Effective and Equitable Supply of Gasoline to Impacted Areas in the Aftermath of a Natural Disaster

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Abstract

The focus of this research is on supplying gasoline after a natural disaster. There are two aspects for this work: determination of which gas stations should be provided with generators (among those that do not have electric power) and determination of a delivery scheme that accounts for increased demand due to lack of public transportation and considerations such as equity. We develop an MIP for this situation. Two case studies based on Hurricane Sandy in New Jersey are developed and solved in CPLEX.

Keywords: humanitarian logistics,disaster operations management,location, allocation, disaster logistics

1 Introduction and Literature Review

In the past few years there have been an increasing number of high-impact events that involved both a natural disaster and man-made hazardous materials; we call these events “nahaz” events. Our purpose is to develop models and algorithms for safe transportation and equitable supply of commodities like gasoline in the aftermath of a disaster, and to provide insights on disaster recovery planning in the face of disruptions. With the continuously rising population and our reliance on hazardous material (hazmat) goods like gasoline, the likelihood of these “nahaz” events has two dimensions: (a) Impact of Hazmat Accidents - After a natural disaster, with damaged infrastructure, the probability of hazmat spill increases significantly, hence hazmat transportation can potentially lead to a catastrophic environmental disaster; (b) Disruption in Hazmat Supply- Limited, inappropriate and inequitable supply of hazmat commodities in the aftermath of a natural disaster can delay the recovery considerably. Due to these potentially devastating impacts, there is an increasing need for research on this topic. This research specifically aims to innovate logistical techniques employed to alleviate the potential impacts of these “nahaz” events.

Dependence on hazardous materials (hazmat), especially petroleum products, is a necessary evil in industrialized societies and, indeed, our society uses thousands of different hazmat today (PHMSA, 2013). Unfortunately, natural diasters such as hurricanes and earthquakes often cause supply chain disruptions of hazmat goods due to lack of available supply, lack of ability to deliver the items to the customer, and damage to the transportation infrastructure. Another key aspect is that the requirements for the hazmat in question can change significantly as a result of a natural disaster. These supply chain disruptions can severely impede the natural diaster recovery process as seen during the mindboggling gasoline shortage after 2012’s Superstorm Sandy; aggravate an existing food shortage as seen after the 2010 Chilean Earthquake; and raise hazmat prices as seen after the 2008 China winter storm. These are only a few of the negative impacts that can result from a supply chain disruption of hazmat commodities after a natural disaster. Secondary disruptions are likely due to the shortage of hazmat energy products such as oil, diesel fuel and gasoline. Important examples of such secondary disruptions include the inability of people to go to work and the difficulty with securing basic supplies due to lack of transportation. Clearly, oil, diesel fuel and gasoline are the three hazmats with the highest probability of being involved in a transportation-related accident after a natural disaster. For example, out of 170 cases of hazmat accidents triggered by flooding reported by the European Directive on dangerous substances, 142 of them were oil, diesel fuel and gasoline (Cozzani et al., 2010).

Supply chain disruptions of hazmat commodities, such as gasoline shortages, resulted in a multitude of problems. For example, after Superstorm Sandy, drivers in the New York City area and parts of New Jersey were waiting for hours in line for the chance to buy gasoline before it ran out. This gasoline shortage impeded relief and recovery efforts and prolonged the time-period for business operations to return to normalcy. The government took many steps to tone down the problem, such as lifting of restrictions banning certain methods of transporting gasoline by the federal and state government as well as gasoline rationing. Even so, the severe gasoline problem lingered for weeks. Palph Bombardiere, head of the New York State Association of Service Stations and Repair Shops believes "Once the gasoline starts to flow, we'll go back to the same old habits." Gongloff and Chun Argued potential solutions to reduce vulnerability to this type of event "could be costly, politically unfeasible or both" (Huffington Post, 2010).

In this paper, we will see the gasoline supply problem as an emergency supply chain management problem that involves hazmat. In this section, we review the related work mainly focus on disaster operations management and emergency logistics. Disaster operations management has four phases: mitigation, preparedness, response, and recovery (Altay and Green, 2006; Caunhye et al., (2012); Galindo and Batta, 2013).

Several research studies in the disaster management literature concentrate on the disaster response phase. Haghani and Oh (1996) propose a multi-commodity multi-modal network flow model to determine the transportation of emergency supplies and relief personnel. Barbarosoglu and Arda (2004) investigate a two-stage stochastic programming model for the transportation planning of vital first-aid commodities. Ozdamar et al. (2004) propose a dynamic time-dependent transportation model, a hybrid model combining the multi-commodity network flow and vehicle routing problems, for emergency logistics planning. Gong and Batta (2007) formulate a model to locate and allocate ambulance in a post of disaster. Sheu (2007) provides a hybrid fuzzy clustering-optimization approach for efficient emergency logistics distribution. Sheu (2010) proposes a dynamic relief-demand management methodology, which involves data fusion, fuzzy clustering, and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), for emergency logistics operations.

Caunhye et al. (2015) focus on casualty response planning for catastrophic radiological incidents and propose a location-allocation model to locate alternative care facilities and allocate casualties for triage and treatment.

Some recent research studies consider combining disaster preparedness and disaster response decisions. Mete and Zabinsky (2010) propose a two-stage stochastic programming model for storing and distributing medical supplies and a mixed integer linear program for subsequent vehicle loading and routing for each scenario realization. Rawls and Turnquist (2010) propose a two-stage stochastic mixed integer program for prepositioning and distributing emergency supplies. Lodree et al. (2012) provide a two-stage stochastic programming model for managing disaster relief inventories. Rawls and Turnquist (2012) extend Rawls and Turnquist (2010) to incorporate dynamic delivery planning. Galindo and Batta (2013) propose an integer programming model for prepositioning emergency supplies for hurricane situations. Rennemo et al. (2014) provide a three-stage stochastic mixed integer programming model for locating distribution centers and distributing aid. Pacheco and Batta (2016) incorporate periodic forecast updates for predictable hurricanes and propose a forecast-driven dynamic model for prepositioning relief supplies. Caunhye et al. (2016) propose a stochastic location-routing model for prepositioning and distributing emergency supplies.

