LOCATING DISASTER RELIEF FACILITY CENTERS IN HOUSTON CITY

by

Dinesh Kandikonda

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by

Dinesh Kandikonda

APPROVED BY

Ki Young Jeong, Ph.D., Chair

Ipek Bozkurt, Ph.D., Committee Member

Xiaojun "Gene" Shan, Ph.D., Committee Member

APPROVED/RECEIVED BY THE COLLEGE OF SCIENCE AND ENGINEERING:

Said Bettayeb, Ph.D., Associate Dean

Ju H. Kim, Ph.D., Dean

ABSTRACT

LOCATING DISASTER RELIEF FACILITY CENTERS IN HOUSTON CITY

Dinesh Kandikonda
University of Houston-Clear Lake, 2018

Thesis Project Chair: Dr. Ki Young Jeong

We study the problem of locating disaster relief facility centers (DRFCs) in the city of Houston which is prone to flood risk hurricanes. We propose a multi-objective optimization programming (MOOP) model for selecting the location of DRFCs. Our multi-objective model attempts to minimize the total logistics cost and at the same time it aims to choose a potential site with lowest flood risk impact. Strategic design phase (SDP) includes the location of the DRFCs while operational level phase (OLP) deals with the robustness. Robustness is analyzed in terms of perturbed MOOP objective through diverse damage scenarios to DRFCs. The impact of factors such as open number of DRFCs, maximum coverage of a DRFC and α on the MOOP objective at different capacity levels are studied. For the MOOP model, two different objective models, total logistics cost (TLC) and flood risk impact (FRI) model are combined using the compromising programming model to obtain a compromise solution. These models are implemented on the real data of Houston. The result obtained from this framework depends on the decision- maker as it is his choice to decide upon the level of flood risk impact he is willing to take. To my best knowledge,

this is a first time approach to locate DRFCs in the city of Houston. This research will provide significant insights to practitioners in designing and implementing mathematical models related to flood affected areas.

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CHAPTER 1

INTRODUCTION

1.1 Research Background and Motivation

Hurricane Harvey, a category 4 storm, struck Houston, Texas in August 2017. This storm has affected a large number of people and also caused significant economic damages (Dottle et al.). Hurricane Harvey has also caused many severe physical damages to the city of Houston and the economic losses are in the billions. A lot of people are low income and did not have the means to leave the city (Hurricane Harvey: Four key effects of Houston floods).Three disaster recovery centers were to be opened in Houston by Federal Emergency Management Agency (FEMA) after the disaster and that suggests a lack of preparedness. This leads to a situation where people get stranded in the city without proper facilities to survive. The current research will help improve both pre-disaster and post-disaster operations by locating disaster relief facility centers (DRFC) in the city of Houston that are resistant to flood impact.

1.2 Problem Identification and its Significance

Floods are one of the most common (Tehrany et al., 2013; Ajin et al., 2013) and destructive phenomenon (Patel & Srivastava, 2013). Compared to other disasters, floods are easier to predict and prevent (Chang et al., 2007). When locating DRFCs, there is a probability that the DRFC location is under the risk of flood. This risk cannot be ignored as it will lead to closure of the DRFC and not only affect the cost but also increase the time to deliver supplies. The flood prevention is generally a mitigation to reduce the risk with the help of tools (Haddow et al., 2011). Pre and post disaster planning helps to improve the disaster responsiveness. Along with the logistics cost, the flood risk impact on the DRFC should be considered to prevent the risk of flooding of the disaster relief facility center. Not only the flood risk, but the logistics cost also plays a major role in deciding the DRFCs. Hence, a multi-objective optimization model is formulated that balances the cost and flood risk impact.

1.3 Aim and Objectives

The aim of the study is to develop a multi-objective optimization model to aid decision making regarding location of DRFCs in the city of Houston. The decision regarding the location of the DRFCs is regarded as the strategic level design as it involves cost, effect of environment, and population. The objective is to analyze the impact of parameters such as open number of DRFCs, maximum coverage of a DRFC and alpha (α) on the multi-objective optimization programming (MOOP) model using taguchi analysis. The study also attempts to analyze the robustness of the objective in operational level phase (OLP).

The following steps are undertaken to accomplish the aim:

- The real time data related to Houston is collected.
- The development of three optimization models to integrate cost and flood risk impact.
- The application of the models to the collected data of Houston to analyze the impact of factors and robustness on the objective.

- Helping the decision maker in choosing α by creating a compromising situation between the total logistics model and flood risk impact model.

1.4 Scope of the thesis

The scope of this research is limited to the location of the DRFCs based on the models formulated. The models developed will focus on preparedness in the strategic design phase (SDP) phase and response in the operational level planning (OLP) phase.

1.5 Contributions

The contributions of this study include (1) a multi-objective optimization programming model with consideration of 'total logistics cost', 'flood risk impact' and 'robustness'. To our best knowledge, most of the previous studies discussed models with focus on the total cost minimization without the main consideration of floods. It is claimed that our research helps decision makers to consider the flood risk on the DRFC along with the logistics cost. The robustness of the MOOP objective is analyzed in OLP. The models are implemented using the real data of Houston to locate the disaster relief facility centers.

CHAPTER 2

LITERATURE REVIEW

We focus on the literature relevant to research in this section. This study introduces the concept of flood risk impact while deciding upon DRFCs. There have been extensive research on the facility location allocation models for decades. In this chapter, a review of research on the location allocation models is provided.

Mostly, studies related to disaster management literature are generally tools specific to regions that suffer from disasters. In a similar way, Görmez et al. (2011) conducted a study in locating DRFCs in Istanbul. They propose a two-tier approach. They analyze trade-offs between objectives of minimizing the average weighted distances between locations and closest facilities, and opening a small number of facilities. Similarly, Dekle et al. (2005) conducted a study in locating DRFCs in Florida. A two stage approach, where the first stage involves determining the optimal DRFCs by solving the covering problem while disregarding the evaluation criteria. In the above mentioned studies, the potential locations were already taken into account without considering the flood risk related to DRFC. In our study, we consider the flood risk related to potential sites in locating the DRFCs. The main effects of mean plot analysis is provided, taking into account different scenarios.

Several researchers have modelled disaster management problems to locate DRFCs based on different criteria. For instance, Kongsomakasakul et al. (2005) proposed a location allocation model. With an objective of determining the location of DRFCs with capacity constraints, they formulated a bi-level programming model. Their study concentrates on the evacuees to choose among the potential DRFCs during floods but no risk flood risk impact on the DRFC was used in locating the potential facility centers.

Kilci et al. (2015) proposed a mixed integer linear programming analysis framework for locating temporary DRFCs. In locating the DRFCs, the model maximizes the minimum weight of the open DRFC. They have used the real data of Kartal, Istanbul, Turkey for their analysis and came to a conclusion that as the average utilization of a DRFC increases, the number of open DRFC decreases.

Taking into account the purpose of this research, most of the literature review will focus on the models related to locating optimal DRFCs. Akgün et al. (2015) used a fault tree analysis introducing the 'vertex p-center model' and 'p-center risk model'. With the objective to locate the potential DRFCs, the former analysis minimizes the maximum distance while the latter analysis minimizes the maximum risk of a demand point. Our approach is similar to this this model, but a multi-objective optimization model is used to locate the DRFCs, considering both distances and risk of the demand points.

Bozorgi-Amiri et al. (2011) proposed a multi-objective model that attempts to minimize the incorporating uncertainty in the demand, supply and cost of procurement and transportation. The model uses the compromising programming method to simultaneously minimize the sum of the expected value and variance of the total cost of relief chain and maximize the affected areas satisfaction levels. Our research is developed on the compromise programming where simultaneously total logistics cost and flood risk impact is minimized.

Jeong et al. (2014) analyzed the robustness in terms of perturbed total cost through diverse damage scenarios to major DRFCs in operation level phase. The robustness level is measured using the expected total perturbed cost and efficiency model. This procedure has been used in our research to learn about the robustness of the MOOP objective. Research on robustness is built upon the work done by Jeong et al. (2014). In our research, the risk probability has been considered similar to the flood risk of the potential site.

To our best knowledge, this is the only research which discussed and used the flood risk impact of the DRFC in the multi-objective programming model. This model has been applied to Houston data where no such work has been done yet. The compromising model helps the decision maker to decide upon the DRFCs by considering both the total logistics cost and flood risk impact of the corresponding DRFCs.

CHAPTER 3

MATHEMATICAL MODELS AND APPLICATIONS

In this chapter, we present all the mathematical models developed to study different approaches to the problem. Firstly, the common assumptions applicable to all models are described. Prior to this, the mathematical models are represented followed by the analysis framework.

3.1 General Assumptions

The following assumptions are made for all the models:

- One site can be assigned to only one DRFC
- A facility has only two states when a disaster occurs i.e. open (not damaged) or closed (damaged)
- DRFCs are identical in terms of demanded supply.
- The potential facilities will survive the disaster, as it is possible to establish facility centers in the low risk lying areas.
- The DRFCs can supply the demand to the sites without any disruptions.

3.2 Mathematical Models

In this section, we introduce three models. The first two models are used in the third model to form a multi-objective optimization model.

3.2.1 Total Logistics Cost and Flood Risk Impact Model (TLCmin and FRImin Model)

The total logistics cost model has a traditional objective that has been used in most of the facility location allocation models. According to Horner & Downs (2010), cost may be specified in any number of ways ranging from weighted or unweighted distance to simpler. Hence, minimization of demand weighted distance is considered as cost in this model. In both the models, we consider a set of potential sites J and a set of demand points M.

Parameters

d_{jm} : Distance between demand point m and facility j

D_m : Demand of point m

F^{Max} : Maximum number of facilities that can be built

$F^{MaxCover}$: Maximum number of neighbors a facility can cover

C_j^{max} : Capacity of facility j

Decision Variables:

F_j : binary variable deciding whether a facility is located at site j

x_{jm} : binary variable deciding whether site m is covered by facility j

$$TLCmin = Min \sum_{j \in J} \sum_{m \in M} D_m d_{jm} x_{jm} \tag{3.1}$$

Subject to

$$\sum_j F_j \leq F^{Max} \tag{3.2}$$

$$\sum_j x_{jm} = 1 \quad \forall \mathrm{m} \tag{3.3}$$

$$x_{jm} \leq F_j \quad \forall \mathrm{m,j} \tag{3.4}$$

$$\sum_m x_{jm} \leq F^{MaxCover} \ \forall \mathrm{j} \tag{3.5}$$

$$\sum_m D_m x_{jm} \leq C_j^{max} \quad \forall \mathrm{j} \tag{3.6}$$

In this model, the objective is to minimize the total logistics cost. Constraint (3.2) ensures that the number of DRFCs established is equal to the maximum number of facilities assigned. Constraint (3.3) ensures that each location is assigned to a facility center. Constraint (3.4) ensures that unless a facility is opened it cannot function. Constraint (3.5) ensures that a facility can cover an assigned number of locations. Constraint (3.6) ensures that demand of the locations is below the capacity of the facility center.

