LOCATING DISASTER RESPONSE FACILITIES IN HOUSTON USING FLOOD RISK AND LOGISTICS COST

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ABSTRACT

We study the disaster response facility (DRF) location problem in the city of Houston, Texas, prone to flood risk by Hurricane. We use a multi-objective optimization model for selecting the location of DRFs to minimize the total logistics cost and the total flood risk impact concurrently using real data of Houston. This research would provide useful insights to practitioners who need to make several decisions to design the disaster relief logistics network.

Keywords: Flood risk, Multi-objective optimization model, Disaster Relief Logistics Network

INTRODUCTION

Hurricane Harvey, a category IV storm, struck Houston, Texas in August 2017. It has caused many severe physical damages and multi-billion economic losses to Houston, leading to a situation where people get stranded in the city without proper facilities to survive [13]. Hundreds of people were rescued, and the state's emergency management department urged everyone in the state not to travel. In fact, flood accompanied by the Hurricane has caused this devastating damage. Flood risk is one of the most common and destructive phenomena of a Hurricane [12]. Compared to other disasters, floods are easier to predict and prevent [3]. When a disaster occurs, it is critically important for a disaster management agency such as the Federal Emergency Management Agency (FEMA) to rescue victims and distribute disaster relief items to the affected areas efficiently and effectively.

The rapid deployment of an appropriate disaster relief logistics network (DRLN) plays an important role in supplying relief items and daily commodities to alleviate the sufferings of victims. Due to the frequent and unexpected natural disruptions over the last decades, facility location-allocation (FLA) decisions under disruption risks have received increasing attention and have become one of the main issues in the area of logistics and supply management. A significant stream of research on supply chain network structure related to disruption management focuses on FLA decisions [8]. FLA decisions consist of two kinds of decision plans. One is a strategic decision plan on the facility location, while the other one is an operational decision plan on the allocation of the facility to the customers. The traditional models for the strategic FLA design models consider an objective of minimizing the total logistics cost (TLC), such as the fixed cost of opening/using the facility plus the transportation or shipping cost, assuming the disaster response facility (DRF) is always available. However, all facilities are susceptible to disruptions due to the natural disasters, accidents, breakdowns, weather, or strikes. Effects of disruptions could be aggravated for DRLN design.

The flood prevention is generally mitigation to reduce the risk with the help of tools [6]. Pre-and post-disaster planning helps to improve disaster responsiveness. Along with the TLC, the total flood risk impact (TFRI) on the DRF should be considered to prevent the risk of flooding of the disaster response facility. Hence, this paper attempts to formulate the locating problem of DRFs as a multi-objective optimization model to balance the total logistics cost and flood risk impact concurrently.

This study aims to develop a multi-objective optimization model to aid decision making regarding the location of DRFs in the City of Houston. The objective is to design an optimal DRLN with respective to TLC and total FRI and to analyze the impact of parameters such as open number of DRFs, maximum coverage of a DRF, weight between objectives, and capacity of DRF on the DRLN. The results obtained from this study will provide many insights to the practitioners who are responsible for disaster management activities in the area.

LITERATURE REVIEW

Designing a DRLN uses a traditional FLA mathematical model. There has been extensive research on the FLA models and their applications for decades. For example, Görmez et al. [5] conduct a study in locating DRFs in Istanbul. They propose a two-tier approach and analyze trade-offs between objectives of minimizing the average weighted distances between locations and closest facilities and opening a small number of facilities. Kongsomakasakul et al. [9] propose an objective of determining the location of DRFs with capacity constraints. They formulate a bi-level programming model and concentrate on the evacuees to choose among the potential DRFs during floods, but flood risk impact is used in locating the potential facility centers. Kilci et al. [10] propose a mixed integer linear programming methodology for locating temporary DRFs. They use the real data of Kartal, Istanbul in Turkey for their analysis and conclude that as the average utilization of a DRF increases, the number of open DRFs decreases. Akgün et al. [1] use a fault tree analysis introducing the ‘vertex p-center model’ and ‘p-center risk model.’ With the objective of locating the potential DRFs, the former analysis minimizes the maximum distance while the latter analysis minimizes the maximum risk of a demand point. Bozorgi-Amiri et al. [2] propose a multi-objective model to minimize the incorporating uncertainty in the demand, supply, and cost of procurement and transportation. Their model uses the compromising programming method to simultaneously minimize the sum of the expected value and variance of the total cost of the relief chain and maximize the affected areas satisfaction levels.

