' : \max \sum_j \sum_k \sum_s -p^s c^s_{jk} X^s_{jk} + \sum_k \sum_s -p^s a W^s_k - \sum_j \sum_k \sum_s \sigma_{jks} Z^s_{jk} \tag{5.37}$$

subject to constraints (5.6), (5.7), (5.12), (5.22), (5.34) and

$$Z^s_{jk} \in \{0,1\} \tag{5.38}$$

However, instead of finding $z^*_{\text{FSP}2_1'}$, it is sufficient to have an upper bound for FSP$2_1'$ (i.e., $z^{UB}_{\text{FSP}2_1'}$). The LP-relaxation of the FSP$2_1'$ results in an upper bound and it can be solved optimally by using the greedy heuristic algorithm given in Figure 5.6 since it is a fractional knapsack problem. The computational complexity of the algorithm is $O(|J||K|\log(|J||K|))$.

The $z^*_{\text{FSP}2_2'}$ can be found using the algorithm in Figure 5.7. Here, d^s_k is assigned to an RC at site j^* which has the maximum negative cost of satisfying d^s_k. If none of the RCs satisfy the time constraint or the negative shortage cost is greater than any of the negative assignment costs related with RCs, then the d^s_k cannot be satisfied which results in shortage. The computational complexity of the algorithm is $O(|K||S||J|)$.

for all j, k **do**

  if $\sum_s \sigma_{jks} - u_{jk} \geq 0$ **then**

    Calculate $r_{jk} = \frac{\sum_s \sigma_{jks} - u_{jk}}{u_{jk}}$

  end if

end for

Sort all r_{jk} by non-increasing order and add the corresponding j, k indices to list $\mathcal{L}$

Find the smallest j and k indices from list $\mathcal{L}$ such that $\sum_j \sum_k u_{jk} > B_U$ and let them as j^* and k^*

Let the sets of all j, k indices placed before and after j^*, k^* in list $\mathcal{L}$ are called as $\mathcal{V}$ and $\mathcal{Y}$, respectively.

$U_{jk} = 1 \; \forall j, k \in \mathcal{V}$

$U_{j^*k^*} = \frac{B_U - \sum_{j,k \in \mathcal{V}} u_{jk}}{u_{j^*k^*}}$

$U_{jk} = 0 \; \forall j, k \in \mathcal{Y}$

Figure 5.6. Greedy heuristic algorithm to solve $\text{FSP2}_1'$.

Initialization Set $z^*_{\text{FSP2}_2'}$=0 and X^s_{jk}, Z^s_{jk}, $W^s_k = 0, \forall j, k, s$

for all k, s **do**

  Let $A = -p^s a d^s_k$

  if $\exists \; j' \in J$ such that $\tilde{t}^s_{j'k} \leq t_{\max}$ and $\; - p^s c^s_{j'k} d^s_k - \sigma_{j'ks} \geq A$ **then**

    Let $j^* = \arg\max_{j'} \left\{-p^s c^s_{j'k} d^s_k - \sigma_{j'ks}\right\}$

    $Z^s_{j^*k} = 1$, $X^s_{j^*k} = d^s_k$, $W^s_k = 0$ and

    $z^*_{\text{FSP2}_2'} = z^*_{\text{FSP2}_2'} - p^s c^s_{j^*k} X^s_{j^*k} - \sigma_{j^*ks}$

  end if

  if $\nexists \; j \in J$ such that $\tilde{t}^s_{jk} \leq t_{\max}$ and $-p^s c^s_{jk} d^s_k - \sigma_{jks} \geq A$ **then**

    $W^s_k = d^s_k$ and $z^*_{\text{FSP2}_2'} = z^*_{\text{FSP2}_2'} + \text{A}$

  end if

end for

Figure 5.7. Algorithm to solve $\text{FSP2}_2'$.

<u>5.3.2.2. Calculation of lower bound for FSP2$'$.</u> We have found feasible values of X^s_{jk}, Z^s_{jk}, D^s_k and W^s_k variables in $\text{FSP2}_2'$ that satisfy all the constraints of FSP2$'$ except constraints (5.11). To have a feasible solution to FSP2$'$ we need to find feasible U_{jk} vari-

ables with respect to Z_{jk}^s variables, constraint sets (5.11) and (5.21). Then, feasible U_{jk} variables can be found by the algorithm given in Figure 5.8, and also the Z_{jk}^s, X_{jk}^s, W_k^s variables are adjusted with respect to obtained values of U_{jk} variables in the algorithm. Regarding the feasible values of all variables, a lower bound can be obtained for FSP2$'$. The computational complexity of the algorithm is $O\left(|J||K|\left(|S| + \log\left(|J||K|\right)\right)\right)$.

Let *sum*=0 and $U_{jk} = 0, \forall j, k$
Sort all u_{jk} by non-decreasing order and add them with their corresponding j, k indices to list $\mathcal{L}$
for all $j, k \in \mathcal{L}$ **do**
  for all s **do**
    if $Z_{jk}^s = 1$ **then**
      if $v_{jk}^s = 0$ **then**
        if $U_{jk} = 1$ **then**
          Continue
        end if
      else
        if $U_{jk} = 1$ **then**
          Continue
        else
          if $sum + u_{jk} \leq B_U$ **then**
            $U_{jk} = 1$ and $sum = sum + u_{jk}$
          else
            $U_{jk} = 0$, $Z_{jk}^s = 0$, $X_{jk}^s = 0$ and $W_k^s = d_k^s$
          end if
        end if
      end if
    end if
  end for
end for

Figure 5.8. Finding feasible variable values for FSP2$'$.

5.4. Third Lagrangean Heuristic Method

In this Lagrangean heuristic method (LHM3), the same constraints with those considered in the LHM2 (Section 5.3) are relaxed, therefore the same two subproblems are obtained, which are solved by using the same algorithms shown in Section 5.3.1. The only difference is in the upper bound generating algorithm that is depicted in Figures 5.9 and 5.10, and described as follows.

At first, the values of $R^{c'}_{km_k}$ and D^s_k variables are determined due to the previous feasible solution generating algorithm given in Section 5.2.2. The variables satisfy the constraints (5.2) and (5.3). The remaining budget B_U for link retrofitting is calculated by fixing the $R^{c'}_{km_k}$ values. The parameter d^s_k is set to D^s_k, i.e, $d^s_k = D^s_k$.

Then, the algorithm seeks for the feasible values of X^s_{jk}, Z^s_{jk} and W^s_k with respect to constraints (5.6),(5.7), (5.8) and (5.12). Each d^s_k is either assigned to a single RC at site j^* with the minimum transportation cost or it cannot be assigned to any of the RCs which causes a shortage of $W^s_k = d^s_k$. The shortage may occur due to the high transportation time (i.e., $\tilde{t}^s_{jk} \leq t_{\max}$) or high transportation cost (i.e., $cost_j \geq A$ where $A = p^s a d^s_k$).

Finally, the U_{jk} variables are determined with respect to constraint (5.11) and the remaining budget B_U, i.e. constraint (5.21). If a demand assignment is done for scenario s on link (j,k) (i.e., $Z^s_{jk} = 1$) and the link is not vulnerable (i.e., $v^s_{jk} = 0$), then it is not necessary to retrofit the link (i.e., $U_{jk} = 0$). However, if the link is vulnerable (i.e., $v^s_{jk} = 1$), then the link should be retrofitted if the remaining budget is sufficient (i.e., $sum_2 + u_{jk} \leq B_U$), otherwise since it cannot be retrofitted, the variables should be refined as follows: $Z^s_{jk}, U_{jk}, X^s_{jk} = 0$ and $W^s_k = D^s_k$.

The computational complexity of this algorithm is $O\left(|K||M|\left(|C| + \log\left(|K||M|\right)\right)\right)$.

// At first, values of **R** and **D** variables are found //

Let sum_1=0 and $R^{c'}_{km_k} = 0$, for all $k \in K, m_k \in M_k, c' \in C_{km_k}$

$B_R = B - \sum_j \sum_k u_{jk} U_{jk}$ where values of U_{jk} are determined by LR_2

for all $k \in K, m_k \in M_k$ **do**

  Let $c^* = \arg \min_{c' \in C_{km_k}} \left[\sum_c b^c_{km_k} r^{cc'}_{km_k} (1+\theta) + \sum_s \sum_d \lambda_d \gamma^{c's}_{kd} \alpha_{km_k} \mu_{ks} \right]$

  $R^{c^*}_{km_k} = 1$

  Add the $R^{c^*}_{km_k}$ variables with their corresponding k, m_k, c^* indices to set $\mathcal{L}$

end for

Let $p^c_{km_k} = \sum_s \sum_d \lambda_d \gamma^{cs}_{kd} \alpha_{km_k} \mu_{ks}$

Sort the $R^{c^*}_{km_k}$ elements of set $\mathcal{L}$ in non-increasing order with respect to:

$Q^{c^*}_{km_k} = \frac{r^{cc^*}_{km_k}}{p^c_{km_k} - p^{c^*}_{km_k}}$ where $c : b^c_{km_k} = 1$

for all $R^{c^*}_{km_k} \in \mathcal{L}$ **do**

  if $sum_1 + r^{cc^*}_{km_k} \le B_R$ **then**

    $R^{c^*}_{km_k} = 1$

    $sum_1 = sum_1 + r^{cc^*}_{km_k}$

  else

    Set $R^{c^*}_{km_k} = 0$ and $R^c_{km_k} = 1$ for $c : b^c_{km_k} = 1$

  end if

end for

Set $D^s_k = \sum_d \lambda_d \sum_{m_k} \sum_{c' \in C_{km_k}} \gamma^{c's}_{kd} \alpha_{km_k} R^{c'}_{km_k}$ and $d^s_k = D^s_k$

$B_U = B - \sum_k \sum_{m_k} \sum_c \sum_{c' \in C_{km_k}} r^{cc'}_{km} R^{c'}_{km}$

// Then, values of **X**, **Z** and **W** variables are found //

Let $X^s_{jk},\ Z^s_{jk},\ W^s_k = 0, \forall j, k, s$

for all j, k, s **do**

  if $v^s_{jk} = 1$ **then**

    Set $cost^s_{jk} = \left(\frac{u_{jk}}{no.of scenarios - s} \right) + p^s c^s_{j^*k} d^s_k$

  else

    Set $cost^s_{jk} = p^s c^s_{j^*k} d^s_k$

  end if

end for

Figure 5.9. Feasible solution generating algorithm of LHM3.

for all k, s **do**
  Let $A = p^s ad_k^s$, sum_2=0
  if $\exists\ j' \in J$ such that $\tilde{t}_{j'k}^s \leq t_{\max}$ and $cost_{j'k}^s \leq A$ **then**
    Let $j^* = \arg\min_{j'} cost_{j'k}^s$ and $Z_{j^*k}^s = 1$, $X_{j^*k}^s = d_k^s$, $W_k^s = 0$
  end if
  if $\nexists\ j$ satisfying $\tilde{t}_{jk}^s \leq t_{\max}$ and $cost_{jk}^s \leq A$ **then**
    $W_k^s = d_k^s$
  end if
end for
//At last, **U** variables are determined and other variables are adjusted//
Let $U_{jk} = 0$, $\forall j, k$. Sort all u_{jk} by non-decreasing order and add them with their corresponding j, k indices to list $\mathcal{V}$
for all $j, k \in \mathcal{V}$ **do**
  for all s **do**
    if $Z_{jk}^s = 1$ **then**
      if $v_{jk}^s = 0$ **then**
        if $U_{jk} = 1$ **then**
          Continue
        end if
      else
        if $U_{jk} = 1$ **then**
          Continue
        else
          if sum_2+$u_{jk} \leq B_U$ **then**
            $U_{jk} = 1$ and sum_2=sum_2+u_{jk}
          else
            $U_{jk} = 0$, $Z_{jk}^s = 0$, $X_{jk}^s = 0$ and $W_k^s = d_k^s$
          end if
        end if
      end if
    end if
  end for
end for

Figure 5.10. Feasible solution generating algorithm of LHM3 (cont'd.).

6. EXPERIMENTAL RESULTS

6.1. Computational Experiments for TSLP

6.1.1. Instance Generation

We performed computational experiments on a set of randomly generated test instances which are labeled with respect to three factors as $I/J/K$ where $|I|$, $|J|$, and $|K|$ denote the number of potential RRC sites, the number of potential LRC sites, and the number of demand points, respectively. The following values are assigned to these factors in the problem instances: $|I| \in \{5, 10\}$, $|J| \in \{10, 20, 40\}$, and $|K| \in \{50, 75, 100, 200, 400, 600, 800\}$. The coordinates of the potential RRC and LRC sites as well as the demand points are generated uniformly on the interval [0,100]. Fixed cost f_i of an RRC and g_j^s of an LRC are integer values drawn randomly from the uniform distribution supported in the intervals $[60000, 140000]$ and $[6000, 12000]$, respectively. Each unit of unsatisfied demand incurs a cost of 10000 monetary units, that is unit penalty cost for shortage $a_l = 10000$. Two scenario types are generated, each consisting of $|S| = 4$ scenarios with the following intensity values: $\boldsymbol{\mu} = (1.0, 1.1, 1.3, 1.8)$. The difference between the scenario types is the probabilities assigned to the scenarios where $\mathbf{p} = (0.25, 0.25, 0.25, 0.25)$ in the first scenario type and $\mathbf{p} = (0.40, 0.25, 0.25, 0.10)$ in the second one. This implies that the probability of the earthquake scenario with the lowest (highest) intensity is increased (decreased) in the second scenario type. The transportation times t_{ij}^s, and transportation costs c_{ijl}^s and c_{jkl}^s depend on the realized scenario s. We generate these values by multiplying the Euclidean distances between the facility sites and customer locations with the intensity μ^s of the corresponding scenario. This implies that the transportation between the nodes of the network becomes more difficult as a result of increased damage realized at higher earthquake intensity values.