Flood risk plays a major role as it involves the risk of getting the potential facility location flooded. The conceptual model introduces the Flood risk impact (FRI) scale that provides the level of risk and this data is collected from National flood service (NFS), a division of Affinity Insurance Services, Inc. The model introduces constraints where the potential facility locations are chosen with the lowest flood risk impact. The TLC model has been modified to achieve this objective.

Parameters

FRR_m : Flood risk rate of m

D_m : Demand of point m

F^{Max} : Maximum number of facilities that can be built

$F^{MaxCover}$: Maximum number of neighbors a facility can cover

C_j^{max} : Capacity of facility j

Decision Variables:

Fj : binary variable deciding whether a facility is located at site j

xjm : binary variable deciding whether site m is covered by facility j

$$FRImin = Min \sum_{j \in J} \sum_{m \in M} D_m FRR_j x_{jm} \tag{3.7}$$

Subject to

$$\sum_j F_j \leq F^{Max} \tag{3.8}$$

$$\sum_j x_{jm} = 1 \quad \forall m \tag{3.9}$$

$$x_{jm} \leq F_j \quad \forall m,j \tag{3.10}$$

$$\sum_m x_{jm} \leq F^{MaxCover} \quad \forall j \tag{3.11}$$

$$\sum_m D_m x_{jm} \leq C_j^{max} \quad \forall j \tag{3.12}$$

In this model, the objective is to find the facility centers among the locations that have the lowest flood risk impact. Constraint (3.8) ensures that the number of facilities established is equal to the maximum number of facilities assigned. Constraint (3.9) ensures that each location is assigned to a facility center. Constraint (3.10) ensures that unless a facility is opened it cannot function. Constraint (3.11) ensures that a facility can cover assigned number of locations. Constraint (3.12) ensures that demand of the locations is below the capacity of the facility center.

3.2.2 Multi-Objective Optimization Model (MOOP Model)

In the above two models, we notice that when the total logistics cost is minimized, the flood risk impact on the facility center is compromised. In contrast, when locations with lowest flood risk impact as DRFCs is the objective, the total logistics cost is compromised. Hence, a multi-objective optimization model is formulated where the multi-objective optimization is achieved by setting the alpha value.

Parameters

FRR_m: Flood risk rate of city

$D_{m:}$ Demand of point m

F^{Max} : Maximum number of facilities that can be built

$F^{MaxCover:}$ Maximum number of neighbors a facility can cover

C_j^{max}: Capacity of facility j

TLCmin: Objective of TLCmin model

FRImin: Objective of FRImin model

α: assigned weight value

Decision Variables:

F_j : binary variable deciding whether a facility is located at site j

x_{jm} : binary variable deciding whether site m is covered by facility j

$$MOOP = Min(\alpha \frac{(\sum_{j\in J}\sum_{m\in M} D_m d_{mj} x_{jm}) - TLCmin)}{TLCmin} + (1-\alpha)\frac{(\sum_{j\in J}\sum_{m\in M} D_m FRR_j x_{jm}) - FRImin}{FRImin}) \tag{3.13}$$

Subject to

$$\sum_j F_j \leq F^{Max} \tag{3.14}$$

$$\sum_j x_{jm} = 1 \quad \forall m \tag{3.15}$$

$$x_{jm} \leq F_j \quad \forall m, j \tag{3.16}$$

$$\sum_m x_{jm} \leq F^{MaxCover} \; \forall j \tag{3.17}$$

$$\sum_m D_m x_{jm} \leq C_j^{max} \quad \forall j \tag{3.18}$$

In this model, the objective is to find the facility centers among the locations that have the lowest flood risk impact and also minimizes the total logistics cost based on the weight assigned. Constraint (3.14) ensures that the number of facilities established is equal to maximum of number of facilities assigned. Constraint (3.15) ensures that each location is assigned to a facility center. Constraint (3.16) ensures that unless a facility is opened it cannot function. Constraint (3.17) ensures that a facility can cover assigned number of locations. Constraint (3.18) ensures that demand of the locations is below the capacity of the facility center.

The solved MOOP model not only results in the MOOP objective but we can also obtain total logistics cost (TLC) and flood risk impact (FRI). Using the weight values of α, both the TLC and FRI are stressed through compromise programming to result in the MOOP objective.

3.3 Analysis Framework

The three mathematical models discussed in the previous section are the tools for the SDP and OLP analysis. We conduct the following steps in the SDP phase before moving into OLP phase.

Step 1: Solve the TLCmin model and obtain TLC_{min}.

Step 2: Solve the FRImin model and obtain FRI_{min}.

Step 3: Solve the MOOP model for various balancing weights of α from 0.1 to 0.9.

The results of steps 1 and 2 are used in step 3. Step 3 requires solving the MOOP model at different α values to analyze the impact of trade-off between cost and flood risk impact. We use various values of α with a 0.1 increment to generate various optimal locations of DRFCs. In some cases, two or more different balancing weights may generate exactly the same optimal locations of DRFCs.

For all the generated objectives in step 3, we can compare and analyze the impact of factors on the MOOP objective. Also, it is important to understand the relationship between the balancing weights α and risk tolerance. Risk tolerance is defined as the amount of risk that a decision-maker is willing to manage and take (Jeong et al., 2014). In this study, when DRFCs are located with more emphasis on total logistics cost (α close to 1), the associated flood risk of the DRFC may be higher as FRI model objective becomes zero (α close to 0). In contrary, to avoid risk of the DRFC from floods, the decision maker may have to compromise with the cost. A balance in between the cost and flood risk impact can be attained by setting α to 0.5. The compromise between total logistics cost and flood risk impact depends on the balancing weight α. It is choice of the decision maker to decide upon the level of α as it leads to a compromising scenario.

In OLP phase, robustness is considered for the optimal DRFCs generated from Step 3 of SDP. As robustness is affected by the location of the DRFCs, all the identical solutions with respect to the SDP should be grouped regardless of α. It will result in a node group which is a set of identical DRFCs.

If a disaster occurs, it is necessary for the decision maker to know the fastest possible way to distribute the emergency relief items with minimum MOOP objective. This objective can be obtained by solving the MOOP model where decision variables about the DRFCs are already given. In this case, all the DRFCs function well without any disruptions. Suppose that some of the DRFCs are shut down after a disaster, it will likely increase the MOOP objective compared to the normal case where all the DRFCs function well. However, if the normally obtained optimal DRFC locations are robust (scenario when all the DRFCs function well), the perturbed MOOP objective may not be significant. The level of robustness can be calculated using the below steps:

Step 1: Classify all DRFCs from the SDP phase into node groups based upon the identical DRFCs. These are represented as node group 'm'.

Step 2: Solve the MOOP model with the given DRFCs. This result will serve as a normal case.

Step 3: For each solution obtained from step 2, define all shut down scenarios of interest, a corresponding weighted flood risk rate, r(s), for any shut down scenario s, and apply MOOP model for all scenarios.

Step 4: Calculate the discrepancy between disruptive scenarios and normal cases in terms MOOP objective and obtain the expected perturbed objective.

$$EPO_m = \sum_s r(s)(MOOP(s) - MOOP(\bar{s})) \tag{3.19}$$

where r(s) and MOOP(s) represent weighted flood risk rate and MOOP objective respectively for a scenario s while MOOP($\bar{s}$) is the objective for normal case with no disruption.

The robustness level (Jeong et al., 2014) is calculated as below:

$$R_k = \frac{\max(EPO) - EPO_k}{\max(EPO) - \min(EPO)} \tag{3.20}$$

If we consider the shutdown of DRFC i as a disruptive scenario, then flood risk impact associated with the DRFC is considered as r(s). As the DRFC locations are identical for each group in 'm', EPO_k is same as EPO_m. Therefore robustness can be known for each group in SDP phase using equation 3.20. max(EPO) and min(EPO) are maximum and minimum EPO among the groups. EPO_k is the expected perturbed objective. The results of R_k range from 0 to 1, where 0 and 1 represent worst and best cases, respectively.

CHAPTER 4

DATA COLLECTION

Data collection performed in this research is based on the publicly data available online.

4.1 Demographical data

The population is the demand in our research. For accuracy of the demand corresponding to the sites, firstly the zip code data related to the Houston city is collected through online resources (Zip-Codes.com.). Later, the population under the zip codes (City-Data.com - Stats about all US cities) is required as demand in the model. All the zip codes are clustered based upon proximity and populations into 31 potential sites that can act as DRFCs. Then one site from each group is selected based upon centroid approach. It is assumed that all the population within the zip codes exists at the potential site. The distance between the sites is considered as the distance between the site groups. Table 4.1 shows all the sites and its population which is used as demand.

The distance between the sites is considered to be the distance between the zip code groups. The flood risk impact for each site collected and is displayed in table 4.2. This is not considered for a group of zip codes as the DRFC may built at a location which would be zip code specific. The flood risk impact corresponding to each location is collected from National flood service (NFS), a division of Affinity insurance service, Inc. The flood risk has been taken on scale of 5, where the risk of flood gets higher in a range from 1 to 5. The potential sites for DRFC are shown in figure 4.1.