We use a multi-objective optimization model to locate the DRFs, considering both the demand weighted distances and total flood risk at all potential DRFs as well as demand sites to minimize the TLC and TFRI of the resulting network, respectively.

MULTI-OBJECTIVE OPTIMIZATION MODEL

We define a multi-objective optimization (MOP) model with TLC and FRI as two objective functions to minimize. The following parameters and decision variables are defined to explain the MOP model.

Indices:
J : index for potential sites
M : index for potential demand points that are supplied by DRFs

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

D_m : Demand of point m
N^{max} : Maximum number of facilities that can be built
F^{max} : Maximum number of sites a facility can cover (maximum coverage)
C_j^{max} : Capacity of facility j
TLC_{min}: Target value of TLC
$TFRI_{min}$: Target value of FRI
α: weight assigned to TLC percentage gap minimization

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

According to [7], the cost may be specified in any number of ways ranging from weighted or unweighted distance to simpler. In this study, the total logistics cost (TLC) is represented by the demand weighted distance as in equation (1).

$$TLC(j,m) = \sum_{j\in J}\sum_{m\in M} D_m d_{jm} x_{jm} \tag{1}$$

Flood risk plays a major role as it involves the risk of getting the potential facility location flooded. The flood risk information is collected from the flood map provided by National Flood Service [11], which provides a flood risk map with color-coded risk. We convert the risk to a linear scale between 0 and 5 and define it as a flood risk impact (FRI) for a specific site with five being the highest risk. The total flood risk impact (TFRI) is represented by the demand weighted flood impact risk as in equation (2).

$$TFRI(j,m) = \sum_{j\in J}\sum_{m\in M} D_m FRI_j x_{jm}. \tag{2}$$

Using these expressions, we define our model as follow:

$$\text{minimize} \quad \alpha\frac{(TLC(j,m)-TLC_{min})}{TLC_{min}} + (1-\alpha)\frac{(TFRI(j,m)-TFRI_{min})}{TFRI_{min}} \tag{3}$$

Subject to

$$\sum_j f_j \leq N^{max} \tag{4}$$

$$\sum_j x_{jm} = 1 \quad \forall\, m \tag{5}$$

$$x_{jm} \leq f_j \quad \forall\, m,j \tag{6}$$

$$x_{jj} - f_j = 0 \quad \forall\, j \tag{7}$$

$$\sum_m x_{jm} \leq F^{max} \quad \forall j \tag{8}$$

$$\sum_m D_m x_{jm} \leq C_j^{max} \quad \forall j \tag{9}$$

The objective is to determine the locations of DRFs and their distribution channels from a facility to demand points (affected areas) with the minimum percentage gap of TLC (first term) and the minimum

percentage gap of FRI (second term), concurrently in Equation (3). Constraint (4) ensures that the number of DRFs established is smaller than or equal to the maximum number of facilities assigned. Constraints (5) ensure that each site is assigned to one facility center. Constraints (6) say that unless a facility is opened, it cannot function. Constraints (7) make sure that an ERF feeds itself. Constraints (8) specify the maximum number of sites that an ERF can serve. Constraints (9) ensure that demand of the sites covered is within the capacity of the facility.

We need the following steps to solve the MOP model for given data.

Step 1: Obtain the target total logistics cost, TLC_{min} by solving the MOP model where equation (7) is the objective function and the same constraints from (4) to (9).
Step 2: Obtain the target floor risk impact, $TFRI_{min}$ by solving the MOP model where equation (8) is the objective function and the same constraints from (4) to (9).
Step 3: Solve the MOP model for various balancing weights of α from 0.1 to 0.9.

CASE STUDY

We use population at a site as the demand at the site. For accuracy of the demand corresponding to the sites, firstly the zip code data related to the Houston city is collected through online resources [14]. Later, the population under the zip codes [4] is required as demand in the model. All the zip codes are clustered based upon proximity and populations into 31 clustered sites. It is assumed that all the population within the zip codes exists at the clustered site. The flood risk has been taken on a scale of 5 as described previously. The distance between the clustered sites is used in the model. Table A.1 (see Appendix) shows all the sites, its population and flood risk impact. We solve the MOP problem using IBM ILOG CPLEX Optimizer running on PC I7 processor with 8 GB of RAM under the Windows 10 environment.