We consider only one relief item l, and its demand d_{kl}^s at demand point k under scenario s is assumed to be proportional to the intensity μ^s. Utilizing the regression analysis for Turkey carried out by Şengezer and Ansal [96] for the relationship between the earthquake intensity and resulting damage, we set $d_{kl}^{s} = \gamma^{s} d_{kl}^{\hat{s}}$ where $d_{kl}^{\hat{s}}$ is the demand corresponding to the scenario with the smallest intensity (i.e., the scenario with $\mu^{\hat{s}} = 1$) and γ^{s} is a scenario-dependent coefficient. The values of $d_{kl}^{\hat{s}}$ follow a discrete uniform distribution defined in the interval [5,12] and $\boldsymbol{\gamma} = (1.0, 2.25, 4.0, 6.25)$. The test instances are further classified as *loose*, *tight* and *cap_inf* on the basis of the ratio of the total demand under the scenario with the largest intensity to the total LRC capacity, which is distributed uniformly in the interval of [0.55, 0.70], [0.80, 0.90] and [1.01, 1.05], respectively. This means that in the case of loose (tight) instances there exist a large (small) slack capacity at the LRCs. In the "cap_inf" class of instances it is not possible to satisfy the demand with the installed capacity. For each instance, two $t_{\max}$ values are defined: $t_l = \max\{t_{\max}^{1}, t_{\text{avg}}^{2}\}$ and $t_h = \max\{t_{\max}^{3}, t_{\text{avg}}^{4}\}$ where $t_{\max}^{s}$ and t_{avg}^{s} represent, respectively, the maximum and the average of transportation times between open RRCs and LRCs under scenario s.

Both the LH and LS phases of the solution approach are implemented in C# and the computations are carried out on a computer with Intel Xeon 3.16 GHz processor and 16 GB of RAM. The following criteria are used as the stopping condition for the LH, which means that as soon as one of these criteria is met, the LH is terminated: (i) the gap between the best upper bound (UB) (or equivalently the objective value of the best feasible solution) and the best lower bound (LB) falls below 0.5%, (ii) the running time exceeds 1800 CPU seconds, (iii) the number of iterations becomes 5000. The Lagrange multipliers are initialized with the values of the dual variables obtained from solving the LP relaxation of the model. Upon the termination of the LH, the LS improvement heuristic runs for at least 5400 seconds so that a time limit of 7200 seconds (two hours) is allotted for the proposed solution approach. To evaluate the performance of the solution approach, the test instances are also solved by commercial solver CPLEX 11.1 [97] within the same time limit.

6.1.2. Experimental Results

The results are displayed in Table 6.1 and 6.2 for scenario type 1 with $\mathbf{p} = (0.25, 0.25, 0.25, 0.25)$, and in Table 6.3 for scenario type 2 with $\mathbf{p} = (0.40, 0.25, 0.25, 0.10)$. They are expressed in terms of percent deviation of both the lower bound and upper bound (objective value of the best feasible solution) found by CPLEX ($z_{\mathrm{LB}}^{\mathrm{CP}}$ and $z_{\mathrm{UB}}^{\mathrm{CP}}$) and the Lagrangean heuristic LH ($z_{\mathrm{LB}}^{\mathrm{LH}}$ and $z_{\mathrm{UB}}^{\mathrm{LH}}$) from the best lower bound $\mathrm{LB}_{\mathrm{best}}$ that is available. Moreover, the percent deviation of the upper bound corresponding to the best feasible solution found by the local search improvement heuristic LS ($z_{\mathrm{UB}}^{\mathrm{LHS}}$) is also reported. Notice that $z_{\mathrm{LB}}^{\mathrm{LH}}$ and $z_{\mathrm{UB}}^{\mathrm{LHS}}$ indicate the final performance of the overall solution method, referred to as LHS. $\mathrm{LB}_{\mathrm{best}}$ is computed by taking the maximum of three quantities: the lower bound given by CPLEX ($z_{\mathrm{LB}}^{\mathrm{CP}}$), the optimal objective value provided by the LP-relaxation of the problem ($z_{\mathrm{LB}}^{\mathrm{LP}}$), and the lower bound obtained by CPLEX when the original problem is solved by relaxing the single-sourcing restriction ($z_{\mathrm{LB}}^{\mathrm{SS}}$). In other words, $\mathrm{LB}_{\mathrm{best}} = \max\left\{z_{\mathrm{LB}}^{\mathrm{CP}}, z_{\mathrm{LB}}^{\mathrm{LP}}, z_{\mathrm{LB}}^{\mathrm{SS}}\right\}$. Then, the percent deviations of the lower bounds are computed as $\mathrm{PD}_{\mathrm{LB}}^{\ell} = 100 \times (z_{\mathrm{LB}}^{\ell} - \mathrm{LB}_{\mathrm{best}})/\mathrm{LB}_{\mathrm{best}}$, where $\ell \in \{\mathrm{CP}, \mathrm{LH}\}$, and those of the upper bounds are computed as $\mathrm{PD}_{\mathrm{UB}}^{\ell} = 100 \times (z_{\mathrm{UB}}^{\ell} - \mathrm{LB}_{\mathrm{best}})/\mathrm{LB}_{\mathrm{best}}$, where $\ell \in \{\mathrm{CP}, \mathrm{LH}, \mathrm{LHS}\}$.

Results in Table 6.1 and 6.2 indicate that LHS performs quite satisfactory with an average percent deviation of 2.55% over all 60 test instances. For the loose instances, it yields solutions that are on the average 2.71% away from the best lower bound, while for the tight instances the average percent deviation is 2.38%. CPLEX, on the other hand, yields feasible solutions that are 10.15% (13.00%) away on the average from the best lower bound for the loose (tight) instances. Especially for larger instances beginning with 5/40/600, the proposed LHS outperforms CPLEX within 7200 seconds of computation time. These average results indicate that LHS gives much better solutions than CPLEX in 7200 seconds. As can be observed by the standard deviations of 1.39% and 1.38% for loose and tight instances, respectively, LHS is also quite robust in terms of generating feasible solutions.

When we investigate the improvement that the LS heuristic brings upon the

Table 6.1. Test results for loose instances with scenario type 1.

Problem	t_{max}	$\text{PD}_{\text{LB}}^{\text{CP}}$	$\text{PD}_{\text{LB}}^{\text{LH}}$	$\text{PD}_{\text{UB}}^{\text{CP}}$	$\text{PD}_{\text{UB}}^{\text{LH}}$	N	$\text{PD}_{\text{UB}}^{\text{LHS}}$
5/10/50	t_l	0.00	-13.86	0.10	1.65	400	1.48
	t_h	0.00	-15.56	0.94	2.93	721	1.30
5/10/75	t_l	0.00	-9.82	0.00	4.65	1057	1.40
	t_h	0.00	-13.36	0.05	2.95	1394	1.87
5/10/100	t_l	0.00	-3.93	0.25	1.14	313	1.14
	t_h	0.00	-5.50	0.09	1.69	100	0.86
5/20/100	t_l	0.00	-7.62	0.94	4.44	1948	1.80
	t_h	-0.24	-8.30	1.86	3.86	324	2.46
5/20/200	t_l	-0.05	-2.49	0.35	2.25	447	1.16
	t_h	-0.27	-3.21	0.22	2.79	2883	1.22
5/20/400	t_l	-0.91	-6.97	0.99	3.44	2476	1.21
	t_h	0.00	-6.96	0.17	3.29	808	1.68
5/40/100	t_l	-0.12	-2.74	3.69	6.50	51	3.62
	t_h	-0.13	-3.08	2.88	8.25	895	3.55
5/40/200	t_l	-0.23	-3.49	3.36	6.67	762	2.18
	t_h	-1.03	-3.39	6.72	6.57	762	2.13
5/40/400	t_l	0.00	-3.56	14.49	7.89	3041	3.94
	t_h	-1.46	-4.80	10.42	7.84	57	2.66
5/40/600	t_l	-0.06	-3.20	33.15	5.16	567	3.79
	t_h	0.00	-3.74	6.81	4.62	2133	3.12
5/40/800*	t_l	-0.62	-3.40	36.42	3.50	1518	1.99
	t_h	-0.83	-3.47	23.60	3.90	2132	3.90
10/40/200	t_l	0.00	-3.46	5.63	8.36	3101	4.03
	t_h	0.00	-3.47	6.73	9.39	802	4.27
10/40/400	t_l	-0.27	-1.69	12.69	3.97	621	1.45
	t_h	-0.34	-1.94	5.67	4.42	1330	3.06
10/40/600	t_l	0.00	-3.17	25.02	6.56	79	5.47
	t_h	0.00	-3.14	38.56	7.32	161	5.66
10/40/800*	t_l	0.00	-2.59	32.53	6.35	1681	3.87
	t_h	0.00	-2.61	30.06	6.13	688	4.99
Average		-0.22	-5.15	10.15	4.95	1047.42	2.71
Std. Dev.		0.37	3.66	12.71	2.24	960.24	1.39

solution provided by LH, we observe that the solution quality of LH is 4.95% for the loose instances and 3.82% for the tight ones. This implies that LS improves the solution by 2.24% and 1.44% on the average for loose and tight instances, respectively. Regarding the running time of LH, 1800 seconds turn out to be sufficient to complete 5000 iterations except for four instances that are marked by "$*$" in Table 6.1 and 6.2.

Table 6.2. Test results for tight instances with scenario type 1.

Problem	t_{max}	$\mathrm{PD}_{\mathrm{LB}}^{\mathrm{CP}}$	$\mathrm{PD}_{\mathrm{LB}}^{\mathrm{LH}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{CP}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LH}}$	N	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHS}}$
5/10/50	t_l	0.00	-7.23	0.04	1.18	3857	0.54
	t_h	0.00	-3.09	0.22	1.63	3051	0.64
5/10/75	t_l	0.00	-4.09	0.03	1.66	340	0.15
	t_h	0.00	-6.53	0.04	1.99	1511	1.19
5/10/100	t_l	0.00	-2.22	0.14	1.11	357	0.29
	t_h	0.00	-3.71	0.05	1.11	1009	0.20
5/20/100	t_l	0.00	-5.78	1.43	3.92	2809	1.94
	t_h	-0.21	-1.62	0.98	2.19	1394	1.56
5/20/200	t_l	-0.10	-2.33	0.21	3.30	1026	0.61
	t_h	-0.11	-2.91	0.21	3.52	1611	1.40
5/20/400	t_l	-0.50	-3.93	1.13	3.57	1534	1.19
	t_h	-0.21	-4.00	0.20	3.66	2984	1.42
5/40/100	t_l	-0.04	-6.07	5.23	9.15	1503	4.54
	t_h	-0.07	-0.97	15.24	5.24	2760	4.41
5/40/200	t_l	-0.10	-1.15	3.63	4.45	2515	2.39
	t_h	-0.22	-1.22	2.95	4.36	1558	2.88
5/40/400	t_l	-1.29	-2.94	7.14	5.31	1123	2.82
	t_h	-1.72	-3.28	3.43	5.43	671	2.41
5/40/600	t_l	0.00	-1.41	12.22	4.72	1602	3.62
	t_h	-0.57	-2.27	61.72	5.43	1830	3.01
5/40/800*	t_l	0.00	-1.24	15.36	3.58	1387	3.15
	t_h	0.00	-1.11	5.52	3.26	708	2.53
10/40/200	t_l	-0.16	-1.01	11.64	4.36	956	2.74
	t_h	-0.05	-0.98	10.96	4.04	1509	2.95
10/40/400	t_l	0.00	-1.15	48.09	4.95	1101	3.84
	t_h	-0.10	-1.20	24.32	5.29	1041	2.91
10/40/600	t_l	-0.06	-1.69	32.81	3.90	1779	3.90
	t_h	0.00	-1.56	48.03	4.25	936	4.25
10/40/800*	t_l	0.00	-1.53	41.32	3.89	704	3.89
	t_h	0.00	-1.43	35.71	4.14	1391	4.14
Average		-0.18	-2.65	13.00	3.82	1749.81	2.38
Std. Dev.		0.39	1.80	17.65	1.67	987.68	1.38

In these tables, N denotes the iteration number at which the best feasible solution is found by LH. The average of the iteration numbers that are calculated by ignoring the four instances with "$*$" is given as 1047.42 and 1749.81 for loose and tight instances, respectively. However, as indicated by the standard deviation of N, which is close to 1000 in both cases, we cannot conclude about the possibility of obtaining better feasible solutions when more time is allotted for Lagrangean iterations. Nevertheless, based on the additional experiments carried out, we can say that the benefit of performing more iterations is not remarkable and hence should not be preferred at the expense of reducing the running time of LS, which improves the solution quality of LH by more than 2% on the average.

A comparison of the percent deviations of the lower bounds reveals that CPLEX outperforms LH for each test instance. In fact, CPLEX provides the best lower bound for half of the 60 instances considered, that is $\mathrm{LB}_{\mathrm{best}} = z_{\mathrm{LB}}^{\mathrm{CP}}$, while $\mathrm{LB}_{\mathrm{best}} = z_{\mathrm{LB}}^{\mathrm{SS}}$ for the remaining instances.

The results obtained for scenario type 2 instances are similar to those of scenario type 1 instances. Therefore, we present them in a more compact form in Table 6.3 by combining loose and tight instances, and excluding the iteration number N corresponding to the best solution of LH as well as the percent deviation of the upper bound $\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LH}}$ obtained by LH. LHS is again better than CPLEX in terms of generating feasible solutions with an average percent deviation of 2.51% and 2.62% for loose and tight instances, respectively. In terms of the lower bounds, CPLEX once again performs better than LH, and provides the best one in 29 out of 60 instances.