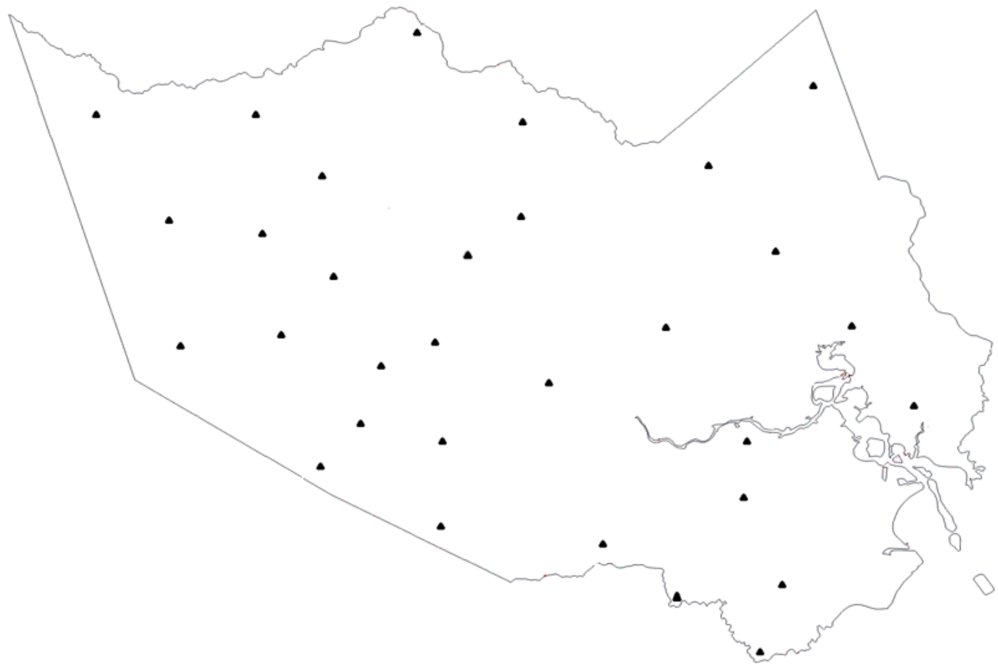

Figure 4.1 Potential sites in Houston Map

No.	Potential sites	Zip code group	Population
1	Waller	77058, 77062, 77598, 77586, 77571	31218
2	Katy	77494, 77493, 77450	188336
3	Sugarland	77478, 77498, 77479, 77099, 77083, 77031, 77407	341168
4	Stafford	77477, 77071, 77085, 77074, 77036, 77072	252673
5	Missouri City	77489, 77053, 77459	132957
6	Addicks - Barker	77084, 77079, 77043, 77077, 77094, 77449, 77082	385112
7	Cypress	77433, 77429	144028
8	Tomball	77375, 77377, 77362	83629
9	Kohrville	77070, 77379, 77069	142683
10	Jersey Village	77041, 77040, 77064, 77086	159666
11	Bellaire	77401, 77081, 77046, 77025, 77096, 77005, 77027, 77098, 77030, 77054, 77035, 77045, 77051	302881
12	Spring	77373, 77386, 77365, 77073	173097
13	Bammel	77090, 77068, 77014, 77388, 77066, 77067	189098
14	Aldine	77060, 77037, 77032, 77039, 77038, 77076, 77088, 77093	228086
15	Houston	77002, 77010, 77003, 77006, 77009, 77004, 77007, 77019, 77020, 77026, 77011, 77008, 77023, 77021, 77022	356237
16	Pasadena	77505, 77504, 77059, 77034, 77503	131681
17	South Houston	77587, 77017, 77502, 77061, 77075, 77087, 77506, 77012, 77547, 77033	288324
18	Pearland	77581, 77584, 77089, 77048, 77047	225081
19	Webster	77484, 77446, 77447	126670
20	Baytown	77523, 77521, 77520	115807
21	Highlands	77530, 77015, 77562, 77536	73458
22	Sheldon	77049, 77044, 77532	97294
23	Humble	77338, 77396, 77339, 77346	186533
24	Huffman	77336, 77345, 77357	63515
25	League city	77573, 77565, 77539, 77546	183999
26	Satsuma	77065, 77095	110125
27	Hillshire Village	77055, 77080, 77092, 77056, 77018, 77091	197433
28	Bunker Hill Village	77024, 77063, 77042, 77057	308186
29	Courben Ln	77078, 77016, 77028, 77050, 77013, 77029	101221
30	Alvin	77511, 77517	53545
31	Shenandoha	77380, 77381, 77382, 77389	134000

Table 4.1 Population and grouping associated with Potential Sites

No.	Potential sites	Flood risk rate
1	Waller	2.5
2	Katy	5
3	Sugarland	5
4	Stafford	2.5
5	Missouri City	2.5
6	Addicks - Barker	2.5
7	Cypress	1
8	Tomball	2.5
9	Kohrville	2.8
10	Jersey Village	2.5
11	Bellaire	5
12	Spring	2.3
13	Bammel	2.3
14	Aldine	2.5
15	Houston	1.9
16	Pasadena	2.5
17	South Houston	5
18	Pearland	4.3
19	Webster	2.5
20	Baytown	2.5
21	Highlands	2.5
22	Sheldon	5
23	Humble	2.5
24	Huffman	5
25	League city	2.5
26	Satsuma	3.3
27	Hillshire Village	2.3
28	Bunker Hill Village	2.3
29	Courben Ln	2.5
30	Alvin	5
31	Shenandoha	2.4

Table 4.2 Flood risk impact data of Potential Sites

CHAPTER 5

ANALYSIS OF RESULTS

In this chapter, we present the computational results and analyze the proposed models behavior using main effects analysis. Later on we will analyze the robustness for three different cases of open number of DRFCs. We solve the models using IBM ILOG CPLEX Optimizer running on PC I7 processor with 8 GB of RAM under the Windows 10 environment. The factorial design is chosen based on the type of analysis. The main effects of mean analysis using Minitab is performed to understand the model behavior and impact of factors.

5.1 Analysis of Main effects

Main effects is known as the effect of the control factors on the response values when the factor's value changes from one level to the other (Roy 2001). The response in main effects helps us to understand the impact of factors on the performance measures.

5.1.1 Main effects plot for means analysis of infinite DRFC capacity (D_{max}):

We generated a 3*3*9 factorial design using Minitab 18 with the factors and levels mentioned in the table 5.1. The open number of DRFCs (Fj) and maximum coverage by a DRFC (FmC) are of three levels and α is of 9 levels as shown in the table. This results in 81 alternatives. The capacity is considered to infinite for all the alternatives in table 5.2.

Factors	Levels
Fj	5,6,7
FmC	7,8,9
α	0.1-0.9

Table 5.1: Factors and Levels for infinity capacity analysis

Main effects plot for means using Minitab 18 is performed for Table 5.2. Figure 5.1 shows the main effects of the factors Fj, FmC and α on the obtained response values of TLC, FRI and MOOP objective. We observe from figure 5.1 that in TLC, total logistics cost decrease with increase in Fj. More number of DRFCs reduces cost in case of TLC. The infinite capacity is considered as D_{max}, such that a single DRFC can cover the demand of all the potential sites along with its own demand. In TLC, as FmC increases, the total logistics cost increases. With the increase in the maximum coverage by a DRFC, the distance between the DRFC and the potential sites also increase, which in turn will affect the cost. The trend in alpha with respect to TLC is as expected. TLC objective should decrease as preference change from flood risk impact to total logistics cost.

From figure 5.2, in case of FRI, there is a slight increase in the flood risk impact when Fj increases. We relate this to the infinite capacity that we consider. As all the DRFCs have the maximum capacity, the DRFCs are chosen based on flood risk rate of the potential sites. As expected, flood risk rate decides the Fj when the capacity is D_{max}. Also in FRI, with the decrease in the flood risk impact, a gradual decrease in FmC is observed. As only demand and flood risk rate are considered in case of flood risk impact, decision on coverage depends on demand satisfaction of the potential sites. The MOOP objective response values depends on both the TLC and FRI. It implies that MOOP model is minimizing both TLC and FRI to obtain the minimized MOOP objective.

Alt	Fj	FmC	alpha	TLCmin	TRImin	TLC	TRI	MOOP Objective
1	5	7	0.1	46145188.7	9203423	79690000	9781100	0.13
2	5	7	0.2	46145188.7	9203423	57891000	10513000	0.17
3	5	7	0.3	46145188.7	9203423	55258000	10722000	0.18
4	5	7	0.4	46145188.7	9203423	53895000	10885000	0.18
5	5	7	0.5	46145188.7	9203423	53895000	10885000	0.18
6	5	7	0.6	46145188.7	9203423	53259000	11025000	0.17
7	5	7	0.7	46145188.7	9203423	48354000	12750000	0.15
8	5	7	0.8	46145188.7	9203423	48188000	12879000	0.12
9	5	7	0.9	46145188.7	9203423	46145000	15589000	0.07
10	5	8	0.1	46145188.7	8865040	81675000	9426600	0.13
11	5	8	0.2	46145188.7	8865040	61245000	10043000	0.17
12	5	8	0.3	46145188.7	8865040	56419000	10346000	0.18
13	5	8	0.4	46145188.7	8865040	53695000	10602000	0.18
14	5	8	0.5	46145188.7	8865040	52296000	10794000	0.18
15	5	8	0.6	46145188.7	8865040	52296000	10794000	0.17
16	5	8	0.7	46145188.7	8865040	48202000	12569000	0.16
17	5	8	0.8	46145188.7	8865040	46145000	12706000	0.12
18	5	8	0.9	46145188.7	8865040	46145000	15589000	0.08
19	5	9	0.1	46145188.7	8547783	80746000	9187900	0.14
20	5	9	0.2	46145188.7	8547783	62771000	9780300	0.19
21	5	9	0.3	46145188.7	8547783	56200000	10171000	0.20
22	5	9	0.4	46145188.7	8547783	53788000	10399000	0.20
23	5	9	0.5	46145188.7	8547783	52835000	10562000	0.19
24	5	9	0.6	46145188.7	8547783	52835000	10562000	0.18
25	5	9	0.7	46145188.7	8547783	47806000	12524000	0.16
26	5	9	0.8	46145188.7	8547783	47806000	12524000	0.12
27	5	9	0.9	46145188.7	8547783	47806000	12524000	0.08
28	6	7	0.1	41336835.3	9203423	68839000	9950800	0.14
29	6	7	0.2	41336835.3	9203423	51947000	10490000	0.16
30	6	7	0.3	41336835.3	9203423	48273000	10780000	0.17
31	6	7	0.4	41336835.3	9203423	47781000	10848000	0.17
32	6	7	0.5	41336835.3	9203423	47417000	10922000	0.17
33	6	7	0.6	41336835.3	9203423	45631000	11438000	0.16
34	6	7	0.7	41336835.3	9203423	42742000	12821000	0.14
35	6	7	0.8	41336835.3	9203423	42742000	12821000	0.11
36	6	7	0.9	41336835.3	9203423	41337000	14389000	0.06
37	6	8	0.1	41336835.3	8865040	67715000	9704600	0.15
38	6	8	0.2	41336835.3	8865040	55499000	10073000	0.18