We solve the 108 different alternatives of a full factorial design using the three factors in Table 1(a). For N^{max}, F^{max}, and α, each level directly implies the physical value of the factor. For example, N^{max} level 6 implies that we consider 6 DRFs. The level of capacity at each organization is summarized in Table 1(b). For example, level 1 implies that at least six DRFs are needed in the network since its capacity is set to the 920K (note that total populations are 5,507K), level 2 with at least five DRFs. Level 3 is set to the total population. Thus, we need at least one facility if there is no other constraint.

TABLE 1(a). Design of experiment

Factors	Levels
N^{max}	6,7
F^{max}	8,9
A	0.1-0.9 by 0.1
C_j^{max}	1, 2, 3

TABLE 1(b). Three capacity levels

Level	Explanation
1	Set to 920K (At least six facilities needed)
2	Set to 1,100K (At least five facilities needed)
3	Set to all population (At least one facility needed)

Table A.2 in Appendix lists the first 36 results obtained with C_j^{max} being set to 1. To understand the behavior of the model, the main effects analysis of each factor is performed using the 108 results. Figure 1(a) represents the main effect plot of TLC_{min} generated with α being set to 1.0. It is independent of α and F^{max}, decreasing when the number of DRFs (N^{max}) increases (This is an intuitive phenomenon). Overall, it significantly decreases when the capacity (C_j^{max}) increases. In Figure 1(b), we observe that $TFRI_{min}$ is sensitive to C_j^{max} and F^{max}, since it provides more diverse options for the network and it contributes to reducing $TFRI_{min}$.

The objective function behaves nonlinearly at α, weight between the two objective terms depending on the decision maker's judgment, and the overall percentage gap increases as the overall capacity increases (Figure 2(a)). We decompose Figure 2(a) into Figure 2(b) and 2(c), the main effect on TLC and TFRI, respectively. Then, the result can be explained more intuitively. In Figure 2(b), as the number of facility increases, TLC decreases but TLC is not sensitive to the maximal coverage (F^{max}). Intuitively, as α increases–as more emphasis is on the TLC–TLC significantly decreases. TLC reacts nonlinearly to the capacity of the facility j (C_j^{max}) whose minimum is observed at capacity level 2. Figure 2(c) indicates that the TFRI is sensitive only to α and capacity. As capacity increases, it decreases probably since higher capacity provides more diverse options to search for a safer combination of the location and channels.