In the context of gasoline supply disruption after a natural disaster, the response phase is most relevant. The response actions involve many emergency logistics problems that do not occur in normal daily operations, and include providing food, clothes, and other critical supplies for evacuees and impacted people. These supply problems to help disaster relief operations are often called humanitarian logistics problems (Van Wassenhove, 2005).

The humanitarian logistics literature that addresses the critical notion of equity is limited (Huang et al., 2012). Relevant models include a max-min approach for customer satisfaction (Tzeng et al., 2007), a min-max approach for unsatisfied demand (Balcik et al., 2007), a multi-objective approach that minimizes unsatisfied demand along with other costs (Lin et al., 2009), a min-max approach for waiting time (Campbell et al., 2008), and multi-objective approach that minimizes the maximum pairwise difference in delivery times (Huang et al., 2012).

2 Modeling

In the aftermath of a natural disaster, especially when supply chain infrastructures were largely destroyed, supply chain disruption occurs. Therefore, the gasoline delivery was highly impacted and limited since there are number of refineries, terminals etc are out of operation. Given the situations that with limited gasoline resource and generators available, effective and equitable gasoline delivery and generators allocation will highly impact on the recovery and rebuild of the community. As illustrated in Figure 1, a typical gasoline supply chain consists of four stages: producing/importing crude oil or, refining into gasoline, blending gasoline with ethanol, and retailing and transportation between them. A disruption by a natural disaster can happen in any stage (U.S. EIA, 2013). Let's take Hurricane Sandy as an example. After Sandy's arrival, a total of 9 refineries in the area were shut down and a total of 57 petroleum terminals were either shut down or were running with reduced capacity (Benfield, 2013). Motivated by such a scenario, we will try to maximize the total gasoline sale of all gasoline stations across the regions, and at the same time incorporate the requirement of equity delivery across the regions. Since it is very important to fulfill the gasoline demands of the communities to have a speedy recovery from disaster, in our model we will not consider any cost or profit factors, instead we aim at moving the gasoline delivery fast and efficient. By putting this into the objective, we will consider all the related constraints, e.g. gas station capacity. We also consider each gas station will have a gasoline sale cap, which is usually not the case to be considered in regular gas station operation. But after Superstorm Sandy, as figure 2 shows, people and cars are waiting in a line to fill gas for their home electric generators and cars. We thus have limited gasoline pumps to fulfill the demands of the community.

Based on the fact that lots of refineries and petroleum terminal were shut down in the aftermath of hurricane Sandy, in this paper we assume that we have a single depot for available gasoline resource and delivery trucks. We further assume that this depot will only supply gasoline to the affected regions. There is very limited gasoline resource available in this single depot. And because of that, we will also assume each gas station in the affected regions will only demand gasoline. Of course these gas stations will have reserve capacity and sale capacity limitations. After Hurricane Sandy, New Jersey and New York city both ordered a mandatory ration to regulate access to gas stations for a few weeks. So we consider our model with a limited time period, this time period can

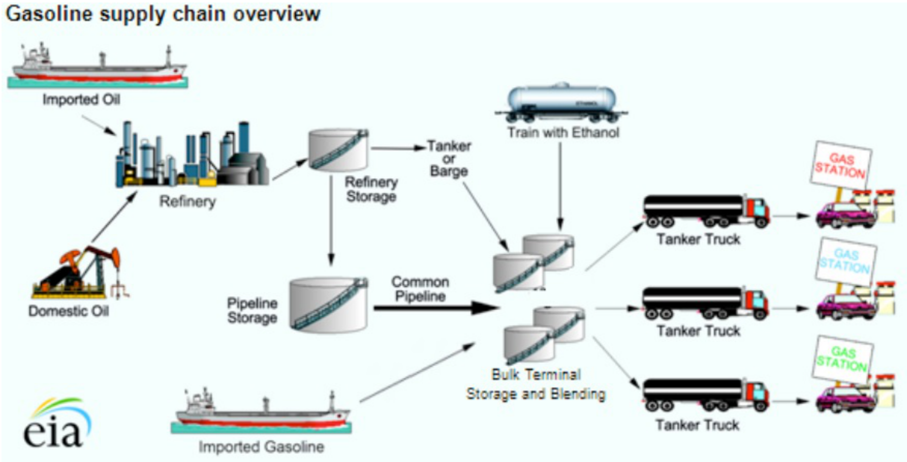

Figure 1: Gasoline Supply Chain Overview (Source: U.S. EIA, 2013)

be short as a day or longer as a few weeks according to the severity of the aftermath of a natural diaster. Since gasoline is one of type of hazmat, we will assume each delivery truck will deliver on a full truck load to one single gasoline station and we can't partially deliver gasoline out. We can also deliver a few truck loads to a single gas station if one single deliver of gasoline truck would not satisfy the demand. In the aftermath of Hurricane Sandy, lots of gasoline stations were out of power even though these stations still had gasoline in stock. To address this we assume a pool of available generators that can be assigned to the gas stations which are out of power. Then, based on the assigned generators, we will assign trucks to deliver full truck load gasoline to those gasoline stations. We assume that there is a set of regions I, indexed by i. Let J be the set of all gas stations in all regions, indexed by j. $J = J_1 \cup J_2$ where J_1 is the set of gas stations with power aftermath, and J_2 is the set of gas stations which are out of power. We assume T as the number of time periods. Let G_i be the set of gas stations in region i. For each gasoline station, let W_j be the storage capacity at gas station j, O_j be the maximum output at gas station j, and V_j be the initial storage inventory at gas station j. Now let us assume there is a set of available generators B. For the simplification of the modeling and at the same time without loss of generality, we assume that there are two types of gasoline delivery trucks available, type 1 truck and type 2 truck. Each truck tank only contains a single compartment (which makes sense after a natural disaster since high demand quantities at gas stations will be highly likely). For the two types of trucks parameters, the total number of available type 1 delivery truck is denoted by A_1, while the total number of