Alt	Fj	FmC	alpha	TLCmin	TRImin	TLC	TRI	MOOP Objective
39	6	8	0.3	41336835.3	8865040	51484000	10303000	0.19
40	6	8	0.4	41336835.3	8865040	47648000	10679000	0.18
41	6	8	0.5	41336835.3	8865040	47648000	10679000	0.18
42	6	8	0.6	41336835.3	8865040	45823000	11221000	0.17
43	6	8	0.7	41336835.3	8865040	45823000	11221000	0.16
44	6	8	0.8	41336835.3	8865040	42742000	12821000	0.12
45	6	8	0.9	41336835.3	8865040	41337000	14389000	0.06
46	6	9	0.1	41336835.3	8547783	75085000	9286300	0.16
47	6	9	0.2	41336835.3	8547783	50454000	10201000	0.20
48	6	9	0.3	41336835.3	8547783	50454000	10201000	0.20
49	6	9	0.4	41336835.3	8547783	48265000	10498000	0.20
50	6	9	0.5	41336835.3	8547783	48265000	10498000	0.20
51	6	9	0.6	41336835.3	8547783	46138000	11085000	0.19
52	6	9	0.7	41336835.3	8547783	45823000	11221000	0.17
53	6	9	0.8	41336835.3	8547783	42742000	12821000	0.13
54	6	9	0.9	41336835.3	8547783	41337000	14389000	0.07
55	7	7	0.1	36848126.7	9203423	57819000	10184000	0.15
56	7	7	0.2	36848126.7	9203423	46340000	10553000	0.17
57	7	7	0.3	36848126.7	9203423	44108000	10741000	0.18
58	7	7	0.4	36848126.7	9203423	43616000	10809000	0.18
59	7	7	0.5	36848126.7	9203423	41649000	11201000	0.17
60	7	7	0.6	36848126.7	9203423	41032000	11382000	0.16
61	7	7	0.7	36848126.7	9203423	39130000	12105000	0.14
62	7	7	0.8	36848126.7	9203423	38848000	12350000	0.11
63	7	7	0.9	36848126.7	9203423	36848000	14054000	0.06
64	7	8	0.1	36848126.7	8865040	65105000	9741900	0.17
65	7	8	0.2	36848126.7	8865040	47167000	10365000	0.19
66	7	8	0.3	36848126.7	8865040	43917000	10609000	0.20
67	7	8	0.4	36848126.7	8865040	43917000	10609000	0.20
68	7	8	0.5	36848126.7	8865040	43917000	10609000	0.19
69	7	8	0.6	36848126.7	8865040	41032000	11382000	0.18
70	7	8	0.7	36848126.7	8865040	39130000	12105000	0.15
71	7	8	0.8	36848126.7	8865040	38848000	12350000	0.12
72	7	8	0.9	36848126.7	8865040	36848000	14504000	0.06
73	7	9	0.1	36848126.7	8547783	70657000	9366800	0.18
74	7	9	0.2	36848126.7	8547783	47844000	10239000	0.22
75	7	9	0.3	36848126.7	8547783	45764000	10403000	0.23

Alt	Fj	FmC	alpha	TLCmin	TRImin	TLC	TRI	MOOP Objective
76	7	9	0.4	36848126.7	8547783	43917000	10609000	0.22
77	7	9	0.5	36848126.7	8547783	43917000	10609000	0.22
78	7	9	0.6	36848126.7	8547783	41032000	11382000	0.20
79	7	9	0.7	36848126.7	8547783	39130000	12105000	0.17
80	7	9	0.8	36848126.7	8547783	38848000	12350000	0.13
81	7	9	0.9	36848126.7	8547783	36848000	14504000	0.07

Table 5.2: L_{81} Factorial design with MOOP objective

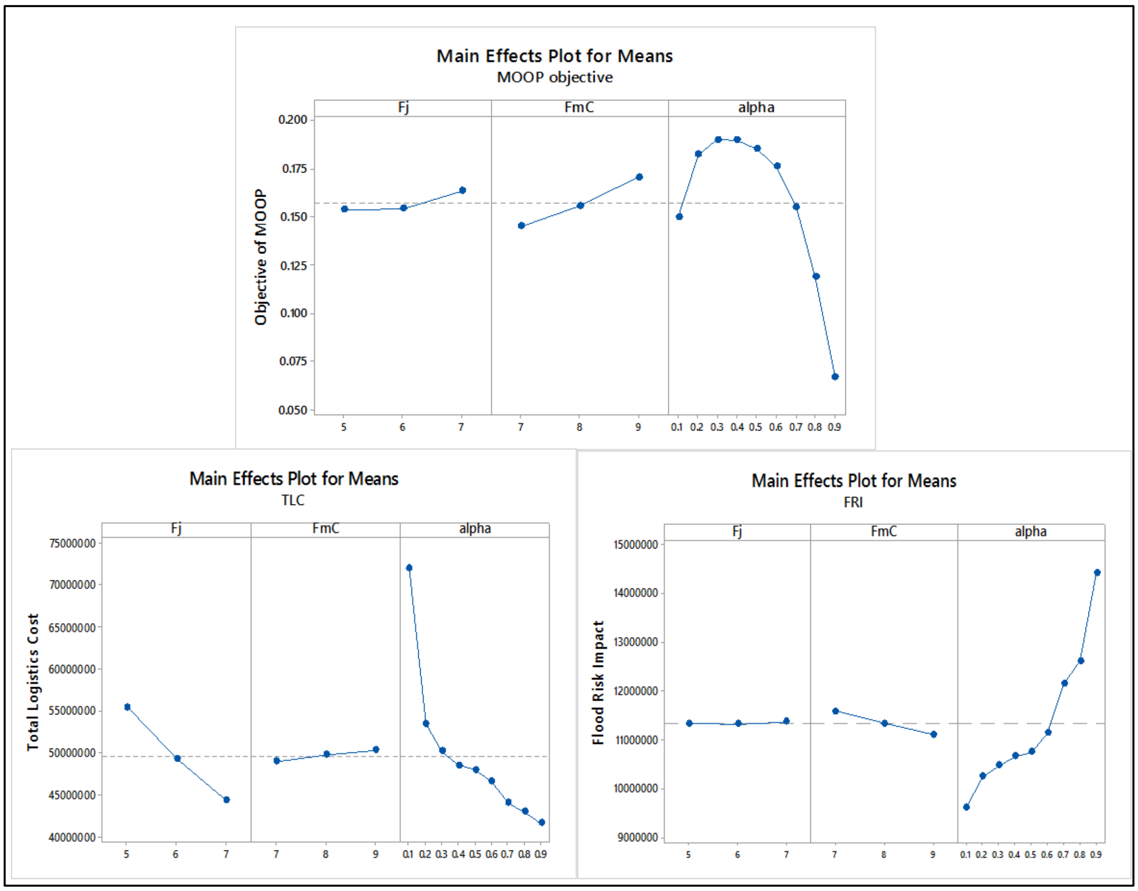

Figure 5.1: Factors and Levels (Plot of main effects of response- MOOP, TLC and FRI)

5.1.2 Capacitated DRFC main effect analysis:

We created a 2*2*9 factorial design using Minitab 18 with the factors and levels mentioned in the table 5.3. The open number of DRFCs (Fj) and maximum coverage by a DRFC (FmC) is of two levels and α is of 9 levels as shown in the table. This results in 36 alternatives.

Main effects plot for means using Minitab 18 is performed on table 5.4 which resulted in figure 5.2. The value of the capacity is chosen in such a way that it is near to $D_{max}/6$. This analysis will help us to understand the impact of factors on the response values when the MOOP model is capacitated.

In TLC of figure 5.2, Fj is increasing with the decrease in the objective. The more number of DRFCs, the lower the total logistics cost. With more number of Fj or open DRFCs, the closest potential sites demand can be fulfilled. FmC i.e. the maximum coverage of DRFC is not much sensitive to the objective in TLC. It however depends on the capacity. As the DRFC capacity is limited, the coverage of DRFC depends upon the satisfaction of the demand rather than distance from DRFC. The trend in alpha is as expected. The increase in alpha will decrease the total logistics cost as the preference towards TRI increases.

In FRI of figure 5.2, the flood risk impact is decreasing with increase in Fj. As the DRFCs are capacitated, the locations of the DRFCs are chosen based on both the demand and flood risk impact. The phenomenal difference could be observed from infinite capacity analysis. FmC is less sensitive to FRI. The FmC input parameters are very much higher such that it having very low effect on objective. Again, the trend in alpha is as expected. The flood risk impact is increasing with increase in alpha.

The MOOP objective in figure 5.2 depends on both the corresponding TRI and FRI. It is because the MOOP model will be stressed to optimize both the TRI and FRI simultaneously.

Factors	**Levels**
Fj	6,7
FmC	7,8,9
α	0.1-0.9

Table 5.3: Factors and Levels for capacitated analysis

Alt	Fj	FmC	alpha	TLCmin	TRImin	TLC	TRI	MOOP Objective
1	6	8	0.1	51494034.6	11104790	64289000	11293000.00	0.04
2	6	8	0.2	51494034.6	11104790	58891000	11474000.00	0.055
3	6	8	0.3	51494034.6	11104790	58891000	11474000.00	0.066
4	6	8	0.4	51494034.6	11104790	58891000	11474000.00	0.077
5	6	8	0.5	51494034.6	11104790	57998000	11657000.00	0.088
6	6	8	0.6	51494034.6	11104790	53064000	12851000.00	0.081
7	6	8	0.7	51494034.6	11104790	53064000	12851000.00	0.069
8	6	8	0.8	51494034.6	11104790	53064000	12851000.00	0.056
9	6	8	0.9	51494034.6	11104790	51593000	15151000.00	0.038
10	6	9	0.1	51494034.6	11104208.5	64289000	11293000.00	0.04
11	6	9	0.2	51494034.6	11104208.5	58891000	11474000.00	0.055
12	6	9	0.3	51494034.6	11104208.5	58891000	11474000.00	0.066
13	6	9	0.4	51494034.6	11104208.5	58891000	11474000.00	0.077
14	6	9	0.5	51494034.6	11104208.5	56603000	11661000.00	0.075
15	6	9	0.6	51494034.6	11104208.5	53064000	12851000.00	0.081
16	6	9	0.7	51494034.6	11104208.5	53064000	12851000.00	0.069
17	6	9	0.8	51494034.6	11104208.5	53064000	12851000.00	0.056
18	6	9	0.9	51494034.6	11104208.5	51593000	15151000.00	0.038
19	7	8	0.1	38452254.8	11104814.6	47044000	11347000.00	0.042
20	7	8	0.2	38452254.8	11104814.6	41055000	11636000.00	0.052
21	7	8	0.3	38452254.8	11104814.6	41055000	11636000.00	0.054
22	7	8	0.4	38452254.8	11104814.6	41055000	11636000.00	0.056
23	7	8	0.5	38452254.8	11104814.6	41055000	11636000.00	0.058
24	7	8	0.6	38452254.8	11104814.6	40225000	11975000.00	0.059
25	7	8	0.7	38452254.8	11104814.6	39941000	12132000.00	0.055
26	7	8	0.8	38452254.8	11104814.6	39941000	12132000.00	0.049
27	7	8	0.9	38452254.8	11104814.6	3869000	14172000.00	0.033
28	7	9	0.1	38452254.8	11103988.9	47044000	11347000.00	0.042
29	7	9	0.2	38452254.8	11103988.9	41055000	11636000.00	0.052
30	7	9	0.3	38452254.8	11103988.9	41055000	11636000.00	0.054
31	7	9	0.4	38452254.8	11103988.9	41055000	11636000.00	0.056
32	7	9	0.5	38452254.8	11103988.9	41055000	11636000.00	0.058
33	7	9	0.6	38452254.8	11103988.9	40225000	11975000.00	0.059
34	7	9	0.7	38452254.8	11103988.9	39941000	12132000.00	0.055
35	7	9	0.8	38452254.8	11103988.9	39941000	12132000.00	0.049
36	7	9	0.9	38452254.8	11103988.9	3869000	14172000.00	0.033