FIGURE 1(a). Main effects for means of $TLC_{\min}$

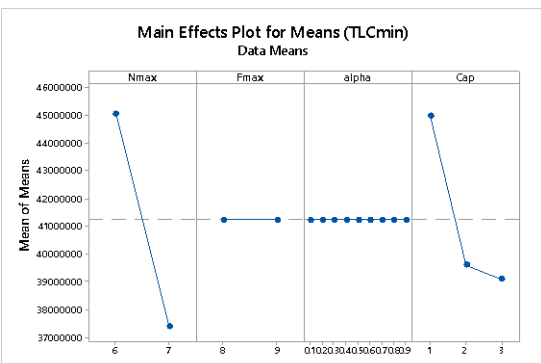


FIGURE 1(b). Main effects for means of $TFRI_{\min}$

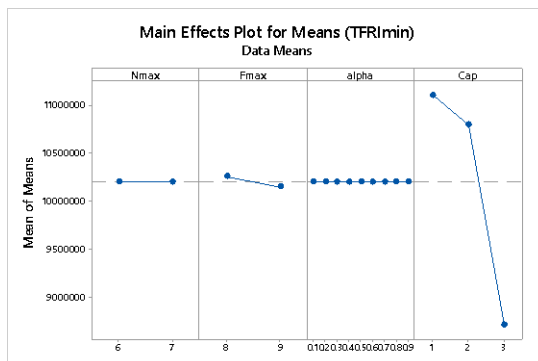


FIGURE 2(a). Main effects of object

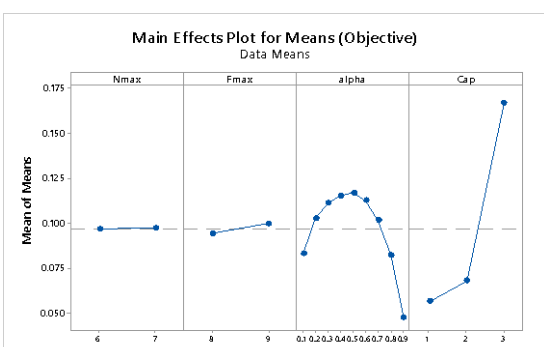


FIGURE 2(b). Main effects for means of *TLC*

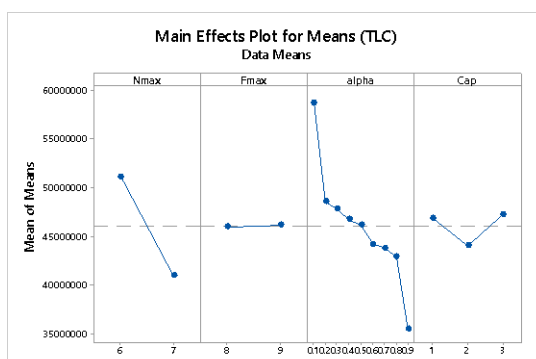
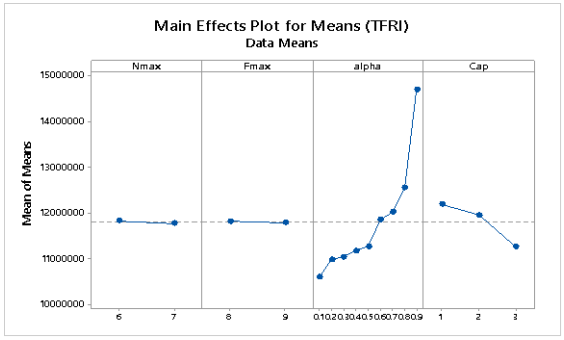
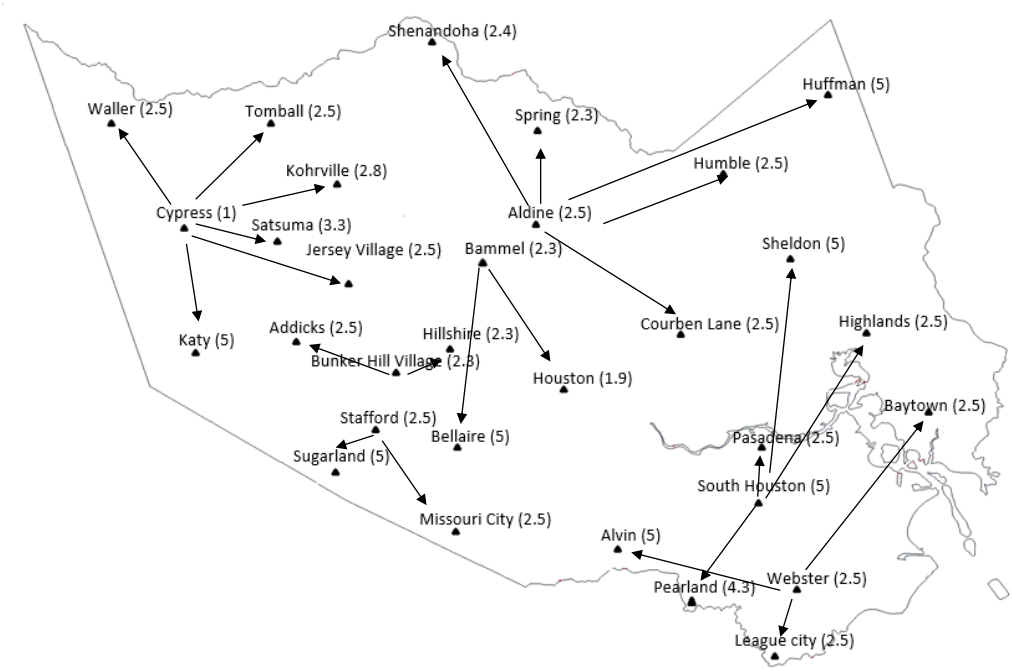


FIGURE 2(c). Main effects for means of *TFRI*



The main effect analysis of TLC and TFRI indicates TLC and TFRI are optimized at C_j^{max} = 2 and C_j^{max} = 3, respectively. However, the actual objective function is minimized with C_j^{max} being set to 1 when both TLC and TFRI are concurrently considered as seen in Figure 2(a). According to Figure 2(a), it is likely that the best case may occur at (N^{max} = 6; F^{max} = 8; α = 0.9; C_j^{max} = 1). However, the actual best case occurs at (N^{max} = 7; F^{max} = 8 or 9; α = 0.9; C_j^{max} = 1) and it is displayed in Figure 3. In fact, it is the alternatives 27 and 36 in Table 2. The gap is generated since the main effect analysis is purely based on the average values of the performance measures per factor and N_{max} and F_{max} are not much sensitive to objective function as seen in Figure 2(a).