When we compare the three approaches used in generating lower bounds, we observe that among all 120 instances reported in Table 6.1–6.3, $z_{\mathrm{LB}}^{\mathrm{CP}}$ is the best lower bound for 59 instances and $z_{\mathrm{LB}}^{\mathrm{SS}}$ is the best one for the remaining 61 instances. It is to be emphasized that for a quite large number of instances solving the original problem optimally by relaxing the single-sourcing restriction to attain $z_{\mathrm{LB}}^{\mathrm{SS}}$ is not possible within 7200 seconds. The optimality gap is greater than 1% in 32 out of 120 instances and in 16 out of 61 instances where the best lower bound is provided by this approach, i.e., $\mathrm{LB}_{\mathrm{best}} = z_{\mathrm{LB}}^{\mathrm{SS}}$. We also observe that $\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHS}}$ does not change significantly depending on $t_{\max}$. It is found to be 2.53% and 2.59% for t_l and t_h, respectively.

We also investigate the total shortage costs for the loose and tight instances given in Table 6.1-6.3. Shortage occurs for 22 out of 60 loose instances and 24 out of

Table 6.3. Test results for scenario type 2.

Instance	t_{max}	Loose				Tight			
		$\text{PD}_{\text{LB}}^{\text{CP}}$	$\text{PD}_{\text{LB}}^{\text{LH}}$	$\text{PD}_{\text{UB}}^{\text{CP}}$	$\text{PD}_{\text{UB}}^{\text{LHS}}$	$\text{PD}_{\text{LB}}^{\text{CP}}$	$\text{PD}_{\text{LB}}^{\text{LH}}$	$\text{PD}_{\text{UB}}^{\text{CP}}$	$\text{PD}_{\text{UB}}^{\text{LHS}}$
5/10/50	t_l	0.00	-11.76	0.22	0.79	0.00	-12.62	0.02	0.77
	t_h	0.00	-15.74	0.26	0.76	0.00	-15.67	0.04	0.83
5/10/75	t_l	0.00	-6.55	0.06	0.74	0.00	-9.00	0.42	1.14
	t_h	0.00	-12.03	0.07	0.81	0.00	-6.20	0.33	0.90
5/10/100	t_l	0.00	-10.10	0.06	0.58	0.00	-5.33	0.54	1.16
	t_h	0.00	-11.32	0.07	0.66	0.00	-5.36	0.57	0.80
5/20/100	t_l	0.00	-7.34	0.22	0.35	-0.05	-21.47	1.28	1.83
	t_h	-0.31	-8.84	0.31	0.63	-0.29	-3.35	0.83	1.13
5/20/200	t_l	0.00	-7.52	0.10	1.48	-0.23	-4.41	0.60	1.12
	t_h	-0.10	-9.79	0.23	1.18	-0.08	-4.67	0.77	1.27
5/20/400	t_l	0.00	-6.36	0.05	1.21	-0.27	-4.99	4.60	4.64
	t_h	-1.78	-6.18	0.23	1.41	-0.04	-4.51	0.56	1.33
5/40/100	t_l	-1.42	-5.05	16.02	2.67	-0.02	-2.95	4.04	3.51
	t_h	-0.07	-5.11	3.04	2.90	0.00	-4.01	4.51	3.71
5/40/200	t_l	-0.78	-4.08	12.86	2.27	-2.57	-5.47	5.96	2.61
	t_h	-1.60	-4.33	9.78	1.94	-0.11	-1.96	4.45	2.99
5/40/400	t_l	-0.70	-3.56	54.46	3.27	-0.27	-2.11	6.67	2.72
	t_h	-1.15	-4.10	10.51	2.71	-0.37	-2.49	3.14	2.24
5/40/600	t_l	0.00	-2.56	10.56	3.47	-0.27	-1.29	13.81	1.75
	t_h	0.00	-2.53	25.09	3.71	-0.06	-1.26	2.96	1.60
5/40/800	t_l	-1.02	-3.17	14.45	3.47	-0.42	-1.79	17.81	5.57
	t_h	-0.38	-2.53	1.82	4.28	0.00	-1.95	26.09	5.33
10/40/200	t_l	-1.15	-3.82	31.74	2.62	-0.41	-1.66	4.22	3.19
	t_h	-0.28	-2.89	15.29	3.40	-0.18	-1.58	4.59	3.35
10/40/400	t_l	0.00	-3.20	7.82	2.96	-0.11	-1.56	15.98	3.16
	t_h	0.00	-3.30	16.74	2.93	0.00	-1.46	17.87	3.98
10/40/600	t_l	0.00	-3.30	48.15	5.05	-0.02	-0.45	18.17	2.74
	t_h	0.00	-3.36	24.46	5.37	0.00	-0.39	7.25	2.80
10/40/800	t_l	0.00	-4.04	25.46	5.47	0.00	-2.35	40.92	5.16
	t_h	0.00	-3.33	24.10	6.30	0.00	-2.35	12.04	5.29
Average		-0.36	-5.93	11.81	2.51	-0.19	-4.49	7.37	2.62
Std. Dev.		0.56	3.49	14.51	1.66	0.47	4.69	9.39	1.52

60 tight instances. Although the unit penalty cost for shortage is about the same as the mean fixed cost of an LRC, on the average the percentage of the total shortage cost is 17% and 18% of the total cost, and 61% and 66% of the total facility operating cost for loose and tight instances, respectively. To assess the performance of LHS

for instances with high shortage amounts, we carry out further experiments with 30 "cap_inf" instances where the total capacity of the LRCs is not sufficient to satisfy the relief item demand for some scenarios. This implies that shortage must necessarily occur for these instances. The results are in line with our earlier findings regarding the quality of the upper bounds. The percent deviations of LHS are given as $\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHS}} = 2.3\%$ and $\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHS}} = 2.57\%$ for scenario type 1 and type 2 instances, respectively, while those of CPLEX are $\mathrm{PD}_{\mathrm{UB}}^{\mathrm{CP}} = 5.26\%$ and $\mathrm{PD}_{\mathrm{UB}}^{\mathrm{CP}} = 8.03\%$ for the same instances. We note, however, that the performance of LH in generating lower bounds is better for "cap_inf" instances with $\mathrm{PD}_{\mathrm{LB}}^{\mathrm{LH}} = -1.87\%$ for scenario type 1 and $\mathrm{PD}_{\mathrm{LB}}^{\mathrm{LH}} = -1.24\%$ for scenario type 2. Moreover, the percentage of the total shortage cost is 36% of the total cost and 141% of the total facility operating cost on the average.

When we look at the results in general, we can conclude that the proposed solution procedure LHS is effective in finding good feasible solutions even for large-sized instances including up to 10 potential RRC sites, 40 potential LRC sites, and 800 demand points with four earthquake scenarios. The performance of CPLEX, however, decreases considerably as the size of the problem instance increases.

6.1.3. Expected value of perfect information and value of stochastic solution

If we have the perfect information about the future realization of an earthquake in advance, then we can make an optimal decision for each scenario. The objective value (WS) of the so-called wait-and-see solution is defined as the expected value over the objective values corresponding to the optimal solutions of the scenarios. It is possible to define the expected value of perfect information (EVPI) as the difference between the objective value (SP) of the stochastic programming solution and WS, i.e., EVPI = SP − WS. It can be interpreted as a measure for the cost of uncertainty. The value of the stochastic solution (VSS), on the other hand, is the cost of ignoring uncertainty in making a decision [38]. Instead of solving a two-stage stochastic programming problem, one can obtain a deterministic problem solution by replacing all random parameters by their expected values or by solving a reference scenario. By fixing the first stage decisions of the deterministic solution, the objective values corresponding to all scenario solutions can be computed. This gives rise to the computation of EEV which is defined as the expected value over the objective values associated with the different scenarios. Finally, VSS is expressed as VSS = EEV − SP.

It turns out that in calculating the VSS for our problem instances, it is not appropriate to use the expected values of the random parameters to find the deterministic problem solution and hence EEV because of the fact that when the first stage decisions (RRC locations and amount of relief items stored at the RRCs) are determined with respect to the expected or mean demand values, then scenario solutions for higher demand scenarios (e.g., scenario 4) result in large amounts of shortages. This occurs since the stored amounts of relief items do not suffice to meet the demand for these scenarios, which results in high values of EEV and thus VSS. Therefore, we calculate the deterministic problem solution with respect to the parameters of the highest demand scenario that constitutes the reference scenario.

Table 6.4 includes the EVPI and VSS values expressed in terms of percentages for scenario type 1 and scenario type 2 instances. Namely, EVPI% $= 100 \times (\text{SP} - \text{WS})/\text{SP}$ and VSS% $= 100 \times (\text{EEV} - \text{SP})/\text{EEV}$. Since we limit the computation time for finding the optimal solution of each scenario to be used in calculating WS and for determining the optimal solution of each scenario by fixing the first stage decisions that are used in computing EEV, it turns out that some instances can only be solved with an optimality gap. Furthermore, we also have best LB and best UB values for the SP solutions as displayed in Table 6.1–6.3. Hence, EVPI% and VSS% values can only be reported as intervals rather than single numbers.

The *average* EVPI% and VSS% values calculated over 60 instances are in the range of [5.1%, 9.8%] and [3.9%, 6.2%]. VSS% is close to zero for some instances, while it is about 20% for some others. This indicates that solving the problem using stochastic programming may indeed be useful. When the number of opened RRC facilities is larger in the reference scenario (scenario 4) solution than that in the SP solution, higher VSS% values can be obtained since high fixed costs of RRCs result in high EEV values.

Table 6.4. EVPI and VSS values for scenario type 1 and type 2 instances.

Instances	Scenario Type	Loose EVPI	Loose VSS	Tight EVPI	Tight VSS
5/10/50	1	[1.5, 1.6]	[0.0, 0.1]	[14.0, 14.0]	[0.0, 0.0]
	2	[2.6, 2.8]	[9.0, 9.2]	[29.3, 29.4]	[0.0, 0.0]
5/10/75	1	[1.8, 1.8]	[0.0, 0.0]	[1.9, 1.9]	[0.0, 0.0]
	2	[2.4, 2.5]	[0.0, 0.1]	[10.9, 11.3]	[0.0, 0.1]
5/10/100	1	[2.1, 2.4]	[0.0, 0.1]	[2.0, 2.1]	[0.0, 0.1]
	2	[2.9, 3.0]	[0.0, 0.1]	[6.8, 7.4]	[0.0, 0.5]
5/20/100	1	[3.5, 4.4]	[0.0, 0.5]	[17.6, 19.0]	[0.0, 1.3]
	2	[2.4, 2.6]	[0.0, 0.2]	[23.2, 24.5]	[0.0, 1.1]
5/20/200	1	[1.9, 2.2]	[13.8, 14.1]	[1.8, 2.0]	[0.0, 0.2]
	2	[3.5, 3.6]	[0.0, 0.1]	[4.4, 5.0]	[13.8, 14.3]
5/20/400	1	[7.0, 7.9]	[4.5, 5.5]	[9.1, 10.2]	[3.8, 5.0]
	2	[9.7, 9.8]	[10.2, 10.5]	[7.8, 12.5]	[10.7, 14.7]
5/40/100	1	[0.0, 4.7]	[0.0, 2.0]	[6.6, 14.1]	[0.0, 3.6]
	2	[1.8, 6.1]	[0.0, 3.3]	[0.1, 5.9]	[0.0, 2.3]
5/40/200	1	[4.4, 7.5]	[1.3, 4.5]	[1.7, 7.4]	[4.6, 7.9]
	2	[4.5, 11.0]	[14.5, 16.8]	[10.8, 14.6]	[0.0, 1.7]
5/40/400	1	[2.9, 11.2]	[0.0, 3.3]	[5.8, 10.7]	[0.0, 1.9]
	2	[4.7, 12.2]	[3.0, 6.6]	[5.1, 11.1]	[8.9, 12.4]
5/40/600	1	[1.8, 10.4]	[4.9, 10.2]	[7.0, 11.8]	[4.9, 8.9]
	2	[3.4, 13.3]	[5.4, 8.8]	[6.4, 12.5]	[0.0, 0.8]
5/40/800	1	[4.9, 10.3]	[2.9, 5.6]	[3.7, 8.2]	[6.2, 9.8]
	2	[5.3, 14.1]	[0.0, 0.4]	[5.4, 16.9]	[4.6, 10.4]
10/40/200	1	[3.6, 12.0]	[20.9, 24.3]	[0.5, 7.7]	[3.8, 7.9]
	2	[2.3, 10.1]	[12.8, 15.9]	[2.8, 10.8]	[5.3, 9.6]
10/40/400	1	[3.1, 7.3]	[6.8, 9.4]	[2.8, 11.1]	[0.0, 3.6]
	2	[2.3, 12.5]	[12.1, 15.0]	[2.5, 11.3]	[19.3, 22.6]
10/40/600	1	[2.7, 12.6]	[6.1, 12.1]	[2.3, 12.4]	[1.8, 6.3]
	2	[6.0, 15.3]	[5.6, 10.7]	[5.3, 10.4]	[2.0, 5.6]
10/40/800	1	[2.8, 11.5]	[1.5, 5.7]	[3.1, 12.3]	[0.0, 3.8]
	2	[4.1, 16.6]	[4.6, 10.1]	[3.7, 16.2]	[3.7, 9.9]
Average	1	[2.9, 7.2]	[4.2, 6.5]	[5.3, 9.7]	[1.7, 4.0]
	2	[3.9, 9.0]	[5.2, 7.2]	[8.3, 13.3]	[4.5, 7.1]

It can be observed that the EVPI% and VSS% values are higher for scenario type 2 instances. High VSS% values can be attributed to the fact that the solution of the reference scenario cannot represent the optimal first stage decisions adequately due to the relatively low probability assigned to the this scenario.