Table 5.4: L_{36} Design with MOOP objective

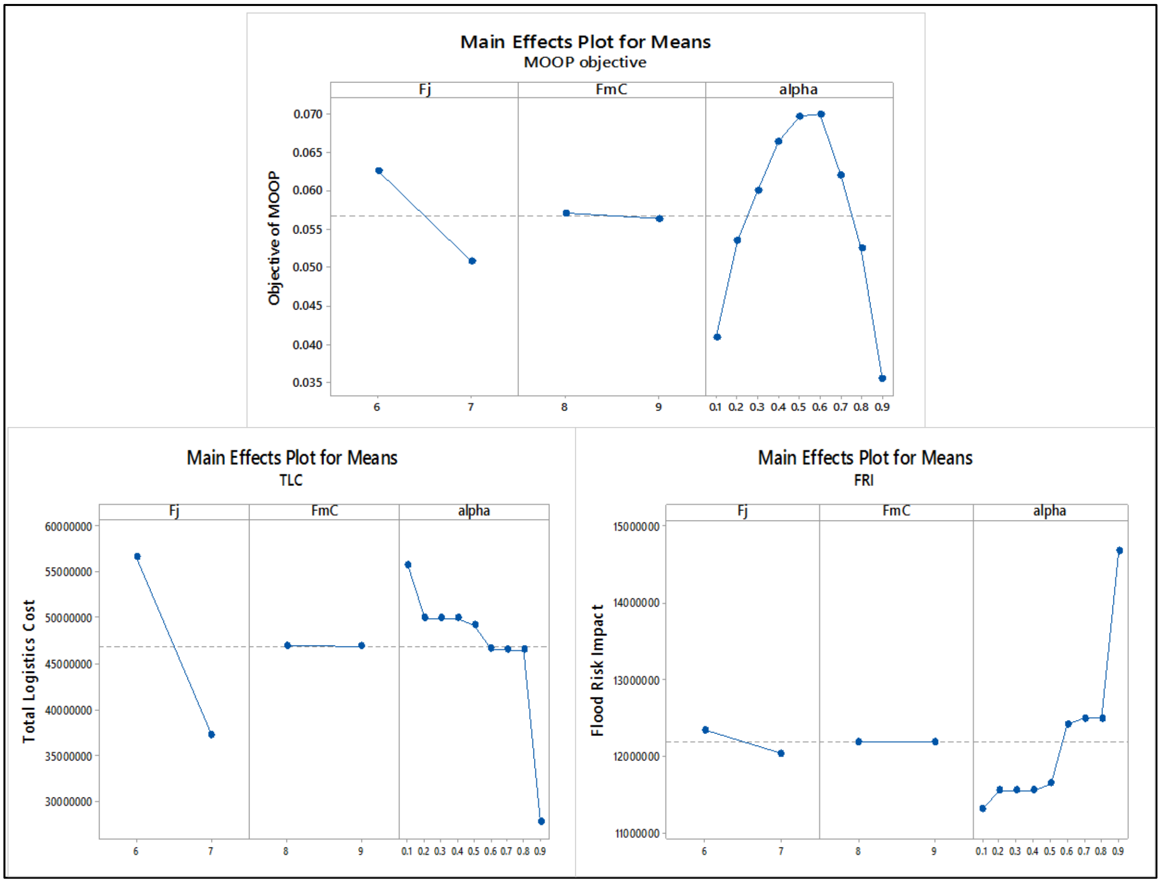

Figure 5.2: Plot of main effects of response- MOOP, TLC and FRI

From the above analysis we understand that open number of DRFCs (Fj), maximum coverage by DRFC (FmC) and capacity of a DRFC impact the response measure in a drastic way. It can be stated that with the increase in the capacity of DRFC there is a decrease in the open number of DRFCs and vice versa.

5.2 Robustness based on α in OLP phase

We consider three cases where open number of DRFCs range from 5 to 7. The following parameters are predetermined for the three cases. The maximum coverage of a DRFC is set to 8 in all the three cases. In order to manage simultaneous DRFC shutdown scenarios, we consider the DRFCs to have infinite capacity i.e. D_{max}. The parameters considered are shown in the table 5.5. Furthermore, we assume that only one facility shuts down at a time. This reduces the number of possible scenarios for demonstration purpose. The MOOP model is solved using CPLEX optimizer.

First, both TLCmin and FRImin models are solved to obtain the TLCmin and FRImin for all the three cases. These results are used to run MOOP model. The MOOP model results with no disruption scenarios are displayed in table 5.6, 5.7 and 5.8. When there is no disruption such as closing of a DRFC, the lowest MOOP objective is observed in all the cases when $\alpha = 0.9$. Figures 5.3, 5.4, 5.6, 5.7, 5.9 and 5.10 represent the networks of supply at extreme α values for each case. In all the three cases, when α equals 0.1, it implies that the location of the DRFCs are the safest with low flood risk impact as shown in the figures 5.4, 5.7 and 5.10. When there is least consideration of flood risk impact, the MOOP objective is lowest at $\alpha = 0.9$ in all the three cases and the associated network supply is displayed in figures 5.3, 5.6 and 5.9. If the decision makers priority is to consider the least MOOP objective with least consideration towards flood risk impact, then cases with $\alpha = 0.9$ will be his choice. Also, map figures 5.5, 5.8 and 5.11 display the network of supply points when $\alpha = 0.5$. It implies equal preference is given to both TLC and FRI. We analyze that with the change in the preference to TLC and FRI the location of the DRFCs are affected and on the whole it impacts the cost. When $\alpha = 0.5$, the cost will be relatively higher compared to α being 0.1 or 0.9. This is because the MOOP model is subjected to stress in minimizing the TLC and FRI equally. The difference in the results could be observed for all the cases with different α.

For the OLP phase, firstly total 9 networks of each case in SDP (tables 5.6, 5.7 and 5.8) are classified into node groups based upon the identical DRFCs. They are represented in tables 5.9, 5.10 and 5.11 and we can notice that each case has 5 node groups (A-E). For example, α's ranging from 0.2 to 0.4 in table 5.6 generates the same DRFCs set represented by {Stafford, Cypress, Spring, Houston, Webster}, and they grouped as a node group B. For each node group, all shutdown scenarios are considered in the 'Shutdown scenarios' rows. Then the corresponding MOOP model with predetermined Fj is solved to obtain the shutdown scenario objective. For example, in table 5.9, when Cypress is shutdown, the shutdown objective obtained is 0.410. The No damage scenarios in the tables represent the objective when none of the DRFCs are closed. The objectives in the 'No damage scenario' row of the table 5.9, 5.10 and 5.11 are computed by average of objectives within the node groups. Then, shutdown scenarios are experimented as described in the shutdown scenarios rows. Expected perturbed objective (EPO) for each scenario is estimated using equation 3.19. Equation 3.20 gives the robustness level. Now, we observe that node group A is the most robust in all the cases. Node group E in tables 5.9, 5.10 and 5.11, though yield the least objective when not under risk, they are the most vulnerable to damage with zero robustness. This is because TLC is more determined when compared to FRI. A closure of the DRFC when more preference is given to TLC will result in higher perturbed objective. The DRFCs link to the potential sites depends on both the distance and demand in case of TLC whereas in case of FRI, it depends flood risk rate and demand. The logistics network is highly sensitive to the demand weighted distance.

According to the tables 5.9, 5.10 and 5.11, the high ratio of EPO to 'No damage objective' indicates that DRFC shutdown will have a very high impact on the robustness. When $\alpha = 0.1$, the DRFCs are decided with least consideration of TLC and vice versa when $\alpha = 0.9$. It is also observed that robustness level is greater than 0.65 when $\alpha \leq 0.5$.

Case	Open DRFCs	FmC	α	Capacity
1	5	8	0.1-0.9	D_{max}
2	6	8	0.1-0.9	D_{max}
3	7	8	0.1-0.9	D_{max}

Table 5.5 Cases with Factors

α	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
MOOP objective	0.134	0.172	0.184	0.183	0.175	0.167	0.157	0.118	0.076
Rank	3	6	9	8	7	5	4	2	1
Waller	0	0	0	0	0	0	0	0	0
Katy	0	0	0	0	0	0	0	0	0
Sugarland	0	0	0	0	0	0	0	0	0
Stafford	0	1	1	1	1	1	1	1	1
Missouri City	0	0	0	0	0	0	0	0	0
Addicks - Barker	0	0	0	0	0	0	1	1	1
Cypress	1	1	1	1	1	1	0	0	0
Tomball	0	0	0	0	0	0	0	0	0
Kohrville	0	0	0	0	0	0	0	0	0
Jersey Village	0	0	0	0	0	0	0	0	0
Bellaire	0	0	0	0	0	0	0	0	0
Spring	1	1	1	1	0	0	1	1	1
Bammel	0	0	0	0	0	0	0	0	0
Aldine	0	0	0	0	0	0	0	0	0
Houston	1	1	1	1	1	1	1	1	1
Pasadena	0	0	0	0	0	0	0	0	0
South Houston	0	0	0	0	0	0	0	0	1
Pearland	0	0	0	0	0	0	0	0	0
Webster	0	1	1	1	1	1	1	1	0
Baytown	0	0	0	0	0	0	0	0	0
Highlands	1	0	0	0	0	0	0	0	0
Sheldon	0	0	0	0	0	0	0	0	0
Humble	0	0	0	0	1	1	0	0	0
Huffman	0	0	0	0	0	0	0	0	0
League city	1	0	0	0	0	0	0	0	0
Satsuma	0	0	0	0	0	0	0	0	0
Hillshire Village	0	0	0	0	0	0	0	0	0
Bunker Hill Village	0	0	0	0	0	0	0	0	0
Courben Ln	0	0	0	0	0	0	0	0	0
Alvin	0	0	0	0	0	0	0	0	0
Shenandoha	0	0	0	0	0	0	0	0	0