Figure 2: People Lined up for Gasoline After Hurricane Sandy (Source:Associated Press, 2012).

available type 2 delivery truck is denoted by A_2. Let C_1 be the capacity of type 1 delivery truck, C_2 be the capacity of type 2 delivery truck. In our model, we have a combined demand for each region for each time period since we assume that the customers can only fulfill their demands within their residential regions. Let D_{it} represents the total demand in region i at time period t and E_i be the truck delivery efficiency for region i. This region efficiency number means that if the region has a efficiency value as 2, the single one truck delivering gasoline to this particular region can be utilized twice on the single period. Finally, we assume that the quantity of available gasoline resource at time t is R_t.

Let s_{jt} denote the variable for usable inventory at gas station j at time t. We want to place generators into gas stations which are out of power aftermath. Let x_j be the binary variable, which is equal to 1 if we locate a generater to gas station j in the set of J_2, 0 otherwise. After placing the generators, we are able to allocate the available gasoline resource to the gas stations. Define y^1_{jt} as the nonnegative integer variable which represents the number of type 1 truck deliveries to the gas station j at time t, and y^2_{jt} as the nonnegative integer variable which represents the number of type 2 truck deliveries to the gas station j at time t. Let q_{jt} be the fulfilled quantity at gas station j at

Table 1: The complete list of notations

Symbol	Description
I	The set of regions, indexed by i
J_1	The set of gas stations which still operate aftermath
J_2	The set of gas stations which run out of power aftermath
J	The set of all gas stations, indexed by j. $J = J_1 \cup J_2$
G_i	The set of gas stations in region i
T	Time period indexed by t
W_j	The storage capacity at gas station j
O_j	The maximum output at gas station j
V_j	The initial inventory at gas station j
B	Total number of generators available
A_1	Total number of type 1 trucks available
A_2	Total number of type 2 trucks available
C_1	The capacity of type 1 trucks
C_2	The capacity of type 2 trucks
E_i	Efficiency of truck delivery for region i
D_{it}	The total demand of region i at time period t
R_t	The total available gasoline resource at time period t
λ	The parameter for equity variable
s_{jt}	The usable inventory variable for gas station j at time period t
x_j	binary variable equal to 1 if a generator is located at gas station j, 0 otherwise
y^1_{jt}	The integer variables for the number of type 1 truck deliveries to gas station j at time t
y^2_{jt}	The integer variables for the number of type 2 truck deliveries to gas station j at time t
q_{jt}	The output of gas station j at time period t
z	The equity variable

time t. Last, define z as the equity variable with parameter λ. Here we maximize the minimum of the equity value cross all regions in all time periods.

We have formulated the following linear binary integer program model:

The objective function (1) is to maximize the total fulfilled gasoline outputs plus equity. Constraint (2) makes sure that the number of generators that we will locate in the set of J_2 are less than or equal to the total number of available generators. Constraint (3) assigns initial inventory in the set J_1. Constraint (4) assigns initial inventory in the set of J_2 since only inventories in those gas stations located with generators are countable. Constraint (5) sets next day usable inventory

$$
\begin{aligned}
&[\text{Obj}] \quad \max && \textstyle\sum_{t=1}^{T}\sum_{j\in J} q_{jt} + \lambda z && && (1)\\
&\text{s.t.} && \textstyle\sum_{j\in J_2} x_j \le B, && && (2)\\
& && s_{j,0} = V_j, && \forall j \in J_1, && (3)\\
& && s_{j,0} = x_j V_j, && \forall j \in J_2, && (4)\\
& && s_{j,t} = s_{j,t-1} + C_1 y^1_{j,t} + C_2 y^2_{j,t} - q_{j,t}, && \forall j \in J,\ \text{for } t = 1,2,...,T, && (5)\\
& && q_{jt} \le O_j, && \forall j \in J,\ \text{for } t = 1,2,...,T, && (6)\\
& && C_1 y^1_{jt} \le W_j x_j, && \forall j \in J_2,\ \text{for } t = 1,2,...,T, && (7)\\
& && C_2 y^2_{jt} \le W_j x_j, && \forall j \in J_2,\ \text{for } t = 1,2,...,T, && (8)\\
& && s_{j,t-1} + C_1 y^1_{jt} + C_2 y^2_{jt} \le W_j, && \forall j \in J,\ \text{for } t = 1,2,...,T, && (9)\\
& && q_{jt} \le s_{j,t-1} + C_1 y^1_{j,t} + C_2 y^2_{j,t}, && \forall j \in J,\ \text{for } t = 1,2,...,T, && (10)\\
& && \textstyle\sum_{j\in G_i} q_{jt} \le D_{it}, && \forall i \in I,\ \text{for } t = 1,2,...,T, && (11)\\
& && \textstyle\sum_{i\in I}\sum_{j\in G_i} (1/E_i) y^1_{jt} \le A_1, && \text{for } t = 1,2,...,T, && (12)\\
& && \textstyle\sum_{i\in I}\sum_{j\in G_i} (1/E_i) y^2_{jt} \le A_2, && \text{for } t = 1,2,...,T, && (13)\\
& && \textstyle\sum_{j\in J} (C_1 y^1_{jt} + C_2 y^2_{jt}) \le R_t, && \text{for } t = 1,2,...,T, && (14)\\
& && z \le \frac{\sum_{j\in G_i} q_{jt}}{D_{it}}, && \forall i \in I,\ \text{for } t = 1,2,...,T, && (15)\\
& && x_j \in \{0,1\}, && \forall j \in J, && (16)\\
& && s_{jt} \ge 0, && \forall j \in J,\ \text{for } t = 1,2,...,T, && (17)\\
& && q_{jt} \ge 0, && \forall j \in J,\ \text{for } t = 1,2,...,T, && (18)\\
& && y^1_{jt}, y^2_{jt} \in I^+, && \forall j \in J,\ \text{for } t = 1,2,...,T, && (19)\\
& && z \ge 0. && && (20)
\end{aligned}
$$