6.1.4. Effect of the number of scenarios on the solution quality

We also assess the performance of our solution method on instances with 10 and 25 scenarios. Based on the results given in Section 6.1.2, we can say that parameter $t_{\max}$ and the scenario type do not have an important effect on the performance. Thus, we conduct numerical experiments with instances having 10 and 25 scenarios for $t_{\max} = t_l$ and scenario type 1. It is assumed that each scenario has the same probability. The intensity values are set to $\mu^s = 1 + 0.1 \times (s - 1)$ in the 10 scenario case and $\mu^s = 1 + 0.05 \times (s - 1)$ in the 25 scenario case. The values of γ^s coefficients are taken as $\gamma^s = (\mu^s)^2$ for scenario s in both the 10 and 25 scenario cases. All the cost parameter values, the time limit for the runs and the time allocation for LH and LS in the solution method are the same as the previous settings given in Section 6.1.1.

Table 6.5. Results for 10 scenario instances.

	Loose				Tight			
Instance	$\mathrm{PD}_{\mathrm{LB}}^{\mathrm{CP}}$	$\mathrm{PD}_{\mathrm{LB}}^{\mathrm{LH}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{CP}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHS}}$	$\mathrm{PD}_{\mathrm{LB}}^{\mathrm{CP}}$	$\mathrm{PD}_{\mathrm{LB}}^{\mathrm{LH}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{CP}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHS}}$
5/10/50	-0.26	-11.49	0.27	0.66	0.00	-8.03	0.53	1.09
5/10/75	0.00	-4.33	0.19	0.89	0.00	-18.03	0.22	1.11
5/10/100	0.00	-10.96	0.57	1.00	0.00	-8.28	0.18	1.04
5/20/100	-0.03	-6.53	2.99	1.89	0.00	-9.29	4.20	2.11
5/20/200	-0.11	-3.91	32.27	3.81	0.00	-4.62	4.82	4.83
5/20/400	0.00	-4.26	26.22	5.66	0.00	-4.74	5.65	2.03
5/40/100	0.00	-3.36	5.16	4.33	0.00	-6.82	3.25	3.69
5/40/200	-0.19	-1.50	9.44	2.89	0.00	-0.58	3.99	2.88
5/40/400	0.00	-2.42	25.58	5.41	0.00	-0.53	69.78	4.06
5/40/600*	0.00	-1.54	13.93	5.32	0.00	-1.20	24.83	5.76
5/40/800*	0.00	-1.44	4.43	4.64	0.00	-1.20	54.63	5.98
10/40/200	0.00	-1.39	15.02	3.88	0.00	-0.81	83.78	5.60
10/40/400	0.00	-2.27	175.63	6.95	0.00	-0.32	94.48	5.66
10/40/600	0.00	-2.04	197.93	6.73	-0.06	-1.03	111.47	4.65
10/40/800*	0.00	-1.59	46.09	5.31	0.00	-5.44	52.64	3.28
Average	-0.04	-3.93	37.05	3.96	0.00	-4.73	34.30	3.58
Std. Dev.	0.08	3.30	62.40	2.08	0.02	4.89	39.70	1.81

The results for the instances with 10 scenarios show that on the average, LHS finds feasible solutions with 3.96% and 3.58% deviation from the best LB for loose and

Table 6.6. Results for 25 scenario instances.

Instance	Loose				Tight			
	PD_{LB}^{CP}	PD_{LB}^{LH}	PD_{UB}^{CP}	PD_{UB}^{LHS}	PD_{LB}^{CP}	PD_{LB}^{LH}	PD_{UB}^{CP}	PD_{UB}^{LHS}
5/10/50	-0.05	-9.33	1.19	0.36	0.00	-13.15	1.55	2.34
5/10/75	-0.92	-12.13	0.81	1.50	-0.13	-1.47	1.17	2.58
5/10/100	-0.16	-3.98	0.84	0.66	-0.01	-4.80	1.98	1.74
5/20/100	-0.02	-4.60	2.79	1.91	0.00	-4.35	4.05	2.48
5/20/200	0.00	-3.84	36.40	4.66	0.00	-1.84	29.44	4.91
5/20/400	0.00	-2.96	33.17	3.11	0.00	-2.44	39.62	4.75
5/40/100	0.00	-1.94	5.79	3.14	0.00	-0.86	26.12	5.99
5/40/200	0.00	-2.44	147.68	6.87	0.00	-0.66	93.67	3.55
5/40/400*	0.00	-1.46	61.13	8.44	0.00	-0.84	70.89	6.41
5/40/600*	0.00	-2.79	87.51	6.86	0.00	-2.48	47.76	5.86
5/40/800*	0.00	-5.16	143.71	5.30	0.00	-7.06	21.15	6.99
10/40/200†	0.00	-3.61	60.42	6.76	0.00	-1.24	53.75	6.35
10/40/400†	0.00	-1.97	61.46	6.31	0.00	-1.30	82.38	8.42
10/40/600†	0.00	-2.65	25.24	7.75	0.00	-1.68	52.40	7.02
10/40/800†	0.00	-2.11	133.87	7.54	0.00	-1.77	166.18	4.37
Average	-0.08	-4.06	53.47	4.74	-0.01	-3.06	47.92	4.92
Std. Dev.	0.24	2.95	53.07	2.75	0.03	3.30	46.10	2.03

tight instances, respectively. The performance of CPLEX is rather poor since the best solutions it produces are 37.05% and 34.30% away from the best LB on the average. Moreover, since CPLEX cannot provide a feasible solution within a time limit of 2 hours for 3 out of 15 instances, we run it for 10 hours to solve these instances. We note, however, that PD_{LB}^{LH} and PD_{UB}^{LHS} values are still obtained within 2 hours running time. As displayed in Table 6.6, similar results are obtained for the instances with 25 scenarios, where LHS produces feasible solutions that are 4.74% and 4.92% away from the best LB for loose and tight instances, respectively. CPLEX is given 10 hours to provide a feasible solution for the instances that are labeled with an "$*$". Since for the instances with 10 potential RRC sites and 40 demand points, which are labeled with a "†", CPLEX either does not yield a feasible solution or gives an inferior solution even after running 10 hours, a time limit of 24 hours is alloted to CPLEX for these instances. When we evaluate the overall results, we can assert that the proposed solution method LHS is capable of solving instances up to 25 scenarios in an efficient manner.

6.2. Computational Experiments for IRRP

6.2.1. Instance generation

We performed computational experiments on a set of randomly generated test instances which vary from each other by one of the following factors: the number of rescue centers $|J|$, the number of districts $|K|$, and the distribution of the number of buildings in each district. We assume that the number of buildings in district k (i.e., $|M_k|$) is determined randomly from a discrete uniform distribution. Two different discrete uniform distributions, supported in the intervals [1000, 3000] and [3000, 5000], are used. The coordinates of the RC sites as well as the district sites are generated uniformly on the interval [0,100]. We assume four earthquake scenarios with the associated occurrence probabilities ($\mathbf{p}$) and the intensity values ($\boldsymbol{\mu}$), that are displayed in Table 6.7. The probabilities are given such that the weaker (stronger) scenario has a higher (lower) probability.

Table 6.7. Earthquake scenarios and related parameters.

Scenarios	1	2	3	4
$\mathbf{p}$	0.50	0.25	0.15	0.10
$\boldsymbol{\mu}$	1	1.1	1.3	1.8

There are four seismic code levels for the buildings ($c \in \{1, 2, 3, 4\}$) and the cost of retrofitting from any level c to the next level $c + 1$ is assumed as 10 monetary units. Prior to the mitigation, the percentage of buildings that have been at different code levels is equal (i.e., 25%). Three damage types (light, moderate, heavy) are modelled as three damage levels, $d \in \{1, 2, 3\}$. Since retrofitting cost of each link (u_{jk}) differs due to its different structural properties (numbers of bridges, viaducts and overpasses on the link as well as the length, height, design, age and load levels of every bridge/viaduct etc.), u_{jk} parameters are generated uniformly on the interval $[50, 300]$.

The transportation times, $\tilde{t}^s_{jk}$, and transportation costs, c^s_{jk}, depend on the realized scenario s. We generate $\tilde{t}^s_{jk}$ values by multiplying the Euclidean distances between rescue centers (RCs) and districts with the intensity μ^s of the corresponding scenario. t_{max} is determined as the expected value of the highest transportation time over all scenarios, i.e., $t_{max} = \sum_s p^s \tilde{t}_{jks}^{max}$ where $\tilde{t}_{jks}^{max}$ is the highest transportation time in scenario s. The c_{jk}^s values are determined as follows: $c_{jk}^s = \beta \tilde{t}_{jk}^s$ where β indicates the transportation cost of a unit of relief item and it is set as $\beta = 0.01$. The formula implies that the transportation between the nodes of the network gets more difficult as a result of increased damage realized at higher earthquake intensity values.

It is explained in Section 5.1 that the amount of relief item demand at district k under scenario s is proportional to the following parameters: damage levels of buildings due to scenario s (which is determined by parameter γ_{kd}^{cs}), the number of residents in building m (α_{km}) and the demand coefficient for each damage level (λ_d). γ_{kd}^{cs} is determined as $\gamma_{kd}^{cs} = \tilde{\gamma_d^{cs}} \kappa^k$, where κ^k is the seismicity index for each district at site k. It takes on values randomly from the uniform distribution supported in the interval $[0.80, 1]$. The $\tilde{\gamma_d^{cs}}$ parameters used in this study are illustrated in Figure 6.1. The x-

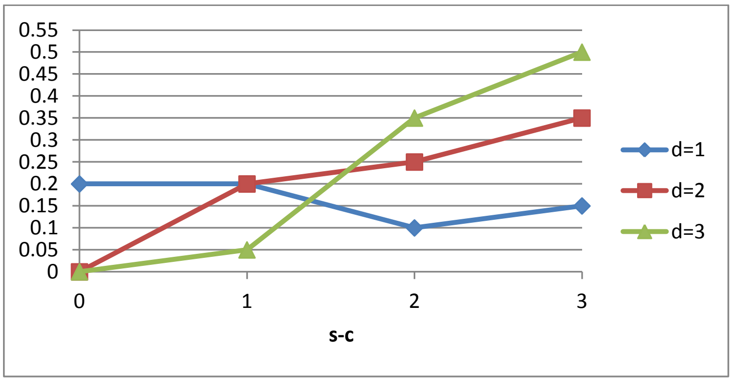

Figure 6.1. Gamma parameter.

axis indicates the difference (s-c) between the earthquake intensity scenario and seismic code level of the building. If this difference is low, then it is more likely to observe light damage instead of moderate or heavy damage. By contrast, as this difference increases, the probabilities associated with moderate damage and heavy damage increase as well. This setting is in line with the results of [2], in which similar building damage ratios for Zeytinburnu district of İstanbul is found by using two different scenarios described by JICA [113]. The λ_d parameter is taken as 10, 20 and 40 for damage levels 1, 2 and

3, respectively. The number of residents in each building (α_{km_k}) is an integer value drawn randomly from the uniform distribution supported in the interval $[1, 40]$.

The solution approaches for all methods are implemented in C# and the computations are carried out on a computer with Intel Xeon 3.16 GHz processor and 32GB of RAM. The following criteria are used as the stopping condition for each LHMs, which means that as soon as one of these criteria is met, the LHMs are terminated: (i) the running time exceeds 7200 CPU seconds (2 h), (ii) the number of iterations exceeds 5000. The Lagrangean heuristics applied to solve LR2 of LHM2 (also LHM3) and FSP2 of LHM2 are terminated after 10 iterations.

We have also generated two additional solution methods called LHM4 and LHM5, by hybridizing LHM1 with LHM2 and with LHM3, respectively. LHM4 has the same lower and upper bound generating procedures with LHM2, but different from LHM2, at every 100th iteration for the next 10 consecutive iterations, the LR2 and FSP2 subproblems are solved by CPLEX instead of the described Lagrangean relaxation algorithms. Similarly, LHM5 executes different solution procedures from LHM3 at every 100th iteration for the next 10 consecutive iterations. In these iterations, the LR2 is solved by CPLEX and the upper bound generation is handled as in LHM2, where FSP2 is solved by CPLEX.

To evaluate the performances of the solution approaches, the test instances are also solved by the commercial MILP solver CPLEX 11.2. The results of the computational experiments are presented in the next section.

6.2.2. Experimental results

We compared the performances of CPLEX, LHM1, LHM2, LHM3, LHM4 and LHM5 on randomly generated test instances with different sizes where $|J| \in \{5, 10\}$ and $|K| \in \{50, 100, 200, 300, 400, 500\}$. For each problem size, two types of instances are generated, where either $|M_k| \sim DU[1000, 3000]$ or $|M_k| \sim DU[3000, 5000]$.

The tests are performed for three budget levels. For that purpose a dummy run is executed by relaxing the budget constraint (i.e., there is no budget limit) to determine the optimal total mitigation cost B_{opt}. Then the instances are tested by setting $B = f_B \times B_{\text{opt}}$, where f_B is set to 0.70, 0.90 and 1.00.

The test results are displayed in Table 6.8, 6.9 and 6.10 for the instances with $f_B = 1$, $f_B = 0.9$, and $f_B = 0.7$, respectively. The values indicate the percent deviation of the best upper bound provided by each solution method (and/or CPLEX) from the best lower bound available. They are computed as

$$PD^k_{\text{UB}} = 100 \times (z^k_{\text{UB}} - LB_{\text{best}})/LB_{\text{best}} \tag{6.1}$$

where k=LHM1, LHM2, LHM3, LHM4, LHM5, CP^2, CP^{10} and CP^{24}. Here, CP^2, CP^{10} and CP^{24} indicate 2, 10 and 24 hours computation of CPLEX.

Note that, the z^k_{UB} indicates the best upper bound for each solution method k and LB$_{\text{best}}$ stands for the best lower bound which is the maximum of the following values: the LP relaxation value, the best lower bound found among all LHMs and CPLEX.