Table 5.6: Case 1 SDP MOOP result

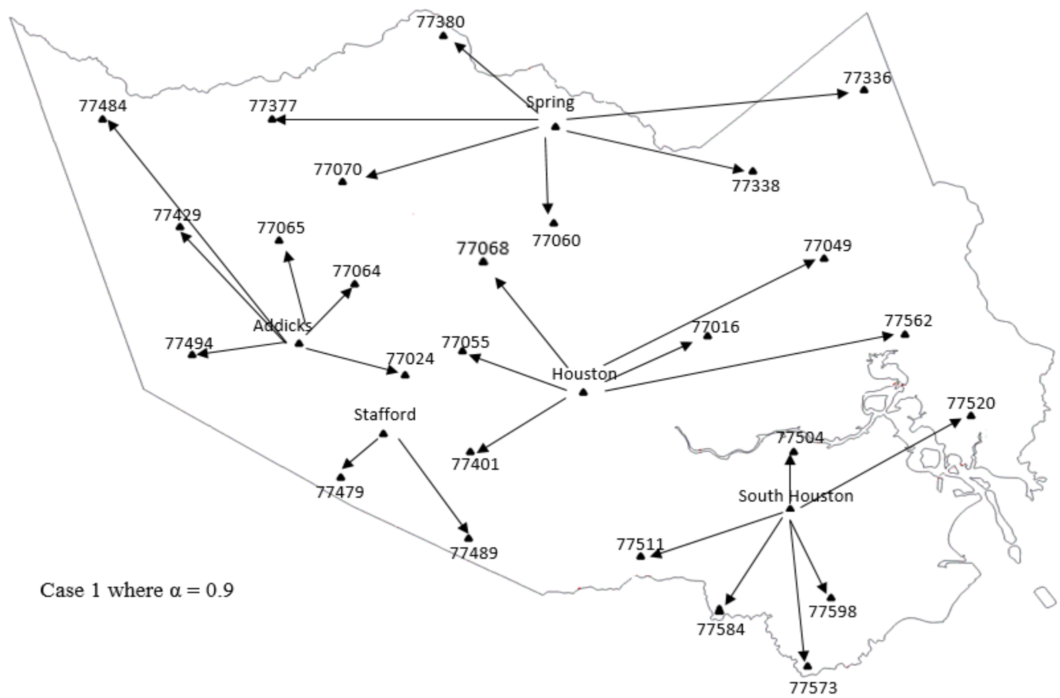

Figure 5.3: Case 1 α =0.9 (rank 1 with high flood risk impact)

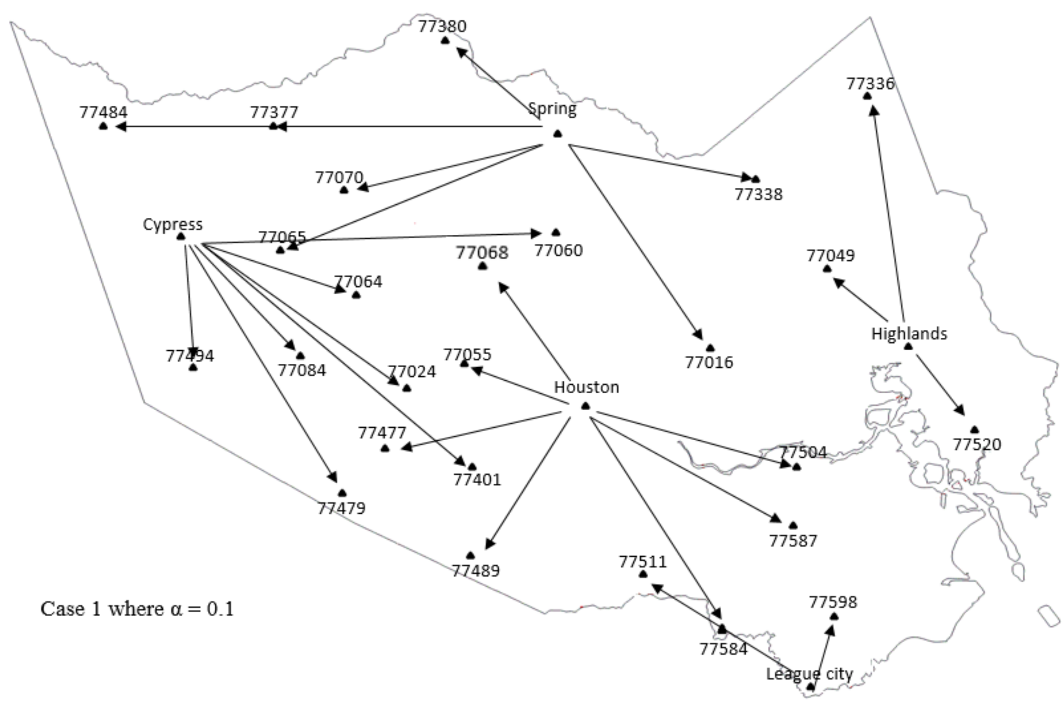

Figure 5.4: Case 1 α =0.1 (lowest flood risk impact)

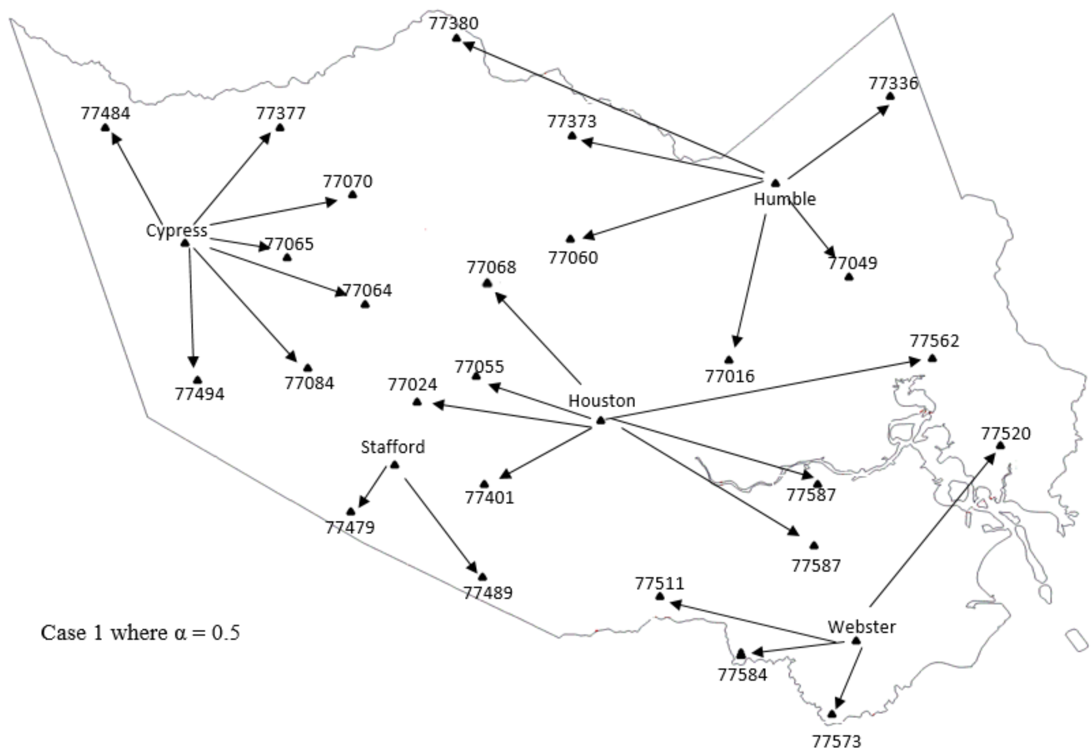

Figure 5.5: Case 1 α =0.5

α	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
MOOP objective	0.149	0.178	0.187	0.184	0.179	0.171	0.156	0.116	0.062
Rank	3	6	9	8	7	5	4	2	1
Waller	0	0	0	0	0	0	0	0	0
Katy	0	0	0	0	0	0	0	0	0
Sugarland	0	0	0	0	0	0	0	0	0
Stafford	1	1	1	1	1	1	1	1	1
Missouri City	0	0	0	0	0	0	0	0	0
Addicks - Barker	0	0	0	0	0	0	0	1	1
Cypress	1	1	1	1	1	1	1	0	0
Tomball	0	0	0	0	0	0	0	0	0
Kohrville	0	0	0	0	0	0	0	0	0
Jersey Village	0	0	0	0	0	0	0	0	0
Bellaire	0	0	0	0	0	0	0	0	0
Spring	1	1	1	1	1	1	1	1	1
Bammel	0	0	0	0	0	0	0	0	0
Aldine	0	0	0	0	0	0	0	0	0
Houston	1	1	1	1	1	1	1	1	1
Pasadena	0	0	0	1	1	0	0	1	0
South Houston	0	0	0	0	0	0	0	0	1
Pearland	0	0	0	0	0	0	0	0	0
Webster	0	0	0	0	0	1	1	1	1
Baytown	0	0	0	0	0	0	0	0	0
Highlands	1	1	1	0	0	0	0	0	0
Sheldon	0	0	0	0	0	0	0	0	0
Humble	0	0	0	0	0	0	0	0	0
Huffman	0	0	0	0	0	0	0	0	0
League city	1	1	1	1	1	0	0	0	0
Satsuma	0	0	0	0	0	0	0	0	0
Hillshire Village	0	0	0	0	0	0	0	0	0
Bunker Hill Village	0	0	0	0	0	1	1	0	0
Courben Ln	0	0	0	0	0	0	0	0	0
Alvin	0	0	0	0	0	0	0	0	0
Shenandoha	0	0	0	0	0	0	0	0	0

Table 5.7: Case 2 SDP MOOP result

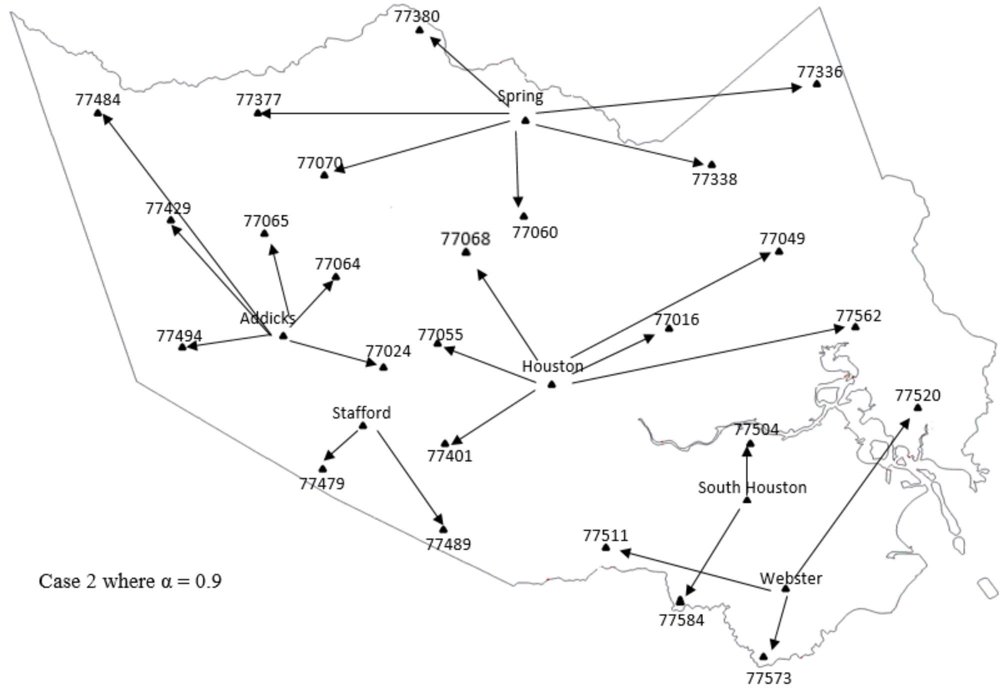

Figure 5.6: Case 2 α =0.9 (rank 1 with high flood risk impact)