for each gas station at time period t. Constraint (6) ensures that the fulfilled gasoline quantity at each gas station is less or equal to the maximum output of the gas station at time period t. Constraints (7, 8) ensure that only gas stations located with generators in the set J_2 can have gasoline deliveries. Constraint (9) makes sure that the usable inventory is less than the capacity of the gas station. Constraint (10) ensures the fulfilled gasoline output is less than or equal to the usable inventory of the gas station at time period t. Constraint (11) makes sure that the total output quantity in each region is less than or equal to the regional demand at time t. Constraints (12, 13) ensure that the number of utilized trucks does not exceed the total number of available trucks of each type. Constraint (14) makes sure the total allocated gasoline resource could not exceed the available resource at time t. Constraint (15) is the equity constraint, here we set our equity as the maximum of the minimum ration of total output quantities over the region's demands. Constraint (16) is the binary constraint to place generators. Constraints (17, 18, 20) are the nonnegative constraints since we can't sell any gasoline if our inventory stock is negative. Constraint (19) is the nonnegative integer constraint which means that we could deliver multiple truck loads of gasoline to one single gas station based upon the appropriate situation e.g. the gas station is the only station that still open within the region.

3 Numerical Example

We now provide a numerical example to explain the model. For problem simplicity, we will only consider four small regions with gas stations. Figure 3 shows the regions, along with a gasoline station diagram where gas stations with/without power are indicated. In order to simplify the display, we will just assume that the single depot is located in the center of four region. We test different efficiency parameters for different regions. If the efficiency parameter is 2, it means that each single truck can transport two truck loads to the region. Thus the utilization of each type of trucks assigned to those regions with efficiency parameter 2 will be doubled. Table 2 lists all the parameters and their values.

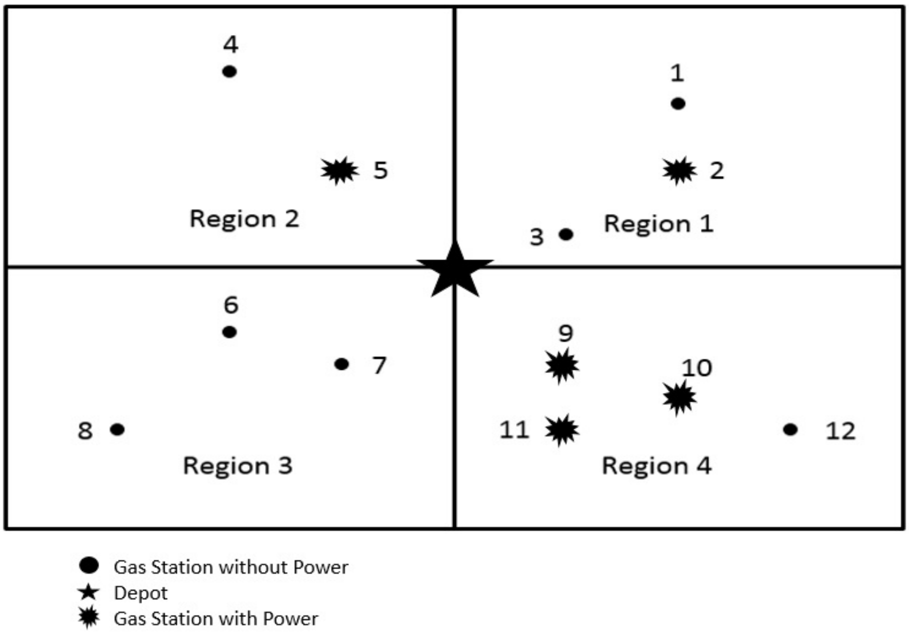

Figure 3: An Illustrative Example.

We tested three values of λ: 0, 100 and 200 for different equatability scenarios to gain a perspective on the impact on the performance of parameter λ. We run this model using IBM Ilog

Table 2: Parameter Values

Parameter	Description	Value
I	Set of regions	$\{1, 2, 3, 4\}$
J_1	Set of gasoline stations which still operate aftermath	$\{2, 5, 9, 10, 11\}$
J_2	Set of gasoline stations which run out of power aftermath	$\{1, 3, 4, 6, 7, 8, 12\}$
J	The set of all gas stations, indexed by j. $J = J_1 \cup J_2$	$\{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12\}$
W_j	The storage capacity at gas station j	20,10,8,24,30,26,12,18,20,24,30,26 for station 1..12
O_j	The maximum output at gas station j	10,5,4,12,15,14,6,9,10,12,15,13 for station 1..12
V_j	The initial inventory at gas station j	12,2,3,20,4,19,6,12,0,12,5,18 for station 1..12
T	Time period indexed by t	1,2,3,4,5
B	Total number of generators available	2
A_1	Total number of type 1 trucks available	3
A_2	Total number of type 2 trucks available	6
C_1	The capacity of type 1 trucks	10
C_2	The capacity of type 2 trucks	6
D_{it}	The total demand of region i at time period t	200 for each region at period t
R_t	The total available gasoline resource at time period t	30 for each period t
E_i	Efficiency of truck delivery for region i	E_1=3, E_2=2, E_3=2,E_4=3
λ	The parameter for equity variable	0,100,200

Cplex for a total of three scenarios. All these scenarios utilize the same parameter data set as listed in table 2. For scenario 1, we set parameter λ for equatability z as 0, scenario 2 with the values of λ as 100, and scenario 3 with the values of λ as 200. Figure 4 shows us the result where we are going to place the generators.