The percent deviation values of CPLEX for 2, 10 and 24 h running time are indicated in columns $\text{PD}^{\text{CP}^2}_{\text{UB}}$, $\text{PD}^{\text{CP}^{10}}_{\text{UB}}$ and $\text{PD}^{\text{CP}^{24}}_{\text{UB}}$, respectively. In some instances CPLEX gives a very bad feasible solution or cannot not obtain a feasible solution in 2 h solution time. For these instances we run CPLEX for 10 h and report the percent deviations in column $\text{PD}^{\text{CP}^{10}}_{\text{UB}}$. Furthermore, if solution time of 10 h is not enough either, then CPLEX is run for 24 hours and the resulting percent deviation is reported as $\text{PD}^{\text{CP}^{24}}_{\text{UB}}$.

If an instance can be solved by CPLEX in 2 h (10 h), then there is no need to give 10 (24) h to solve it. Hence, the corresponding values in the $\text{PD}^{\text{CP}^{10}}_{\text{UB}}$ ($\text{PD}^{\text{CP}^{24}}_{\text{UB}}$) column are left blank for that instance. However, if an instance cannot be solved in 2 or 10 h, then the corresponding column values are marked by an asterisk (“$*$”).

Table 6.8. Test results for the instances with f_B=1.0.

	$\lvert M_k\rvert \sim DU[1000, 3000]$							$\lvert M_k\rvert \sim DU[3000, 5000]$							
Problem	$\text{PD}_{\text{UB}}^{\text{CP}^2}$	$\text{PD}_{\text{UB}}^{\text{CP}^{10}}$	$\text{PD}_{\text{UB}}^{\text{LHM1}}$	$\text{PD}_{\text{UB}}^{\text{LHM2}}$	$\text{PD}_{\text{UB}}^{\text{LHM3}}$	$\text{PD}_{\text{UB}}^{\text{LHM4}}$	$\text{PD}_{\text{UB}}^{\text{LHM5}}$	$\text{PD}_{\text{UB}}^{\text{CP}^2}$	$\text{PD}_{\text{UB}}^{\text{CP}^{10}}$	$\text{PD}_{\text{UB}}^{\text{CP}^{24}}$	$\text{PD}_{\text{UB}}^{\text{LHM1}}$	$\text{PD}_{\text{UB}}^{\text{LHM2}}$	$\text{PD}_{\text{UB}}^{\text{LHM3}}$	$\text{PD}_{\text{UB}}^{\text{LHM4}}$	$\text{PD}_{\text{UB}}^{\text{LHM5}}$
5/50/	0.00		0.01	0.02	0.03	0.01	0.01	0.01			0.02	0.02	0.04	0.02	0.02
5/100/	0.00		0.01	0.00	0.04	0.01	0.01	0.00			0.01	0.01	0.02	0.01	0.01
5/200/	0.01		0.05	0.04	0.10	0.05	0.05	8.88			0.01	0.02	0.02	0.03	0.01
5/300/	0.63		0.01	0.03	0.09	0.01	0.01	*	4.64		0.06	0.07	0.07	0.06	0.06
5/400/	13.74		0.01	0.00	0.05	0.01	0.01	*	*	0.73	0.02	0.05	0.04	0.01	0.02
5/500/	*	1.42	0.02	0.01	0.05	0.02	0.02	*	*	12.67	0.06	0.06	0.07	0.06	0.14
10/50/	0.00		0.01	0.01	0.05	0.02	0.02	0.00			0.01	0.02	0.02	0.01	0.01
10/100/	0.00		0.01	0.01	0.05	0.03	0.03	0.00			0.01	0.01	0.03	0.00	0.01
10/200/	0.00		0.00	0.08	0.12	0.25	0.25	25.76			0.01	0.00	0.03	0.01	0.01
10/300/	15.28		0.02	0.03	0.06	0.05	0.02	*	17.02		0.07	0.07	0.09	0.07	0.07
10/400/	46955		0.09	0.01	0.06	0.21	0.10	*	*	13.56	0.06	0.06	0.05	0.04	0.06
10/500/	*	4.81	0.05	0.08	0.12	0.07	0.05	*	*	19.41	0.14	0.14	0.16	0.14	0.16
Average			0.03	0.03	0.07	0.06	0.05				0.04	0.04	0.05	0.04	0.05
Std. Dev.			0.03	0.03	0.03	0.08	0.07				0.04	0.04	0.04	0.04	0.05

*This instance cannot be solved within the specified time

Table 6.9. Test results for the instances with f_B=0.9.

	$\|M_k\| \sim DU[1000,3000]$							$\|M_k\| \sim DU[3000,5000]$							
Problem	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{CP}^2}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{CP}^{10}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM1}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM2}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM3}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM4}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM5}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{CP}^2}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{CP}^{10}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{CP}^{24}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM1}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM2}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM3}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM4}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM5}}$
5/50/	0.00		0.44	0.83	0.52	0.72	0.49	0.00			0.41	0.64	0.75	0.43	0.53
5/100/	0.00		0.77	0.88	0.95	0.83	0.86	0.00			0.42	0.61	0.66	0.56	0.57
5/200/	0.00		0.58	0.97	0.94	0.77	0.77	10.95			0.63	0.41	0.46	0.64	0.74
5/300/	0.09		0.65	0.91	0.97	0.75	0.74	*	3.81		0.85	0.56	0.58	1.06	0.93
5/400/	5719		0.96	0.90	1.02	1.02	1.53	*	*	1.23	0.80	0.51	0.55	0.89	1.30
5/500/	*	1.16	1.76	0.96	1.06	0.98	1.25	*	*	1148	0.97	0.60	0.62	1.16	3.08
10/50/	0.00		0.42	2.22	1.86	0.60	0.47	0.00			0.26	1.13	1.14	0.33	0.30
10/100/	0.00		0.53	1.83	1.84	0.57	0.71	0.00			0.36	0.91	0.88	0.54	0.55
10/200/	0.00		0.29	2.64	2.52	0.41	0.43	13766			0.62	0.80	0.83	0.70	0.60
10/300/	8.96		0.49	2.15	2.21	0.45	0.49	*	15.76		0.53	1.01	1.05	0.57	0.63
10/400/	*	0.01	0.49	2.61	2.66	0.48	0.56	*	*	10.75	0.63	0.79	0.83	0.68	1.66
10/500/	*	4.50	0.55	2.32	2.34	0.55	0.53	*	*	*	0.76	1.18	1.16	1.30	0.82
Average			0.66	1.60	1.57	0.68	0.73				0.60	0.76	0.79	0.74	0.98
Std. Dev.			0.39	0.75	0.74	0.20	0.34				0.22	0.25	0.23	0.30	0.76

*This instance cannot be solved within the specified time

Table 6.10. Test results for the instances with f_B=0.7.

	$\lvert M_k\rvert \sim DU[1000, 3000]$							$\lvert M_k\rvert \sim DU[3000, 5000]$							
Problem	$PD_{UB}^{CP^2}$	$PD_{UB}^{CP^{10}}$	PD_{UB}^{LHM1}	PD_{UB}^{LHM2}	PD_{UB}^{LHM3}	PD_{UB}^{LHM4}	PD_{UB}^{LHM5}	$PD_{UB}^{CP^2}$	$PD_{UB}^{CP^{10}}$	$PD_{UB}^{CP^{24}}$	PD_{UB}^{LHM1}	PD_{UB}^{LHM2}	PD_{UB}^{LHM3}	PD_{UB}^{LHM4}	PD_{UB}^{LHM5}
5/50/	0.00		2.18	3.08	3.19	2.76	2.83	0.00			2.19	3.32	2.88	2.23	2.23
5/100/	0.00		2.99	2.92	3.10	2.84	3.21	0.00			2.08	2.28	2.50	2.57	2.46
5/200/	0.00		2.82	3.55	3.29	2.94	3.02	8.18			2.84	2.44	2.42	2.83	2.78
5/300/	0.14		3.14	4.34	4.02	3.80	3.35	*	1.56		2.95	2.36	2.49	2.77	3.09
5/400/	12267		3.17	3.51	3.80	3.67	4.50	*	*	0.26	3.25	3.33	3.21	3.43	7.61
5/500/	*	0.22	3.50	3.34	3.40	3.91	3.91	*	*	8941	3.41	2.73	2.55	3.23	8.38
10/50/	0.01		1.98	4.94	5.17	2.22	2.51	0.00			1.48	2.69	2.68	1.76	1.74
10/100/	0.00		2.31	4.14	4.23	2.62	2.72	0.01			1.98	2.41	2.57	2.06	2.08
10/200/	0.00		1.63	4.40	4.28	1.68	1.68	11263			3.01	2.50	2.62	2.45	2.52
10/300/	4.00		1.92	4.59	4.46	1.97	1.94	*	2799		2.06	3.18	3.16	2.47	3.06
10/400/	*		1.77	4.64	4.57	1.90	1.92	*	*	11.05	2.20	2.80	2.74	2.32	4.40
10/500/	*	0.01	2.10	4.65	4.60	2.42	2.27	*	*	*	5.26	2.80	2.98	2.46	2.20
Average			2.46	4.01	4.01	2.73	2.82				2.72	2.74	2.73	2.55	3.54
Std. Dev.			0.63	0.69	0.66	0.75	0.84				0.99	0.37	0.27	0.47	2.19

*This instance cannot be solved within the specified time

The test results indicate that level of the mitigation budget significantly affects the solution quality. The run with $B_{\text{opt}} = \infty$ can be solved within 1 h even for the largest instance. For f_B=1, the number of instances for which a feasible solution cannot be found by CPLEX in two hours is 8, whereas it is 9 for f_B=0.9 and f_B=0.7. Moreover, some of the instances cannot be solved by CPLEX even in 24 h of computation time for f_B=0.9 and f_B=0.7. Also, the average deviations of all LHMs increase significantly at lower budget levels. While the averages are in the range of [0.03%,0.07%] when f_B=1, they vary in the intervals [0.60%,1.60%] and [2.46%,4.01%] for f_B=0.9 and f_B=0.7, respectively.

The performance of CPLEX falls down remarkably as the number of buildings, i.e. $|M_k|$, increases. In Table 6.8, although a feasible solution can be obtained for ten problems within 2 h when $|M_k| \sim DU[1000, 3000]$, the number of problems is only six when $|M_k| \sim DU[3000, 5000]$. A similar observation can also be made for the other tables. In addition, for the case of $|M_k| \sim DU[1000, 3000]$ all instances can be solved within 10 h, whereas 13 of the 36 instances cannot be solved or solved very badly (deviation is greater than 1000%) within 10 h for $|M_k| \sim DU[3000, 5000]$. More dramatically, the instances with $|M_k| \sim DU[3000, 5000]$, $|K| = 500$ and f_B=0.9 (and also f_B=0.7) are solved very badly or not at all in 24 h.

On the other side, one cannot argue that the performance of any LHM decreases by the number of buildings. In all of the tables, the average deviations of LHMs for the two distribution types are close to each other. Moreover, we can realize that some of the LHMs have smaller average deviation for the instances with $|M_k| \sim DU[3000, 5000]$ than the ones with $|M_k| \sim DU[1000, 3000]$. Therefore, the proposed LHMs are robust in terms of the number of buildings.

Regarding the test results, the number of districts is another important factor. For all f_B levels and $|M_k|$ distributions, CPLEX is not able to find optimal or near optimal solutions within 2 h when $|K| > 300$. In addition, for the instances with $|M_k| \sim DU[3000, 5000]$ when $|K| \geq 400$ and $|K| \geq 500$, respectively, 10 h and 24 h of computation time become insufficient to obtain a feasible or a near optimal solution.

Different from CPLEX, the LHM solutions are very robust with respect to problem sizes, which can be highlighted by the low standard deviations of LHM solutions in each of the tables. The standard deviations are all below 1% with an exception (in Table 6.10 when $|M_k| \sim DU[3000, 5000]$, LHM5 has 2.19% standart deviation).

The solution quality of each LHM can be investigated separately for three budget levels. When f_B=1, all the LHMs have similar performance. For any of the instances in Table 6.8, any of the LHMs finds a solution that is very close to optimal. For f_B=0.9, LHM1 results in the best performance although for an instance its deviation is the highest (5/500 problem with $|M_k| \sim DU[3000, 5000]$). Here, the performances of LHM2 and LHM3 are remarkably low regarding the other LHMs when $|M_k| \sim DU[1000, 3000]$. For the same instances, the low performances of LHM2 and LHM3 appear also when f_B=0.7.

LHM1 results in the best performance for f_B=1, f_B=0.9 and also for f_B=0.7 when $|M_k| \sim DU[1000, 3000]$. The good performance of LHM1 is due to the use of CPLEX in solving subproblem LR2 and the FSP problem in the upper bound generating heuristic. But when f_B=0.7 and $|M_k| \sim DU[3000, 5000]$, LHM1 is not the best method. In this case, LHM4 results the best average solution and LHM1, LHM2 and LHM3 have nearly the same average deviation value (i.e., 2.72, 2.74 and 2.73). A notable point is that the standard deviations of LHM2, LHM3, and LHM4 are significantly better than the standard deviation of LHM1 which is mostly related with the bad performance for the instances with $|K| = 500$. The performance of LHM1 is also remarkably bad for the 5/500 instance with distribution $|M_k| \sim DU[1000, 3000]$ in Table 6.10.

The reason of this bad performance is mostly related with the low number of iterations executed by LHM1. LHM1 takes the advantage of using CPLEX to solve the LR2 and the FSP subproblems, when the problem sizes are relatively small. As the size of the problem instances get larger, it takes much time to solve these subproblems by CPLEX, which is in parallel with the previously mentioned low performance of CPLEX for relatively large instances. Therefore, using CPLEX can result in low number of iterations in 2 h of computation time and this may result in immature feasible solutions among the Lagrangean relaxation procedure.