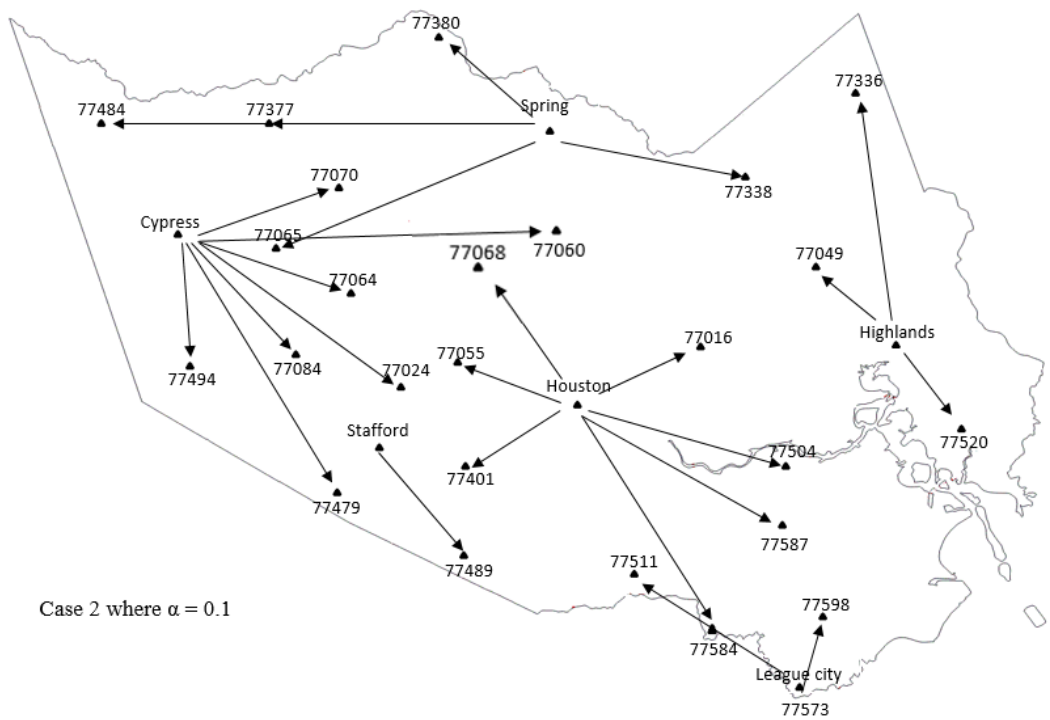

Figure 5.7: Case 2 α =0.1 (lowest flood risk impact)

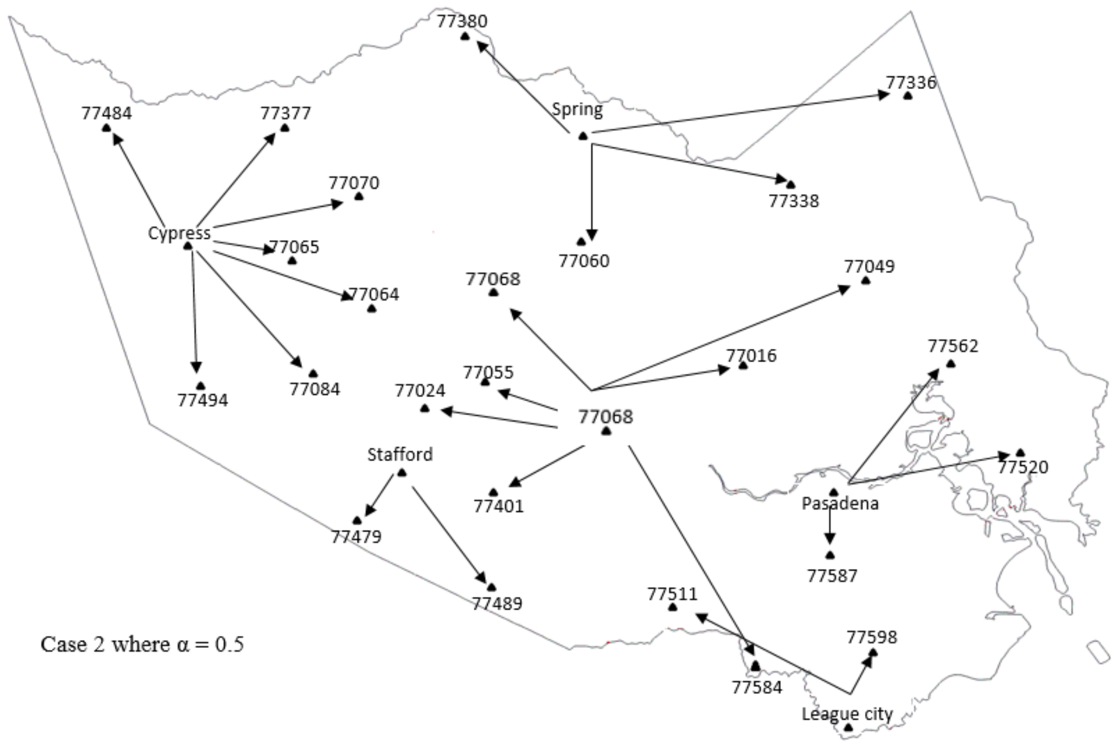

Figure 5.8: Case 2 α =0.5

α	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
MOOP objective	0.166	0.191	0.195	0.195	0.194	0.182	0.153	0.122	0.064
Rank	4	6	8	8	7	5	3	2	1
Waller	0	0	0	0	0	0	0	0	0
Katy	0	0	0	0	0	0	0	0	0
Sugarland	0	0	0	0	0	0	0	0	0
Stafford	1	1	1	1	1	1	1	1	1
Missouri City	0	0	0	0	0	0	0	0	0
Addicks - Barker	0	0	0	0	0	0	0	0	1
Cypress	1	1	1	1	1	1	1	1	0
Tomball	0	0	0	0	0	0	0	0	0
Kohrville	0	0	0	0	0	0	0	0	0
Jersey Village	0	0	0	0	0	0	0	0	0
Bellaire	0	0	0	0	0	0	0	0	0
Spring	1	1	1	1	1	1	0	0	1
Bammel	0	0	0	0	0	0	1	1	0
Aldine	0	0	0	0	0	0	0	0	0
Houston	1	1	1	1	1	1	0	0	1
Pasadena	0	0	0	0	0	1	1	1	0
South Houston	0	0	0	0	0	0	0	0	1
Pearland	0	0	0	0	0	0	0	0	0
Webster	0	0	0	0	0	0	1	1	0
Baytown	0	0	0	0	0	0	0	0	0
Highlands	1	1	1	1	1	0	0	0	1
Sheldon	0	0	0	0	0	0	0	0	0
Humble	1	0	0	0	0	0	1	1	0
Huffman	0	0	0	0	0	0	0	0	0
League city	1	1	1	1	1	1	0	0	1
Satsuma	0	0	0	0	0	0	0	0	0
Hillshire Village	0	0	0	0	0	0	0	0	0
Bunker Hill Village	0	1	1	1	1	1	1	1	0
Courben Ln	0	0	0	0	0	0	0	0	0
Alvin	0	0	0	0	0	0	0	0	0
Shenandoha	0	0	0	0	0	0	0	0	0

Table 5.8: Case 3 SDP MOOP result

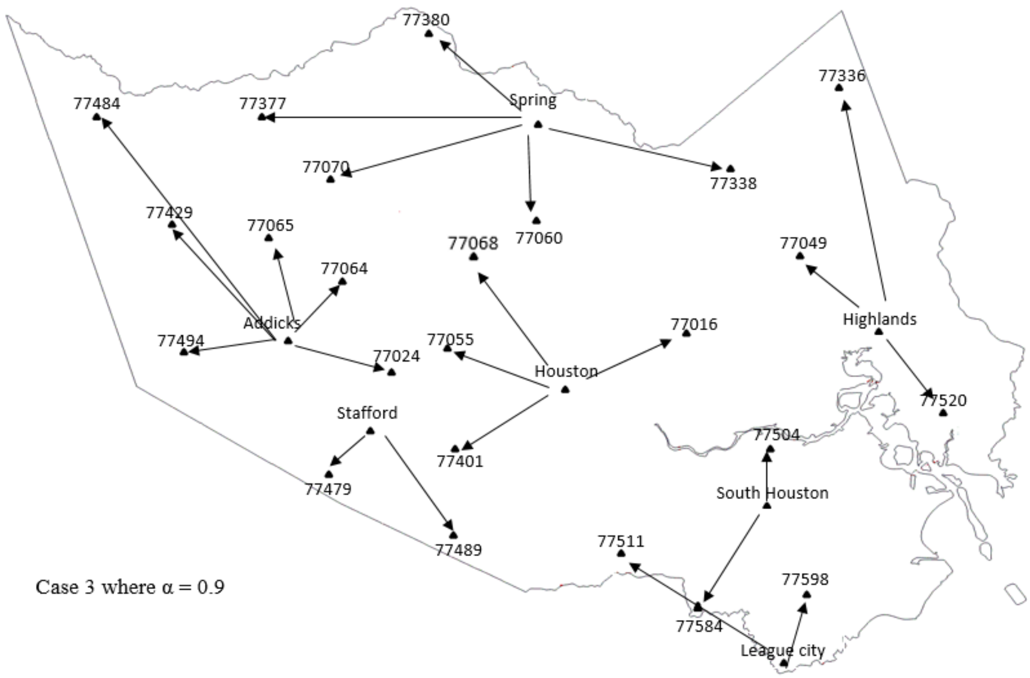

Figure 5.9: Case 3 α =0.9 (rank 1 with high flood risk impact)