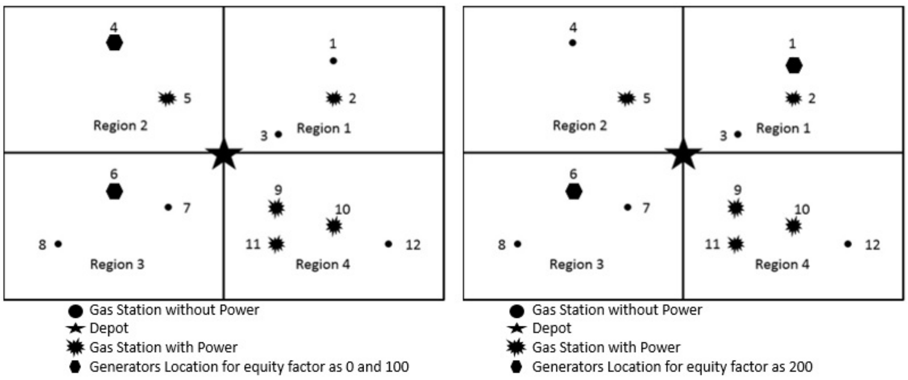

Figure 4: Generator Placement for Illustrative Example.

We can see that, for scenario 1 where the values of λ is zero, we tend to place the only 2 available generators to the gas stations 4 and 6 with the objective value as 212. This makes intuitive sense, since when equity factor λ is zero, we simply try to maximize the total gasoline sale since those two gas stations have the largest initial gasoline inventory. Consider scenario 2. In this case, we will still place the two available generators to gas station 4 and gas station 6, but since we slightly increase the weight of the equity factor λ to 100, we obtain the objective value as 216.67 with the equity value z=0.0467. So when we increase the weight of equity factor λ but not big enough to overcome the impact of big initial inventories, we will still place our available generators to the gas station with large initial inventory. Now let's look at scenario 3 where values of λ is equal to 200. In this case, we place the two generators at gas station 1 and gas station 6 which will produce the objective value as 224 while generating the largest equity value z as 0.1 across these three cases. We note that the first two scenarios only produce equity value as 0 and 0.0467 instead.

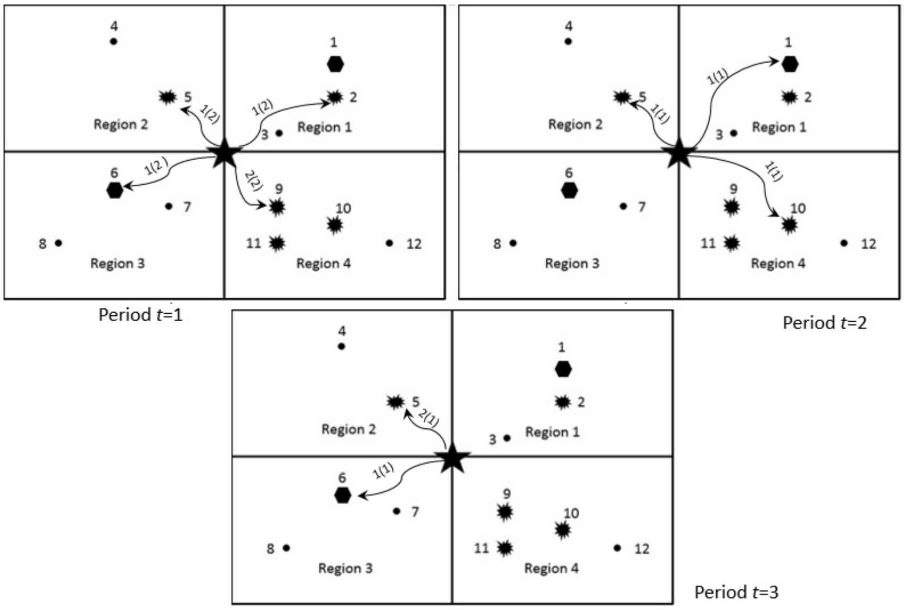

Figure 5: Truck Assignments for Scenario 3.

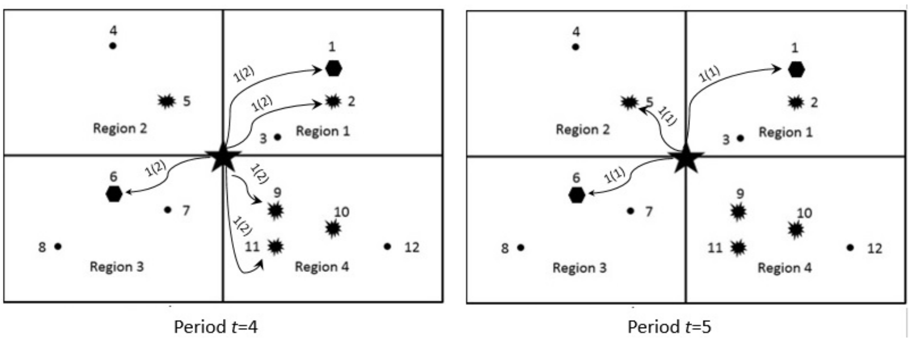

Figure 6: Truck Assignments for Scenario 3 (continued).