Thus, we seek for the performances of LHMs on some larger instances, the results are given in the Table 6.11-6.13. Six different problem sizes are tested. The percent deviations are obtained again for 2 h running of LHMs. The first three problems in tables have $|M_k| \sim DU[1000, 3000]$, whereas $|M_k| \sim DU[3000, 5000]$ for the other three problems.

Table 6.11. Test results of large test instances with f_B=1.

Problem	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM1}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM2}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM3}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM4}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM5}}$
$10/650/U \sim [1000, 3000]$	0.79	0.85	0.91	0.36	0.67
$10/800/U \sim [1000, 3000]$	0.36	0.28	0.33	0.28	0.28
$20/1000/U \sim [1000, 3000]$	2.89	4.62	4.52	1.26	0.71
$10/650/U \sim [3000, 5000]$	0.15	0.14	0.14	0.14	0.24
$10/800/U \sim [3000, 5000]$	0.41	0.25	0.27	0.25	0.88
$20/1000/U \sim [3000, 5000]$	2.38	4.58	2.55	0.15	2.64
Average	1.16	1.79	1.45	0.41	0.90
Std. Dev.	1.17	2.20	1.75	0.43	0.89

Table 6.12. Test results of large test instances with f_B=0.9.

Problem	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM1}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM2}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM3}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM4}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM5}}$
$10/650/U \sim [1000, 3000]$	0.92	2.89	2.84	1.58	1.06
$10/800/U \sim [1000, 3000]$	4.33	2.57	2.53	1.16	1.08
$20/1000/U \sim [1000, 3000]$	3.47	4.27	4.64	1.17	1.01
$10/650/U \sim [3000, 5000]$	0.88	1.15	1.18	0.98	1.08
$10/800/U \sim [3000, 5000]$	3.82	1.42	1.38	0.92	5.13
$20/1000/U \sim [3000, 5000]$	2.50	3.51	4.43	2.80	3.03
Average	2.65	2.64	2.83	1.44	2.06
Std. Dev.	1.48	1.20	1.47	0.71	1.70

The results indicate that LHM1's performance is significantly low for these large instances. In particular, LHM1 has the 4th best and the worst average deviations for f_B=0.9 and f_B=0.7, respectively. Moreover, when $|M_k| \sim DU[3000, 5000]$ and f_B=0.7, its solution deviates from the $\mathrm{LB}_{\mathrm{best}}$ by 6 to 11%. On the other side, in all of the tables LHM4 results in the lowest average percent deviations. Additionally, the standard

Table 6.13. Test results of large test instances with f_B=0.7.

Problem	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM1}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM2}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM3}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM4}}$	$\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM5}}$
$10/650/U \sim [1000, 3000]$	2.26	4.46	4.46	2.27	2.28
$10/800/U \sim [1000, 3000]$	2.57	4.79	4.82	2.65	4.65
$20/1000/U \sim [1000, 3000]$	3.91	6.42	6.81	1.93	2.29
$10/650/U \sim [3000, 5000]$	6.63	2.85	2.80	2.86	7.45
$10/800/U \sim [3000, 5000]$	6.41	4.25	2.97	2.42	7.12
$20/1000/U \sim [3000, 5000]$	11.77	5.28	4.52	3.50	4.05
Average	5.59	4.68	4.40	2.60	4.64
Std. Dev.	3.55	1.18	1.45	0.54	2.26

deviation of $\mathrm{PD}_{\mathrm{UB}}^{\mathrm{LHM4}}$ values, which is not more than 0.71%, implies the robustness of LHM4 with respect to problem sizes and budget levels.

For example, the number of iterations executed in LHM1, LHM2, LHM3, LHM4 and LHM5 for the largest instance ($20/1000/|M_k| \sim DU[3000, 5000]$) with f_B=0.7 are as follows: 127, 325, 333, 277 and 292. Then for these large instances LHM1 could make the least number of iterations which is reflected on the results as the worst performance. Notify that LHM4 and LHM5 use CPLEX in some of the iterations to solve LR2 and FSP2 subproblems, therefore they can make less iterations compared to LHM2 and LHM3. But, although they can make less iterations, using of CPLEX in some iterations can improve the solution. Then, they can benefit from both the speed of algorithms used in LHM2 or LHM3 and the solution quality of CPLEX. The good performance of LHM4 may be related to this inference.

6.2.3. Expected value of perfect information and value of stochastic solution

The EVPI% and VSS% values are calculated for six of the problem instances with f_B=0.7 given in Table 6.10. The results for the instances in which $|M_k| \sim DU[1000, 3000]$ and $|M_k| \sim DU[3000, 5000]$ are presented in Table 6.14 and 6.15, respectively. For each of the instances, stochastic programming (SP), wait and see (WS), expected value (EEV) solutions and EVPI% and VSS% values are reported.

The EVPI% and VSS% values are calculated as defined before in Section 6.1.3. In order to obtain some comparable VSS% values, we use the reference scenario approach in calculating the EEV solutions. They are calculated as the deterministic problem solution with respect to the parameters of the highest impact scenario that constitutes the *reference scenario*. This is beceause of the fact that for some instances if the first stage link retrofit decisions (i.e., U_{jk}'s) are given with respect to the *expected* vulnerability and transportation time values, then for some higher impact scenarios some of the districts cannot be reachable due to not retrofitting related links. Thus, the relief item demand of such a district arises as shortage which results in very high values of EEV and VSS%. Therefore, the reference scenario approach is accepted in calculating EEV and VSS% values.

Table 6.14. EVPI% and VSS% values for $|M_k| \sim DU[1000, 3000]$ instances.

Problem	SP	WS	EEV	EVPI%	VSS%
5/50	1147728	1077900	1203059	6.08	4.60
5/200	4779884	4494249	5028985	5.98	4.95
5/400	9701664	8964648	10174021	7.60	4.64
10/50	1075146	1029881	1125107	4.21	4.44
10/200	4024599	3969777	4208189	1.36	4.36
10/400	7973845	7964253	8454710	0.12	5.69
Average				4.22	4.78

Table 6.15. EVPI% and VSS% values for $|M_k| \sim DU[3000, 5000]$ instances.

Problem	SP	WS	EEV	EVPI%	VSS%
5/50	2342242	2190818	2451756	6.46	4.47
5/200	9673405	9016702	10225700	6.79	5.40
5/400	18329743	17248596	19196258	5.90	4.51
10/50	1949673	1939689	2053212	0.51	5.04
10/200	8533478	8046485	8914331	5.71	4.27
10/400	16298279	15608850	17026236	4.23	4.28
Average				4.93	4.66

It is observed that the number of buildings does not have a significant effect on EVPI or VSS values: the EVPI% (VSS%) is 4.22 (4.78) and 4.93 (4.66) in Table 6.14 and 6.15, respectively. The EVPI% values vary in a range of [0.12,7.60], while the VSS% values are much more robust (the standard deviation of VSS% values is 0.46).

For the low EVPI% instances (e.g., 10/400 instance in Table 6.14), the districts are relatively close to the RCs such that the assignments of districts to RCs do not change very much as the impact of the scenarios increase. Note that if some $\tilde{t}_{jk}(s)$ value is higher than t_{max} for a scenario s, then district k cannot be assigned to RC at site j. If the assignments stay similar with respect to scenarios, then the mitigation decisions do not change significantly, which means that the SP solution can adequately hedge against either of the future scenarios. The low EVPI values are also related with the level of retrofitting costs, the higher retrofit cost results in higher EVPI% value.

Since the magnitudes of the costs arising in disaster management are huge, the average value of 4.72% for VSS corresponds to very high actual costs in fact. Therefore, instead of solving a deterministic problem, it can be stated that the decision maker must consider the future scenarios by using a stochastic program.

6.2.4. Inferences on the IRRP model

We can have some insights on the behaviour of IRRP model under different mitigation spending levels by using an instance with 5 RCs, 50 districts and $|M_k| \sim DU[1000, 3000]$. The change of the response costs and total system costs are demonstrated in Figure 6.2. The horizontal axis shows the different f_B levels while the vertical axis shows corresponding costs.

At the first glance, one can see the lucid tradeoff between the pre-disaster mitigation spending and post-disaster response costs. Therefore, it can be inferred that the proposed model IRRP formulation properly models the actual situation in a real world.

When mitigation budget is close to zero, the total system cost is very high, however, as some amount of mitigation is executed the total system cost decreases substantially implying that mitigation is crucial for the system efficiency. The total system cost decreases as the mitigation budget is increased up to its optimal level ($f_B = 1$).

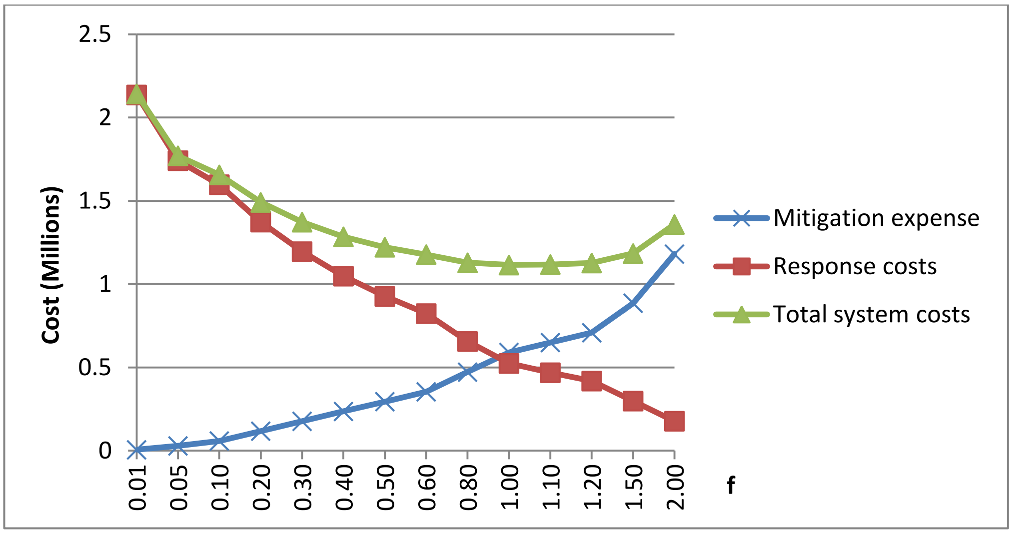

Figure 6.2. Mitigation vs. Total Cost.

In IRRP formula setting the mitigation budget as $f_B > 1$ does not cause any increase for the optimal mitigation spending (i.e., B_{opt}) and the optimal total cost, since the model would not use above of the optimal mitigation budget. However, assume that the decision maker does not have an information on the optimal mitigation budget, so he/she can decide to make much mitigation than the optimal level. Note that, this can be the case if budget constraint is in IRRP is an equality constraint and the right hand side is above the B_{opt}. From Figure 6.2 we can observe that a mitigation expense above the B_{opt} causes to a monotone increase for the total system costs and on the contrary a monotone decrease in response costs. This behaviour shows us that neither zero-mitigation nor mitigation up to the top-resistance level can be the optimal choice.

We have generated a small instance (Inst-A) with 3 RCs, 10 districts to make analyses on the model behaviour and parameters. The number of buildings at each district is determined by $|M_k| \sim DU[500, 1000]$. Note that we use small instances for the ease of studying and explaining our observations. On the basis of several experiments we obtain similar results with different instances. The coordinates of RCs and districts are on the graph in Figure 6.3. IRRP is solved under $f_B = 1$.

The percentage of buildings that belong to seismic code levels $c = 1, 2, 3$ and 4 are 25.1%, 24.9%, 24.6% and 25.4%, respectively. It is observed that although the

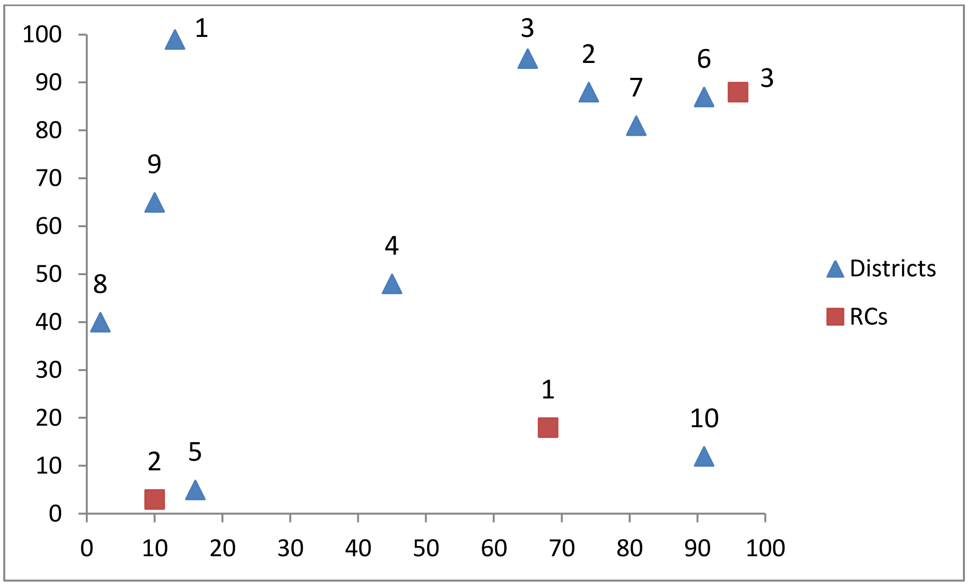

Figure 6.3. Location of districts and RCs for Inst-A.

problem is solved without the budget constraint, all of the buildings are not mitigated up to code level 4 after the mitigation. The optimal percentages of building code levels after mitigation are 5.7%, 13.1%, 17.6% and 63.6%, respectively for c=1,2,3 and 4.