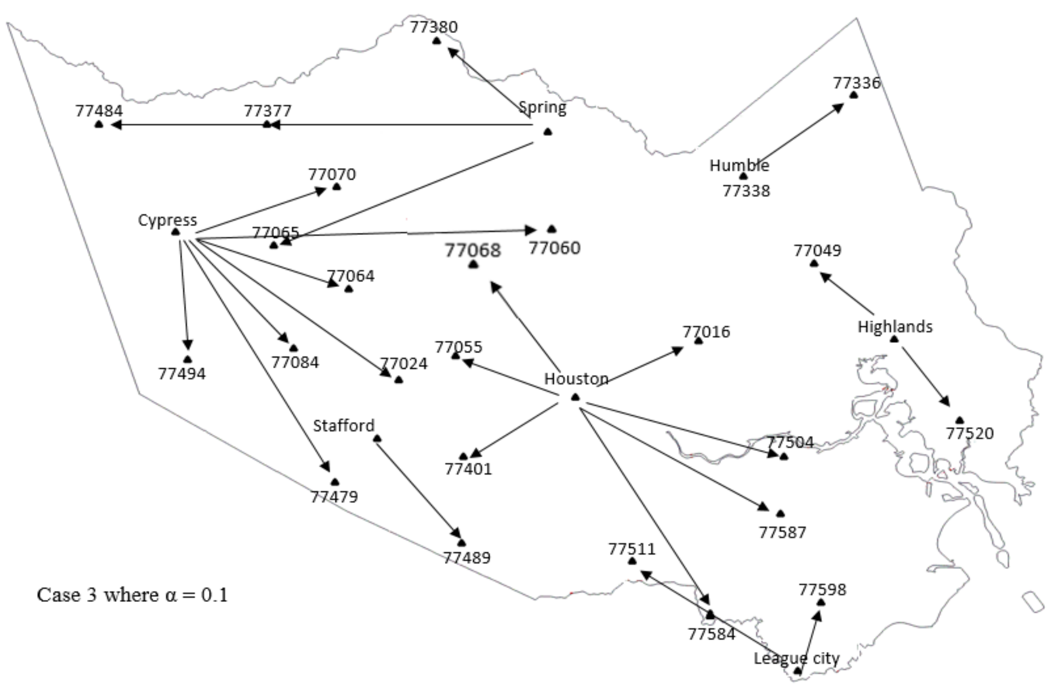

Figure 5.10: Case 3 α =0.1 (lowest flood risk impact)

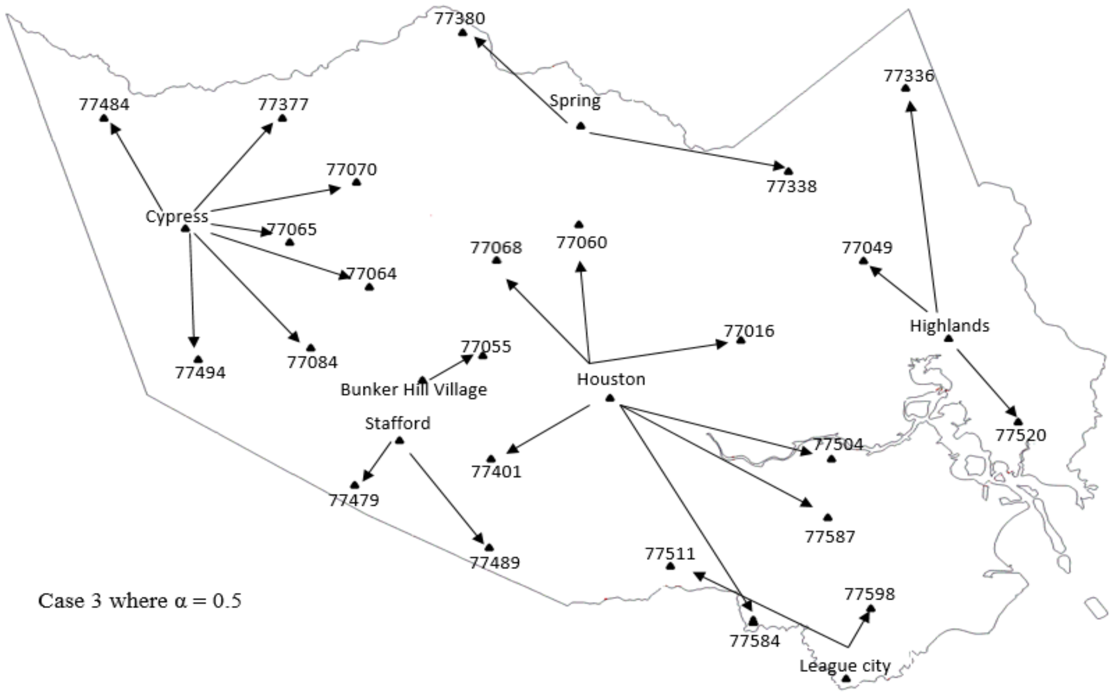

Figure 5.11: Case 3 α =0.5

Node group	A	B	C	D	E
α	0.1	0.2-0.4	0.5-0.6	0.7-0.8	0.9
Stafford		0.269	0.344	0.347	0.309
Addicks - Barker				0.433	0.398
Cypress	0.410	0.415	0.484		
Spring	0.198	0.272		0.407	0.353
Houston	0.258	0.343	0.389	0.415	0.322
Pasadena					
South Houston					0.338
Webster		0.268	0.313	0.352	
Highlands	0.150				
Humble			0.331		
League city	0.151				
No damage objective	0.134	0.179	0.171	0.137	0.076
PO	0.073	0.127	0.184	0.252	0.268
Ratio	0.542	0.708	1.073	1.832	3.532
Robustness	1.000	0.721	0.431	0.084	0.000

Table 5.9 Case 1 OLP MOOP result

Node group		A	B	C	D	E
α		0.1-0.3	0.4-0.5	0.6-0.7	0.8	0.9
4	Stafford	0.223	0.317	0.306	0.340	0.323
6	Addicks - Barker	-			0.406	0.409
7	Cypress	0.394	0.401	0.272		
12	Spring	0.226	0.282	0.302	0.353	0.346
15	Houston	0.305	0.354	0.357	0.320	0.294
16	Pasadena	-			0.215	
17	South Houston	-				0.187
19	Webster	-		0.350	0.244	0.181
21	Highlands	0.197	0.246			
25	League city	0.210	0.252			
28	Bunker Hill Village	-		0.258		
	No damage objective	0.171	0.182	0.164	0.116	0.062
	EPO	0.070	0.114	0.146	0.196	0.212
	Ratio	0.409	0.630	0.896	1.691	3.416
	Robustness	1.000	0.688	0.461	0.110	0.000

Table 5.10 Case 2 OLP MOOP result

Node group		A	B	C	D	E
α		0.1	0.2-0.5	0.6	0.7-0.8	0.9
	Stafford	0.175	0.268	0.320	0.306	0.349
	Cypress	0.393	0.331	0.295	0.320	
	Addicks - Barker					0.421
	Spring	0.189	0.259	0.295		0.345
	Bammel				0.307	
	Houston	0.266	0.336	0.357		0.306
	Pasadena			0.257	0.261	
	South Houston					0.205
	Webster				0.273	
	Highlands	0.178	0.238			0.174
	Humble	0.169			0.319	
	League city	0.181	0.271	0.287		0.186
	Bunker Hill Village		0.234	0.263	0.313	
	No damage objective	0.166	0.194	0.182	0.138	0.064
	EPO	0.037	0.076	0.107	0.161	0.180
	Ratio	0.225	0.391	0.586	1.174	2.819
	Robustness	1.000	0.731	0.515	0.133	0.000

Table 5.11 Case 3 OLP MOOP result

CHAPTER 6

CONCLUSION

In this research, we consider a real-time problem of locating disaster relief facility centers in the city of Houston. We have formulated a multi-objective programming model to simultaneously optimize the logistics cost and flood risk impact in locating the DRFC. Our model consists of two stages, the first stage determines the location of the DRFCs with a optimizing both the total logistics cost and flood risk impact in SDP, and the second stage determines the robustness level of the MOOP objective in OLP. To analyze the effectiveness of the model, the real data of Houston has been implemented on it. Main effects mean plot analysis has been performed on the MOOP model with different capacity constraints to understand its effects on the objective.

We conclude that capacity is one of the key factors in deciding the open number of DRFCs. When infinite capacity of a DRFC was considered, we could find a gradual decrease in the MOOP objective with decrease in the open number of facilities and maximum coverage of a DRFC. But, when a capacitated DRFC was considered, we could find a gradual decrease in the MOOP objective with the increase in the open number of DRFCs and maximum coverage of a DRFC. This impact majorly depends on the associated total logistics cost and flood risk impact. It could be concluded that capacity is one of the key elements in minimizing the objective.

In order to understand the robustness of the objective, firstly DRFCs were located in SDP. In OLP, based on the identicality of DRFCs, several node groups were formed for each case. For each case, the node group is evaluated in terms of robustness level that is defined using perturbed MOOP objective. Based on what-if-scenario, stress tests were conducted by shutting down major facilities for each case. We conclude that there is maximum robustness when α ranges from 0.1 to 0.4 for all the three cases. Though in the SDP, MOOP objective is of rank 1 when α equals 0.9, it has maximum flood risk impact. The results can be utilized differently based on the flood risk impact tolerances. Decision makers may have different flood risk tolerances based on budget constraints, hence our approach will provide diverse alternatives whose objective functions are mainly to minimize flood risk along with logistics cost.

Our approach has several limitations. We consider only shutdown scenarios of single DRFCs though our mathematical model includes direct arc shutdown. Not all the shutdown scenarios of DRFCs have been considered in our approach as it will lead to increase in the size and complexity. Therefore, researchers should note to reduce the possible shutdown scenarios in model to high-impacting ones as adopted in our approach. One other limitation we did not consider a scenario where DRFC can act as a shelter point for the evacuees, instead DRFCs are considered as a supply points.

For future research, it would be interesting to develop an approach where we consider vehicle routing problems to the potential sites. Vehicle routing is an important criteria as the required demand quantities have to be distributed to the potential sites from DRFCs. Several limitations may arise while deciding on the routes as the paths to the potential sites may be blocked due to floods. With this future research a complete model can be developed using the existing research.

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APPENDIX A: LIST OF ACRONYMS

DRFC disaster relief facility center

EPO expected perturbed objective

FRI flood risk impact

MOOP multi-objective optimization programming

OLP operation level phase

TLC total logistics cost

SDP strategic design phase