In our numerical study we test 5 periods. Figures 5 and 6 provide us detailed information regarding truck assignments for each period. The case that we show in Figures 5 and 6 is for scenario 3 where we use the equity factor λ as 200. From figure 5, we can see that for period 1, we will assignment one type 2 truck to gas stations 2, 5, 6 and two type 2 trucks to gas station 9 since gas station 9 has power but with zero initial inventory available. As for period 2, we will assign one type 1 truck to gas stations 1, 5 and 10. In period 3 we will continue to assign two type 1 trucks to gas station 5 and one type 1 truck to gas station 6. We then assign one type 2 truck to gas stations 1 ,2 6, 9 and 11 in period 4. Finally, in period 5, one type 1 truck is assigned to gas stations 1, 5 and 6. The total sale value is 204 for all periods with 42, 40, 40, 41 and 41 for each period respectively. As we mentioned earlier, for scenario 3 we have equity factor λ as 200 and an equity variable value as 0.1. Our finally objective is 224, including the total sale quantity and equity weight. From this numerical case study we can see that our model is quite flexible and sensitive when we want to maximize sale quantity with the equity weight considered. We can see that as the value of parameter λ increases, the equatability variable z gets larger, and the objective value gets bigger. When we consider just maximizing the outputs of all gasoline stations, we tend to place generators to the stations with large initial inventories. When we increase the importance of equatability, we tends to evenly distributed generators to regions so as to improve the equity value.

4 Case Study for Two Counties in the State of New Jersey

In this paper, we will consider Superstorm Sandy as the case that we want to study. In the late October of 2012, hurricane Sandy hit the Eastern Coastal areas of the United States, the total loss or damage by Superstrom Sandy was roughly about 72 billion dollars (comfort etc. 2013). Among them, the state of New Jersey and New York City were badly hit by Sandy (Aon Benfield, 2013). In this case study, we utilize gasoline station data we obtained from the New Jersey Office of GIS Open Data source online to apply our model (New Jersey Office of GIS Open Data). After Superstorm Sandy, most of the refineries and terminals are shut down due to the damage of the storm, the state of New Jersey encountered gasoline shortage and trucks are waiting in the line to fill gas. Houses, cars and trucks etc were out of power, and the need of gasoline dramatically increased. As we see from the Figure 2, trucks and individuals are lined up in the queue to wait for gas fulfillment.

Among counties in the state of New Jersey, we will pick Monmouth and Ocean Counties for

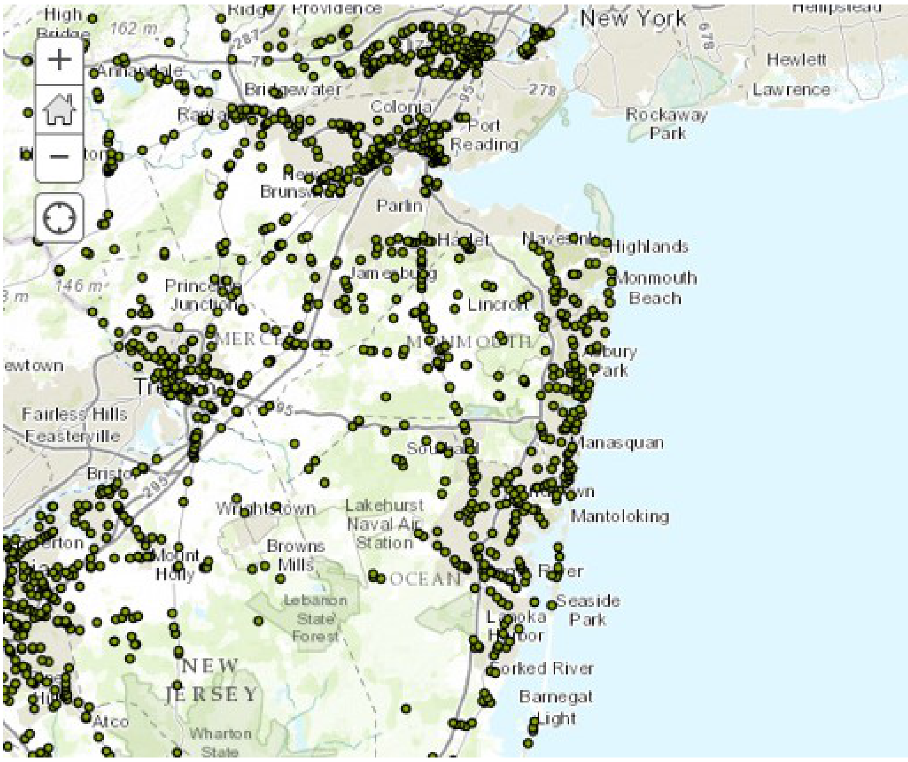

Figure 7: Gas Station Map for Monmouth and Ocean Counties in New Jersey

our case study since these two counties are the most hit counties across New Jersey state. Figure 7 provides a glance at the gas station map in these two counties. After Superstorm Sandy, about of 40 percent of gasoline stations in New Jersey closed either because of power loss or gasoline shortage (CNN, 2012). In this case study, we will consider the case with 40 percent of gas stations out of power. In order to reflect the fact of the gasoline demand crisis, we will assume our demand is three times of maximum gasoline outputs for all gasoline stations within the region. The gasoline stations within the same region will share the demand of the region. We also assume customers within the region will be only serviced by the gasoline stations in the region.