FIGURE 3. Best logistics network at (N^{max} = 7, F^{max} = 8 or 9, α = 0.9, C_j^{max} = 1)



CONCLUSIONS

We want to design and optimize disaster relief logistics network (DRLN) for the City of Houston using real data. We have formulated a multi-objective optimization (MOP) model to simultaneously optimize the total logistics cost (TLC) and total flood risk impact (TFRI). The results of the MOP model are

analyzed concerning the maximum number of facilities, maximal coverage per facility, weight between (TLC) and TFRI, and capacity of each facility using Main effect analysis.

We notice that the result of the MOP is very different from the single objective (SOP) model. In the SOP model with TLC as an objective function, a maximum number of facilities, weights between performance measures and capacity of facility affect the design of DRLN while in the model with TFRI model, only weight and capacity of a facility affect it. However, in the MOP model, only weights and capacity significantly affect the design. The reason is that each SOP problem reacts differently to some parameters. Thus, the MOP model should be sought when a decision makes pursue a balanced solution between two SOP problems. Overall, MOP is very sensitive to weight between performance measures and capacity. However, the balanced optimal solution indicates that the facility capacity does not need to be incapacitated, indicating a way to save investment cost when we optimize a DRLN. In addition to the optimization, this study evaluates the impact of each parameter of interest from a decision maker's perspective on the DRLN using the main effect analysis. The DRLN is critically and non-linearly affected by the weight between performance measures while the capacity of a facility piece-wise linearly affect the DRLN. Using this main effect analysis, decision-makers can determine a best or near-best DRLN.

For future research, it would be interesting to add a vehicle routing problem to the potential sites and resolve the DRLN again. Vehicle routing is an important criterion as the required demand quantities have to be distributed to the potential sites from disaster response facilities.

APPENDIX

Table A.1. Information on clustered sites

No.	Potential sites	Zip code group	Population	Flood risk impact
1	Waller	77058, 77062, 77598, 77586, 77571	31218	2.5
2	Katy	77494, 77493, 77450	188336	5
3	Sugarland	77478, 77498, 77479, 77099, 77083, 77031, 77407	341168	5
4	Stafford	77477, 77071, 77085, 77074, 77036, 77072	252673	2.5
5	Missouri City	77489, 77053, 77459	132957	2.5
6	Addicks - Barker	77084, 77079, 77043, 77077, 77094, 77449, 77082	385112	2.5
7	Cypress	77433, 77429	144028	1
8	Tomball	77375, 77377, 77362	83629	2.5
9	Kohrville	77070, 77379, 77069	142683	2.8
10	Jersey Village	77041, 77040, 77064, 77086	159666	2.5
11	Bellaire	77401, 77081, 77046, 77025, 77096, 77005, 77027, 77098, 77030, 77054, 77035, 77045, 77051	302881	5
12	Spring	77373, 77386, 77365, 77073	173097	2.3
13	Bammel	77090, 77068, 77014, 77388, 77066, 77067	189098	2.3
14	Aldine	77060, 77037, 77032, 77039, 77038, 77076, 77088, 77093	228086	2.5
15	Houston	77002, 77010, 77003, 77006, 77009, 77004, 77007, 77019, 77020, 77026, 77011, 77008, 77023, 77021, 77022	356237	1.9
16	Pasadena	77505, 77504, 77059, 77034, 77503	131681	2.5
17	South Houston	77587, 77017, 77502, 77061, 77075, 77087, 77506, 77012, 77547, 77033	288324	5
18	Pearland	77581, 77584, 77089, 77048, 77047	225081	4.3
19	Webster	77484, 77446, 77447	126670	2.5
20	Baytown	77523, 77521, 77520	115807	2.5
21	Highlands	77530, 77015, 77562, 77536	73458	2.5
22	Sheldon	77049, 77044, 77532	97294	5
23	Humble	77338, 77396, 77339, 77346	186533	2.5
24	Huffman	77336, 77345, 77357	63515	5
25	League city	77573, 77565, 77539, 77546	183999	2.5
26	Satsuma	77065, 77095	110125	3.3
27	Hillshire Village	77055, 77080, 77092, 77056, 77018, 77091	197433	2.3
28	Bunker Hill Village	77024, 77063, 77042, 77057	308186	2.3
29	Courben Ln	77078, 77016, 77028, 77050, 77013, 77029	101221	2.5
30	Alvin	77511, 77517	53545	5
31	Shenandoha	77380, 77381, 77382, 77389	134000	2.4