It is remarkable that in district 1 every building is retrofitted up to $c = 4$. The reason of this situation is as follows: district 1 cannot receive relief item from any of the RCs in scenario 4 since the transportation time from any of the RCs is not less than $t_{\max}$. Since district 1 cannot be assigned to any RC there exists shortage for relief item demands of district 1 and hence buildings are mitigated to the highest code level to minimize the damage. Moreover, note that $t_{\max}$=134 and the average transportation time between the assigned RC-district pairs among all scenarios is 48.6.

Now, consider district 6 and 9; they are assigned to RC3 and RC2 which are at 9.18 and 111.6 distance units away, respectively. It is intriguing that in district 6 only 7.5% of the buildings at $c = 1$ are retrofitted to $c = 2$ and none of the buildings at higher levels are retrofitted. However, in district 9, 47.3% of the buildings are retrofitted at a higher level and in particular 38.1% of them are retrofitted to $c = 4$ (as a result, 90% of the buildings in district 9 are at $c = 4$ after mitigation). The above observations justify the severe effect of the distance between RC-district pairs (which also stands for transportation time) on the mitigation policy. Furthermore, the lower seismicity level of district 9 ($\kappa^9 = 0.89$) relative to seismicity of district 6 ($\kappa^6 = 0.94$) makes the result more striking since a higher κ value implies a higher γ parameter which also means higher relief item demand.

To justify the effect of seismicity level on the mitigation activities, we set this parameter to its minimum and maximum levels (0.80 and 1.00) for each district and compare the mitigation levels. When $\kappa^k = 0.80$ for each district k, 35.3% of the buildings are retrofitted to $c = 4$, whereas 40.1% of the buildings are retrofitted when $\kappa^k = 1$. In addition, in the optimal solution of Inst-A we observe that in areas of higher seismicity, more retrofitting is needed since it is likely to be more cost-effective.

The number of RCs on the network may considerably increase the system performance and thus decrease the total cost. In this manner, we open a new RC on the data of Inst-A and come up with a new instance (Inst-B). The location of the new RC4 is marked in Figure 6.4. The total costs for Inst-A and Inst-B are 7382158.7 and 97370.9, respectively. The reason of the high difference between costs is the shortage in Inst-A, regarding the unassignment of district 1 to any of the RCs.

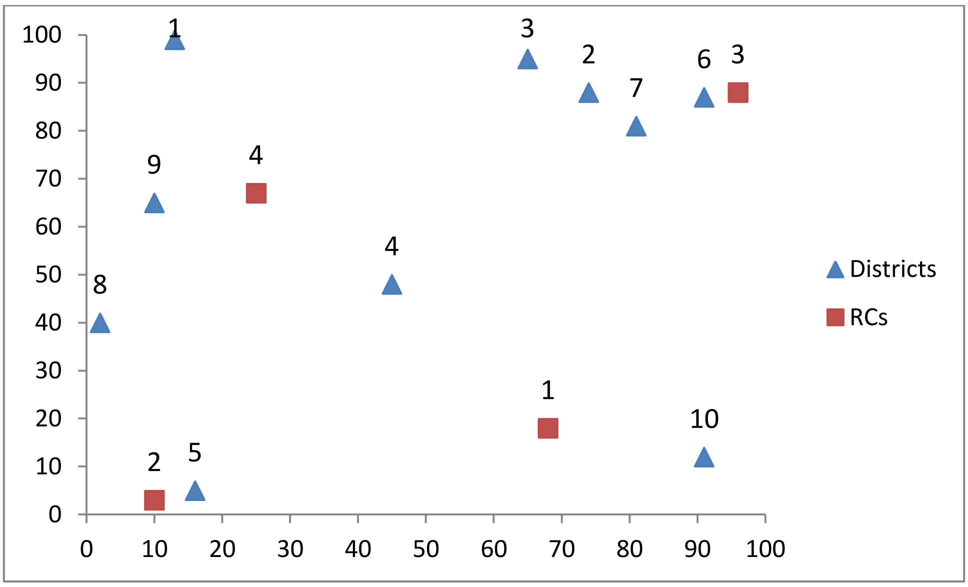

Figure 6.4. Location of Demand Points and RCs for Inst-B.

For the new case Inst-B, district 1 is now assigned to RC4, so its relief item demand can be satisfied. In this case, not all of the buildings in district 1 are retrofitted up to $c = 4$: the percentages of the buildings after mitigation are 2.7%, 6.4%, 15.7%, 75.1% for c=1,2,3 and 4, respectively. Additionally, the mitigation levels for some other districts (4, 8 and 9) have changed significantly. The demands of all these districts are now satisfied from RC4 to take advantage of the shorter distances (i.e., shorter response times). In brief, the whole society can benefit from an increasing number of RCs.

From here on, we continue the analysis on Inst-B. The next issue we investigate is related to how the mitigation strategy differs with respect to the mitigation budget. In Figure 6.5, the percentages of non-retrofitted and retrofitted buildings for four different budget levels (f_B=1, f_B=0.7, f_B=0.5 and f_B=0.3) are illustrated. The level of retrofitting for a building is the difference of the code levels after and before the mitigation. For instance, if a building at code level $c = 1$ is retrofitted to $c' = 3$, then the retrofitting level is equal to 2. It is observed that for f_B=1, only 43% of the buildings are retrofitted. It seems reasonable since approximately 50% of the buildings belong to $c = 3$ and $c = 4$ before the mitigation. These buildings need very low or no retrofit.

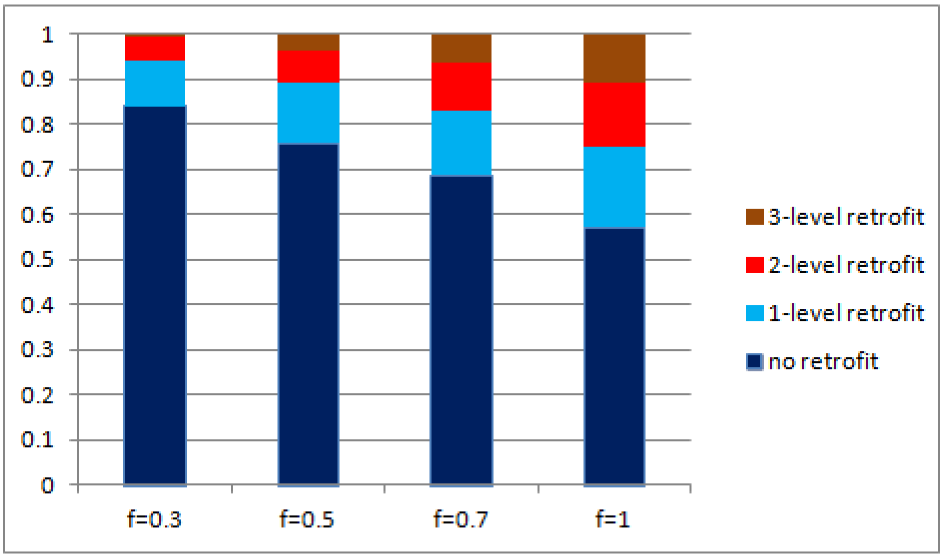

Figure 6.5. Retrofit levels at different budget levels.

When the budget decreases to 30% of the optimum budget level (i.e., f_B=0.3), then only 16% of the buildings can be retrofitted. In particular, the 3-level retrofit decreases down to zero (0.3%), which indeed gives a clue about the change of the mitigation strategy.

In Figure 6.6, the percentages of retrofitting levels among all retrofitted buildings (excluding the non-retrofitted ones) are illustrated for different f_B levels. For f_B=1 the percentages of 1- and 3- level retrofitting are nearly the same and the 3-level retrofitting is as high as 24%. As the budget decreases, we observe that the percentage of 1-level retrofit increases and the percentage of 3-level retrofit decreases substantially. Moreover, the 1-level retrofit strategies mostly consist of retrofitting the buildings at $c = 1$ or $c = 2$ 1-level up, very few of the buildings at $c = 3$ is retrofitted (the percentage of retrofitting from $c = 3$ to $c' = 4$ is 0.14%).

Therefore, we can conclude that under limited budget, the weakest buildings should be retrofitted slightly rather than being retrofitted to higher code levels. The aggregated vulnerability to damage is reduced a relatively large amount if more weak buildings are retrofitted (i.e., cost-effectiveness is much greater for weaker buildings).

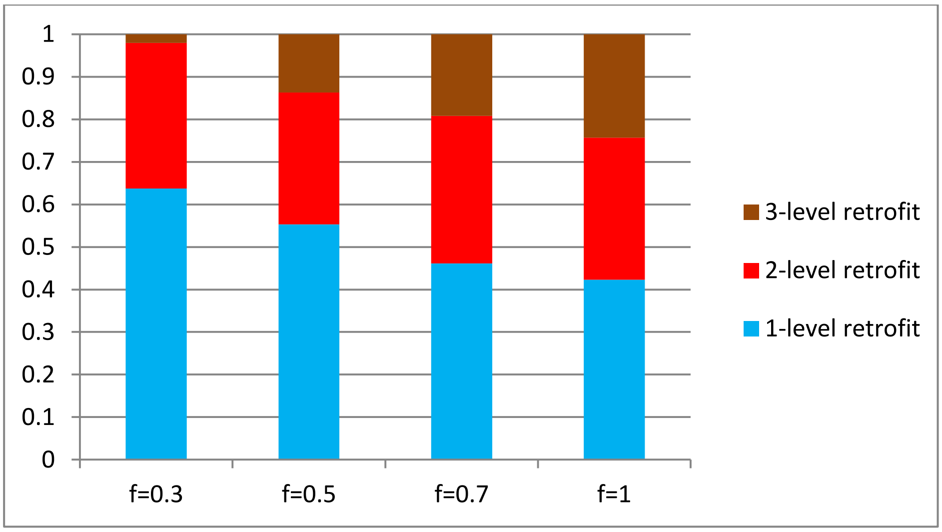

Figure 6.6. Retrofit policy under different budget levels.

6.2.5. Analysis on shortage costs

In the model, it is assumed that a shortage of relief item demand occurs for the following two reasons: it is not possible to reach a district due to collapse of non-retrofitted links and the district cannot be assigned to an RC due to its distance, i.e.,

$\tilde{t}^s_{jk} \geq t_{\max}$. We realize that among the instances solved in Table 6.8, 6.9 and 6.10, only one instance has a demand shortage. Moreover, this shortage is not related with non-retrofitting the links, but it occurs due to non-assignment of a far district. Then, it can be inferred that retrofitting a link is always preferred to not retrofitting, due to high unit shortage cost and high relief item demand (due to a large number of buildings in the district).

It can be assumed that a district can also be reachable by some alternative but much more expensive transportation methods (e.g. helicopter). The shortage cost a, can now be treated as the cost of alternative transportation method. In this case, a vulnerable link may not be retrofitted if it is less costly to transport to a district by helicopter compared with the expense of total link retrofitting and transportation costs. We have analyzed the consequences of this type of a cost.

In this analysis link retrofitting costs, the number of buildings in each district, and building retrofitting costs are expected to be important parameters. Since link retrofitting costs differ greatly (due to the number of bridges and tunnels on it, bridge specifications, location, etc.), we experiment with different levels of retrofitting costs. Federal emergency management agency (FEMA) estimates bridge retrofit costs nearly 22.7% of its replacement cost [114]. Zhou *et al.* [115] recommend 150 $/ft^2 for an average retrofit cost based on Caltrans (California Department of Transportation) data obtained from the seismic retrofit projects for highway bridges. Additionally, referring to the information from a general manager of a constructing firm engaged in seismic retrofit projects in İstanbul, the retrofitting cost of the Mecidiyekoy Viaduct (860 m) is about 20 million dollars.

Thus, we carry out experiments with a number of varying retrofitting cost ranges, however the basic values of link retrofitting cost are taken as follows: retrofitting costs (u_{jk}) in thousand dollars for 80% of the links are drawn from $U[100, 2250]$ while the distribution for the rest of the links is assumed to be $U[2250, 20000]$.

The four mitigation alternatives and their cost schemes proposed for residential buildings in İstanbul by [116] is adopted for our 4-level retrofitting approach. *Status quo* refers to not retrofitting (i.e., $c = c'$) with $r_{km}^{cc'} = 0$, *braced* refers to retrofitting 1 code level up (i.e., $c' = c + 1$) with $r_{km}^{cc'} = 65$, *partial shear wall* refers to retrofitting 2 code levels up (i.e., $c' = c + 2$) with $r_{km}^{cc'} = 80$ and *full shear wall* refers to retrofitting 3 code levels up (i.e., $c' = c + 3$) with $r_{km}^{cc'} = 135$. Again the $r_{km}^{cc'}$ values are given in thousand dollars. The effect of the unit shortage cost is presented in Table 6.16. The basic instance used in the analysis has 3 RCs, 10 districts and $|M_k| \sim DU[500, 1000]$.

The first observation is the decrease in the total mitigation cost and in the total

Table 6.16. Effect of unit shortage costs when $|M_k| \sim DU[500, 1000]$.

a	Total Ret. Cost	Building Ret. Cost	Link Ret. Cost	Amount of Shortage	Cost of Shortage	Total Cost
10000	100121	75120	25001	0	0	141552
6	100121	75120	25001	0	0	141552
4	88258	79410	8848	29963	12021	137729
2.5	87788	78940	8848	31148	7854	133114
2	82885	80260	2625	72361	14627	129891

system cost by decreasing values of a. When unit shortage cost is 10000 (i.e., any shortage is assumed as loss), the model does not allow any shortage. This is also the case for $a = 6$ implying that the alternative transportation method is too expensive to be preferred to retrofitting links. The average transportation cost in this instance is 0.52\$, so $a = 6$ is nearly 12 times of it. But if $a = 4$, then the model allows for 29963 shortage of relief item demand with a cost of 12021 thousand dollars. This shortage occurs as a result of not-retrofitting some of the links but satisfying the district relief item demands by the alternative transportation method. Note that the link retrofit cost decreases from 25001 to 8848 due to less retrofitting. If a is reduced to 2.5, then the total cost of shortage decreases while the amount of shortage increases. The key point here is that the increase in shortage is very limited since it is not related with not retrofitting of another link (link retrofit cost stays at 8848), but due to less retrofitting of buildings (building mitigation cost decreases to 78940). A further decrease in a to 2 causes not-retrofitting some more links (link retrofit cost decreases to 2625), there exists a large increase in the total shortage and shortage cost.