Since we only have the gas station location information, it is impossible to get all the parameters for each single gas stations. So we randomly generate parameters such as W_j the storage capacity at gas station j, O_j the maximum output at gas station j, V_j the initial inventory at gas station j. We randomly generate the storage capacity of gas stations with the range of 8000 gallons to 35000 gallons, and generate initial inventory V_j of each gas station j randomly with the range of 0 gallon to W_j the storage capacity at gas station j. Then we assume the maximum output of each gas station j is half of their respective storage capacity. Based on this same set of gas station parameter data, we construct 12 cases in two groups. For each of the 12 cases, we generate 30 replications based on the fact that 40 percent of gasoline stations out of power. So for each replication, we randomly select gas stations and set these stations with power. These 30 replications are shared by each individual case so that we can conduct valid comparisons on the same data set. All 12 cases are developed based on the factors of truck numbers, truck capacities, number of available generators, equity parameter λ, available resource and region efficiencies. We run our cases by IBM Ilog Cplex (version 12.6.1) with computer processor as Intel(R) Xeon(R) CPU e5-2630 v3 @2.4GHz, 32GM installed memory(RAM). In order to speed up the case study all cases are run with 5 percentage of tolerance gap from optimal.

As we said previously, we conduct these 12 cases in two different groups. One group consists of 8 cases, all these 8 cases are generated by differentiating trucks parameters while keeping the same total delivery capacities. Table 3 provides detailed information regarding each individual case. The objective value, equity z, total delivery and CPU time are average values of the 30 replications for each single case. From table 3, we can see that, with the same total delivery capacity, the size and numbers of each type of trucks affects our result quite significant. We see that when we have more trucks with smaller capacities for both type of trucks, e.g. cases 3, 4, 6 and 7, our objective value, total delivery quantities and equity variable can all achieve better result while the CPU solving time tends to take a much longer. While in the cases where we have large capacities of trucks, e.g. cases 1, 5 and 8, our solution solving time improved dramatically without sacrificing the objective value and equity much. As for case 2, we see that if we have really unbalanced number of types of vehicles and the truck capacity is relatively large, the total delivery quantity wasn't affected much, we actually improve the solution solving time but with sacrifice on equity and objective value.

For group 2, we pick one of the cases in the previous group (case 8), then we fix the trucks parameters such as number of available trucks, capacity of each different size of trucks. We simply change one parameter for each case as listed in table 4. Similar to group 1, We run each of 30 replications again for these 5 cases. The results are listed in table 4. Again, the objective value, equity z, total delivery and CPU time are average cross 30 replications for each case. Case 8 serves as the baseline for this group. We see that if we decrease the equity factor Λ, we will still achieve similar total delivery quantity, but the equity value was hardly affected although the solution solving

Table 3: 8 Cases with Same Delivery Capacity

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Number of Regions	72	72	72	72	72	72	72	72
Number of Gas Stations	453	453	453	453	453	453	453	453
Number of Periods	12	12	12	12	12	12	12	12
Number of Type 1 Truck	50	2	36	59	71	59	71	34
Capacity of Type 1 Truck	15,000	14,000	13,000	12,000	11,000	10,000	9,000	15,000
Number of Type 2 Truck	50	132	124	68	41	80	88	80
Capacity of Type 2 Truck	8,000	8,500	5,500	6,500	9,000	7,000	5,500	8,000
Number of Generators	30	30	30	30	30	30	30	30
Weight of equity(λ)	200,000,000	200,000,000	200,000,000	200,000,000	200,000,000	200,000,000	200,000,000	200,000,000
Resource at $t(R_t)$	1,000,000	1,000,000	1,000,000	1,000,000	1,000,000	1,000,000	1,000,000	1,000,000
Region Efficiency	2	2	2	2	2	2	2	2
Objective Value	26,911,776	15,356,380	29,859,632	29,779,899	15,317,239	29,798,549	29,824,764	26,835,218
Equity z	0.0628939	0.005,151,8	0.077,981,5	0.077,505,6	0.005,197,8	0.077,609,9	0.077,793,4	0.062,386
Total Delivery *Gallons*	14,332,996	14,326,020	14,263,329	14,278,779	14,277,688	14,276,568	14,266,089	14,358,023
CPU time(by replication)	11.72(s)	2.12(s)	360.11(s)	397.88(s)	5.79(s)	303.27(s)	234.72(s)	9.91(s)

time improves much. As for case 10, here we decrease the number of available generators. Usually generators are very expensive and stakeholder of the relative parties (e.g. New Jersey government) would not have lots of generators on hand. So the result of case 10 shows us that the equity will drop significantly even though we only reduced 20 generators. The total delivery drops not much in the fact that we have very limited resource while solving time increases quite a bit. Case 11 is quite obvious since we doubled our available resource. In this case, the objective value, equity value and total delivery quantity increase significantly while solution solving time just increases a little bit. In case 12, we simply change all the region efficiency value from 2 to 1, it means that, each type of truck can only be utilized once for each single periods, while in other cases, each type of trucks can by utilized twice in each period. This implies that we have affectively reduced the total number of available trucks. We see that the solution time time is reduced but other values e.g. objective value, equity and total delivery actually do not change much. In this case, it is because we have very limited resource and the number of available trucks are enough to carry on the delivery job.