Table A.2. Partial result of 108 alternatives (first 36 results; C^{max} = 920K)

Alt	Nmax	Fmax	alpha	Cap	TLCmin	FRImin	Objective	TLC	TRI
1	6	8	0.1	920000	51494034.6	11104790.0	0.04	64289000	11293000
2	6	8	0.2	920000	51494034.6	11104790.0	0.055	58891000	11474000
3	6	8	0.3	920000	51494034.6	11104790.0	0.066	58891000	11474000
4	6	8	0.4	920000	51494034.6	11104790.0	0.077	58891000	11474000
5	6	8	0.5	920000	51494034.6	11104790.0	0.088	57998000	11657000
6	6	8	0.6	920000	51494034.6	11104790.0	0.081	53064000	12851000
7	6	8	0.7	920000	51494034.6	11104790.0	0.069	53064000	12851000
8	6	8	0.8	920000	51494034.6	11104790.0	0.056	53064000	12851000
9	6	8	0.9	920000	51494034.6	11104790.0	0.038	51593000	15151000
10	6	9	0.1	920000	51494034.6	11104208.5	0.04	64289000	11293000

11	6	9	0.2	920000	51494034.6	11104208.5	0.055	58891000	11474000
12	6	9	0.3	920000	51494034.6	11104208.5	0.066	58891000	11474000
13	6	9	0.4	920000	51494034.6	11104208.5	0.077	58891000	11474000
14	6	9	0.5	920000	51494034.6	11104208.5	0.075	56603000	11661000
15	6	9	0.6	920000	51494034.6	11104208.5	0.081	53064000	12851000
16	6	9	0.7	920000	51494034.6	11104208.5	0.069	53064000	12851000
17	6	9	0.8	920000	51494034.6	11104208.5	0.056	53064000	12851000
18	6	9	0.9	920000	51494034.6	11104208.5	0.038	51593000	15151000
19	7	8	0.1	920000	38452254.8	11104814.6	0.042	47044000	11347000
20	7	8	0.2	920000	38452254.8	11104814.6	0.052	41055000	11636000
21	7	8	0.3	920000	38452254.8	11104814.6	0.054	41055000	11636000
22	7	8	0.4	920000	38452254.8	11104814.6	0.056	41055000	11636000
23	7	8	0.5	920000	38452254.8	11104814.6	0.058	41055000	11636000
24	7	8	0.6	920000	38452254.8	11104814.6	0.059	40225000	11975000
25	7	8	0.7	920000	38452254.8	11104814.6	0.055	39941000	12132000
26	7	8	0.8	920000	38452254.8	11104814.6	0.049	39941000	12132000
27	7	8	0.9	920000	38452254.8	11104814.6	0.033	3869000	14172000
28	7	9	0.1	920000	38452254.8	11103988.9	0.042	47044000	11347000
29	7	9	0.2	920000	38452254.8	11103988.9	0.052	41055000	11636000
30	7	9	0.3	920000	38452254.8	11103988.9	0.054	41055000	11636000
31	7	9	0.4	920000	38452254.8	11103988.9	0.056	41055000	11636000
32	7	9	0.5	920000	38452254.8	11103988.9	0.058	41055000	11636000
33	7	9	0.6	920000	38452254.8	11103988.9	0.059	40225000	11975000
34	7	9	0.7	920000	38452254.8	11103988.9	0.055	39941000	12132000
35	7	9	0.8	920000	38452254.8	11103988.9	0.049	39941000	12132000
36	7	9	0.9	920000	38452254.8	11103988.9	0.033	3869000	14172000

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