The number of buildings is an important parameter in analyzing the shortage cost. The same instance is tested when $|M_k| \sim DU[0, 100]$ and $|M_k| \sim DU[1000, 1500]$. The results are given in Table 6.17 and 6.18, respectively. If number of the buildings is low (small districts), then the model decides not to retrofit some links even if $a = 45$ or the alternative transportation method must be very cheap (as $a = 3$) when the districts are really big.

Table 6.17. Effect of unit shortage costs when $|M_k| \sim DU[0, 100]$.

a	Total Ret. Cost	Building Ret. Cost	Link Ret. Cost	Amount of Shortage	Cost of Shortage	Total Cost
10000	31128	7230	23898	0	0	34909
50	31128	7230	23898	0	0	34909
45	16418	7570	8848	3261	14674	34386
20.0	16418	7570	8848	3261	6522	26234
10.0	10495	7870	2625	6985	6990	20257
5.0	9410	8030	1380	9428	4719	16658
2.0	9007	7900	2475	12278	2475	13722

Table 6.18. Effect of unit shortage costs when $|M_k| \sim DU[1000, 1500]$.

a	Total Ret. Cost	Building Ret. Cost	Link Ret. Cost	Amount of Shortage	Cost of Shortage	Total Cost
10000	142900	115710	27190	0	0	211553
4	142900	115710	27190	0	0	211553
3.0	133147	122110	11037	50369	15198	210626
2.0	132477	121440	11037	52567	10631	205405
1.5	127514	122700	4814	120514	18364	200311

Another observation is that even if the number of non-retrofitted links are the same in each case (2 links are not retrofitted in Table 6.17 and 6.18 for $a = 10$ and $a = 3$, respectively), they need not be exactly the same links since the bridge mitigation costs are not equal (2625 and 11037). Moreover, for $a = 10000$ the link retrofit costs are not the same in any of the Tables 6.16, 6.17 and 6.18. These results indicate that the traditional ranking method of links to determine which should be retrofitted may not perform well, since it should select the same links in each of the cases. Rather, it would be better to determine the retrofitting decisions for a system-level model by using an optimization approach.

Another important parameter is the link retrofit costs. We have used various distributions for link retrofitting costs which are given in Table 6.19. Note that $dist^3$ is the basic distribution we have used in the previous tests.

Table 6.19. Analyzed distributions of link retrofit costs.

	Link Retrofit Cost
$dist^1$	$DU[100, 2250]$
$dist^2$	$DU[100, 10000]$
$dist^3$	with $p = 0.8$, $DU[100, 2250]$
	with $p = 0.2$, $DU[2250, 20000]$
$dist^4$	$DU[100, 20000]$

Figure 6.7 illustrates how much shortage occurs for different distributions and a values. For $a = 10000$, no shortage occurs for any of the distributions used, while, the number of retrofitted links is not the same for different distributions. 10 and 8 links are retrofitted when $dist^1$ and $dist^2$ are used, respectively. However, $dist^3$ and $dist^4$ allow only 7 links to be retrofitted in the optimal solution. This is related to the high link retrofitting costs, the model decides a less number of links to be retrofitted. Then relief item transportation to a district may be done on a non-vulnerable (no need for retrofitting) link instead of a retrofitted but much shorter link.

For each a, $dist^4$ results in higher shortage than $dist^1$ and $dist^2$. Although we cannot explicitly compare the shortage amounts of $dist^2$ and $dist^3$, it is trivial that $dist^1$ and $dist^4$ yield the lowest and and the highest amounts.

For $a = 4$ and $a = 5$, $dist^3$ gives more shortage than $dist^4$ since $dist^3$ results in two non-retrofitted links while $dist^4$ results in one. However, for $a = 6$ only $dist^4$ results a demand shortage, since the unique non-retrofitted link in this case has a higher retrofitting cost than the last 2 non-retrofitted links of $dist^3$, and also it is still more economical to compensate the high retrofitting cost of the link instead of satisfying the demand by helicopter. The retrofitting cost of the last non-retrofitted link of $dist^4$ is

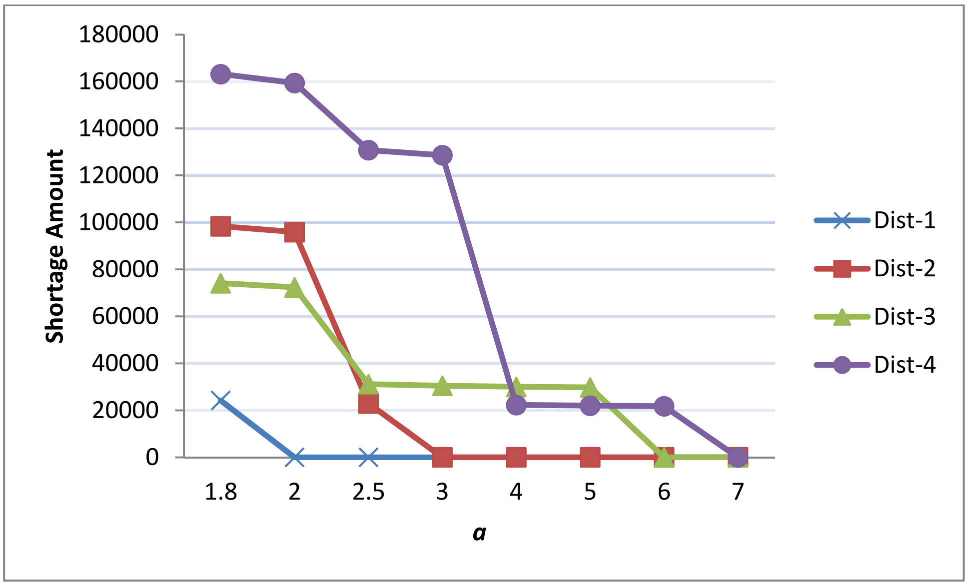

Figure 6.7. Change of shortage by retrofitting costs of links.

not as much as not to be retrofitted when $a = 7$, which is the case when $a = 2$, $a = 3$ and $a = 6$ for $dist^1$, $dist^2$ and $dist^3$. Therefore, in brief, it can be stated that shortage amounts are dependent on link retrofitting costs, as retrofit costs increase (decrease) shortage increases (decreases).

7. CONCLUSION

In this thesis, we propose mathematical models to minimize monetary and human losses in a disaster occurrence. In this manner, the models can be handled as preparedness models that help to give good decisions that may be taken before or after a disaster. First, we consider a new humanitarian relief logistics model (TSLP) which helps to build up an optimal pre-disaster plan for effective post-disaster response. TSLP is a two-echelon stochastic facility location model where the stochasticity arises from the discrete occurrence probabilities of earthquake scenarios. In the model set up two different types of disaster rescue centers are considered to be located at two different echelons of the humanitarian logistics network. The regional rescue centers (RRCs) are located prior to the disaster and store relief items, whereas the local rescue centers (LRCs) are set up following a disaster and behave as the transshipment points that distribute the items originated from RRCs to demand points. The other decisions given in the model are the amount of relief item flows between the two types of rescue centers as well as between the local rescue centers and demand points, the relief item inventory at the regional rescue centers, and the amount of unsatisfied demand also called shortage corresponding to each demand point, item, and scenario triplet. Shortage for any item is penalized with a very high cost.

The TSLP is formulated as a two-stage stochastic programming model with recourse, where the pre- and post-disaster decisions constitute the first and second stage (recourse) decisions, respectively. The model captures the inherent uncertainty in demand and cost resulting from an earthquake.

Although the two echelon rescue center network is commonly applied in real world disaster management applications and studied by researchers a number of times, to our knowledge, the TSLP model we propose is the first model that involves location decisions for both echelons in a stochastic model. To this respect, there exist mixed-integer variables in both stages of the two-stage stochastic program which increases the problem complexity. Moreover, the number of scenario-dependent integer LRC location and LRC-demand point assignment variables may be very large even for medium-size instances. Hence, the TSLP cannot be solved efficiently by a general-purpose mixed-integer linear programming solver.

Thus, we present a Lagrangean heuristic augmented with local search for efficiently solving the problem. The local search takes the best solution found by the Lagrangean heuristic as input and performs moves in the solution space of location variables associated with RRCs and LRCs. The performance of the solution methodology is compared with the performance of CPLEX 11.1. The results obtained on a large set of experiments indicate that the proposed solution methodology yields good feasible solutions measured as a percent deviation from lower bounds on the optimal objective values in a reasonable amount of computation time even for problem instances of realistic size. Furthermore, the value of the stochastic solution that can be used as a measure of the benefit of incorporating uncertainty into the model goes up to 7% on the average (above 20% for some instances).

We also address another two-stage stochastic model (IRRP) that considers both the pre-disaster risk mitigation and post-disaster response related issues in an integrated fashion to get a system level optimal.

Retrofitting decisions are the first stage variables whereas the remaining ones are the second stage variables. The mitigation decisions consist of retrofitting the buildings and transportation links to increase their resistance against earthquakes. For buildings, higher resistance means lower damage and low damage implies less relief item demand. This phenomenon gives inspiration for the IRRP model where retrofitting decisions affect the resistance of buildings and thereby the relief demand which is actually the main input for the post-disaster response decisions.

To the best of our knowledge, modelling the interaction between the retrofitting and response actions is not studied before in the disaster mitigation context. Moreover the building and transportation link retrofitting decisions are considered in the same model for the first time in the literature. The total mitigation budget is optimally allocated between all types of retrofitting alternatives, where link retrofitting prevents the collapse of links (bridges, viaducts) and thus increases the post-disaster connectivity of the network.

Retrofitting decisions of buildings are given for each single building therefore the model enables to track which building is retrofitted and how much. However, this type of a modelling may introduce millions of binary variables related to building retrofitting decisions.

We develop five Lagrangean heuristic methods (LHMs) in order to solve the model, and compare their performance to that of CPLEX. The solution quality is assessed by means of percent deviations from optimal or best lower bound known. All of the LHMs perform better than CPLEX, in particular, for moderate and large sized instances. Among the LHMs, LHM1 results in the best solutions when number of districts less than or equal to 500, whereas for larger instances LHM4 outperforms all the others.

It is observed that the mitigation budget is an important parameter that considerably affects the solvability of the problem. According to the results, the lower the budget is, the harder is the problem.

Various inferences on the IRRP model are also obtained through some detailed analyses on small example instances. The retrofitting strategy may be affected by budget levels, transportation distances and seismicity levels. Under limited budget, the optimal strategy seems to be as retrofitting more weaker buildings slightly instead of retrofitting buildings to higher code levels. Furthermore, remote or high risk districts need much retrofitting. Besides a sensitivity analysis on the shortage costs is conducted on a simple example. When there is an alternative transportation method, which means low shortage cost, then mitigation requirements decrease. Finally, the VSS analysis indicate that using the stochastic programming model instead of a deterministic model will help in saving high amounts of money.

As a future research direction, the developed models can be applied for İstanbul City or Marmara region of Turkey. If adequate data can be gathered for the application, then we believe that decision makers can obtain valuable information and clarify an important amount of uncertainty by the help of proposed models.

The IRRP model can be extended by incorporating any kind of constraints and decisions related to the mitigation, response and recovery phases into the model. For example, facility location and inventory holding decisions for rescue centers can be considered. Also, instead of defining direct links between each rescue center and district pairs, the model can be extended to work on a more realistic network structure, where the transportation of relief item demand from a rescue center to a district occurs along a path. Additionally, in some cases, the mitigation expenses of transportation infrastructure and buildings are compensated by different organizations, therefore a different budget may be allotted for each of them. Then, the aggregate budget constraint should be replaced by two separate budget constraints.

Furthermore, we also consider formulating the IRRP model on a time domain in order to incorporate the expected earthquake occurrence time. Although some of the previous models (e.g., [17–19]) incorporate time periods, none of them consider a conditional probability model. These models use a time independent probability approach (i.e., Poisson process) for earthquake occurrences in which a constant annual occurrence probability for each scenario is used. Thus, they assume that for each consecutive year of the planning horizon a large earthquake can occur with the same probability. But, the Poisson process approach may not be appropriate for large earthquakes in the fault specific case, because of the inherent memoryless property [107].

It is known that due to elastic rebound theory [105] it takes some time to recharge stresses released after an earthquake and it is expected to release all strain energy accumulated on the fault in an earthquake occurrence, which restarts the earthquake cycle [107]. Therefore, earthquake occurrence can be modelled as renewal process where the probability of next event is conditioned on the time passed since the last event,i.e., earthquake occurrence is modelled as time-dependent.

Therefore, the model we want to study on first decides on retrofitting decisions in each time period t, then an earthquake can occur with probability h_t where h_t is the conditional probability of an earthquake occurrence in period t given that it has not occurred before t. A building can be gradually retrofitted in consecutive time periods through the time horizon, therefore the retrofitting decisions taken before time t will determine aftermath of the earthquake occurred in t. Right after the earthquake occurrence response decisions are given in the same period. The model determines the optimal retrofitting and response policy for each t in order to minimize the expected total system cost along the time horizon.

The expected reconstruction requirements for buildings can also be considered in this model and thus the model will include the recovery phase decisions, as well as the mitigation and response decisions.

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