Table 4: Five Cases with Fixed Truck Parameters

	Case 8	Case 9	Case 10	Case 11	Case 12
Number of Regions	72	72	72	72	72
Number of Gas Stations	453	453	453	453	453
Number of Periods	12	12	12	12	12
Number of Type 1 Truck	34	34	34	34	34
Capacity of Type 1 Truck	15,000	15,000	15,000	15,000	15,000
Number of Type 2 Truck	80	80	80	80	80
Capacity of Type 2 Truck	8,000	8,000	8,000	8,000	8,000
Number of Generators	30	30	10	30	30
Weight of equity(λ)	200,000,000	200	200,000,000	200,000,000	200,000,000
Resource at $t(R_t)$	1,000,000	1,000,000	1,000,000	2,000,000	1,000,000
Region Efficiency	2	2	2	2	1
Objective Value	26,835,218	14,256,237	14,834,092	38,364,007	26,851,117
Equity z	0.062,386	0	0.003,912,8	0.064,960,4	0.062,514,6
Total Delivery ($Gallons$)	14,358,023	14,256,237	14,051,529	25,371,920	14,348,197
CPU time(by replication)	9.91(s)	0.83(s)	65.93(s)	12.15(s)	6.29(s)

5 Case Study for All Counties in the State of New Jersey

We follow the same process as the previous case study to utilize gasoline station data which we obtain from the New Jersey Office of GIS Open Data source online to apply to our model (New Jersey Office of GIS Open Data). We still consider the case with 40 percent of gas stations out of power. Same with the previous case study, we will assume our demand is three times of the maximum gasoline outputs for all gasoline stations within each region. The gasoline stations within the same region will share the demand of the region. Customers within the region will be only serviced by the gasoline stations in the region. We also randomly generate gas stations parameters such as W_j, O_j and V_j. The storage capacity of gas stations will also be generated with the range of 8,000 gallons to 35,000 gallons, and initial inventory V_j of each gas station j randomly with the range of 0 gallon to W_j. The maximum output of each gas station j is half of their respective storage capacity. Based on this same set of gas station parameter data, we construct 8 cases. For all these cases, we will only generate one replication based on the fact that 40 percent of gasoline stations out of power. And all these cases will share this same data set. Again we run these 9 cases by IBM Ilog Cplex (version 12.6.1) on the same pc as the previous case study. All cases are run with 5 percentage of tolerance gap from optimal since the data set is really large e.g. there are a total of 3,387 gas stations in the state of New Jersey. Table 5 provides us detailed information regards to each individual case. Since the data set is large when we consider all gas stations in NJ, the region efficiency parameters are set to 2 for some regions close to the depot and 1 for the rest of regions. Cases 1 , 2 and 3 in the table shows us that once we increase number of available generators, we can obtain much better equity value while decreasing the solution solving time significantly. Now let us compare cases 4, 5 and 2 since in these cases, we simply change the equity weight parameter value from 0 as in case 4, 20,000 as in case 5 and 200,000,000 in case 2. We see that for the large data set, in order to achieve a better equity value, we have to use a very large value for equity weight parameter. Now compare case 6 with case 2. We see that if we change all the region efficiency parameter to 1, in this case, the change didn't affect the results much. The reason for this is because we have enough trucks available. Last let us compare cases 2, 7 and 8. We see that the available resource affects our objective value very much. When we get more available gasoline resource, our objective value and total delivery increased. The solution solving time for smaller resource value as in case 8 is significantly longer when we try to achieve a better equity value and total delivery. From this large case study, we conclude that our model is effective and efficient.

6 Conclusions and Future Work

In the aftermath of a natural disaster, gasoline supply chain may be disrupted. Gasoline shortage may become a key factor to the recovery of the community. In our model, we consider a single depot and two types of delivery trucks with limited gasoline resource in a limited time period. We

Table 5: Nine Cases for All Gas Stations in New Jersey

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Number of Regions	489	489	489	489	489	489	489	489
Number of Gas Stations	3387	3387	3387	3387	3387	3387	3387	3387
Number of Periods	12	12	12	12	12	12	12	12
Number of Type 1 Truck	400	400	400	400	400	400	400	400
Capacity of Type 1 Truck	15,000	15,000	15,000	15,000	15,000	15,000	15,000	15,000
Number of Type 2 Truck	500	500	500	500	500	500	500	500
Capacity of Type 2 Truck	8,000	8,000	8,000	8,000	8,000	8,000	8,000	8,000
Number of Generators	50	150	300	150	150	150	150	150
Weight of equity(λ)	200,000,000	200,000,000	200,000,000	0	20,000	200,000,000	200,000,000	200,000,000
Resource at $t(R_t)$	9,000,000	9,000,000	9,000,000	9,000,000	9,000,000	9,000,000	12,000,000	5,000,000
Region Efficiency	2,1	2,1	2,1	2,1	2,1	1	2,1	2,1
Objective Value	114,932,000	124,232,295	127,852,956	117,742,400	117,704,400	126,248,192	154,249,049	80,356,812
Equity z	0	0.045	0.040,3	0	0	0.050,8	0.043,9	0.040,8
Total Delivery *Gallons*	114,932,000	115,162,000	119,797,400	117,742,400	117,704,400	116,078,700	145,469,900	72,205,900
CPU time	3871.96(s)	395.68(s)	338.23(s)	318.48(s)	318.60(s)	319.21(s)	715.62(s)	8,124.81(s)

utilize the limited back up generators and optimize the generators assignment and truck deliveries to the gas stations to achieve maximum gasoline delivery, and at the same time incorporate equity factor across the different regions. Our numerical example validates our model and proves that our model works effectively to locate generators to gas stations and assign delivery trucks to gas stations. With different equity parameters λ, we can achieve the desirable level of equity. In the two county case study we found out that different combinations of two types of trucks can affect the performance quite a bit. Different input parameters, e.g. available resource, number of generators, equity parameter affect the deliverable results. From the large case study we conclude that our model is quite efficient and useful to manage gasoline delivery in the aftermath of a natural disaster. To evaluate the true impact of our model we need to understand how individuals seek gas in a gas shortage situation. Analytical models based on queueing and simulation model would be useful in this regard. The development of such models and their interaction with the basic model proposed in this paper can be treated as future work.

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