University Transportation Research Center - Region 2

Final Report

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

Performing Organization: State University of New York,
Rutgers University

February 2016

Sponsor:
University Transportation Research Center - Region 2

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The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

Research

The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

Education and Workforce Development

The modern professional must combine the technical skills of engineering and planning with knowledge of economics, environmental science, management, finance, and law as well as negotiation skills, psychology and sociology. And, she/he must be computer literate, wired to the web, and knowledgeable about advances in information technology. UTRC's education and training efforts provide a multidisciplinary program of course work and experiential learning to train students and provide advanced training or retraining of practitioners to plan and manage regional transportation systems. UTRC must meet the need to educate the undergraduate and graduate student with a foundation of transportation fundamentals that allows for solving complex problems in a world much more dynamic than even a decade ago. Simultaneously, the demand for continuing education is growing – either because of professional license requirements or because the workplace demands it – and provides the opportunity to combine State of Practice education with tailored ways of delivering content.

Technology Transfer

UTRC's Technology Transfer Program goes beyond what might be considered "traditional" technology transfer activities. Its main objectives are (1) to increase the awareness and level of information concerning transportation issues facing Region 2; (2) to improve the knowledge base and approach to problem solving of the region's transportation workforce, from those operating the systems to those at the most senior level of managing the system; and by doing so, to improve the overall professional capability of the transportation workforce; (3) to stimulate discussion and debate concerning the integration of new technologies into our culture, our work and our transportation systems; (4) to provide the more traditional but extremely important job of disseminating research and project reports, studies, analysis and use of tools to the education, research and practicing community both nationally and internationally; and (5) to provide unbiased information and testimony to decision-makers concerning regional transportation issues consistent with the UTRC theme.

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16. Abstract

The focus of this project was on supplying gasoline after a natural disaster. There were 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. A Mixed-Integer Mathematical formulation was developed for this situation. Two case studies based on Hurricane Sandy in New Jersey are developed and solved in CPLEX.

This project utilized the limited supply of back-up generators and optimized the generators assignment and truck deliveries to the gas stations to achieve maximum gasoline delivery, while ensuring equity factor across the different regions. The model works effectively to locate generators to gas stations and assigns delivery trucks to gas stations. Via the New Jersey 2-county case study our study shows that different combinations of two types of trucks can affect the performance significantly. 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.

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EXECUTIVE SUMMARY

The focus of this project was on supplying gasoline after a natural disaster. There were 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. A Mixed-Integer Mathematical formulation was developed for this situation. Two case studies based on Hurricane Sandy in New Jersey are developed and solved in CPLEX.

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The project report first provides and introduction and a comprehensive review of the literature. Next, the modeling framework is developed and presented. T/his is followed by an explanatory numerical example that helps develop a deeper understanding and validation of the model. This report then provides 2-county and a full all-county for the State of New Jersey case studies to establish the efficiency and effectiveness of the model. Finally, the report provides some takeaway conclusions of this project and some directions for further work.

1 Problem Introduction and Review of Literature

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. The purpose of this study 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 finding efficient and effetive solutions. This project 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 risk industrialized societies have to manage and, indeed, our society uses thousands of different hazmat today (PHMSA, 2013). Unfortunately, natural disasters 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 disaster 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 the increase in hazmat prices witnessed 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 in-ability of people to go to work and the difficulty in 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 mitigate 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 project, we show how gasoline supply problem is an emergency supply chain hazmat management problem. Before delving into a solution, we provide a comprehensive 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 Framework

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

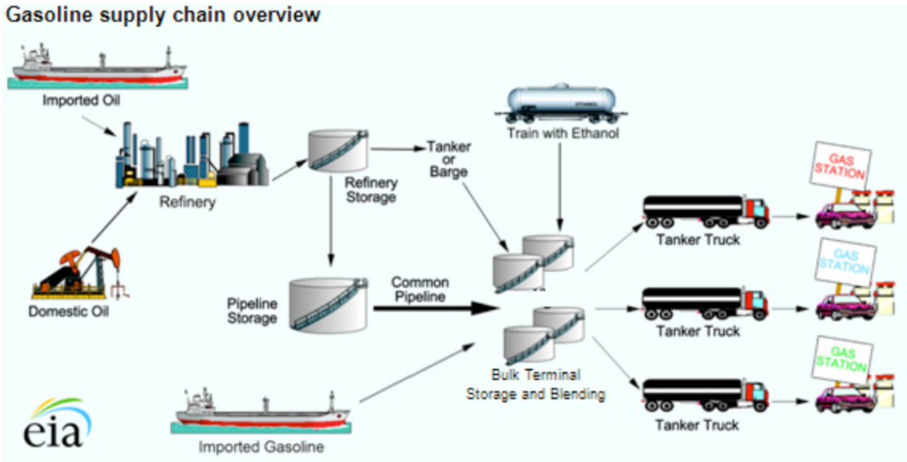


Figure 1: Gasoline Supply Chain Overview (Source: U.S. EIA, 2013)

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 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

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

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 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

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

efficiency for region i. This region efficiency number means that if the region has a efficiency value as of 2, the single one truck delivering gasoline to this particular region can be utilized twice in a 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 following the disaster. Let x_j be

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

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 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 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 Explanatory 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 regions. 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.

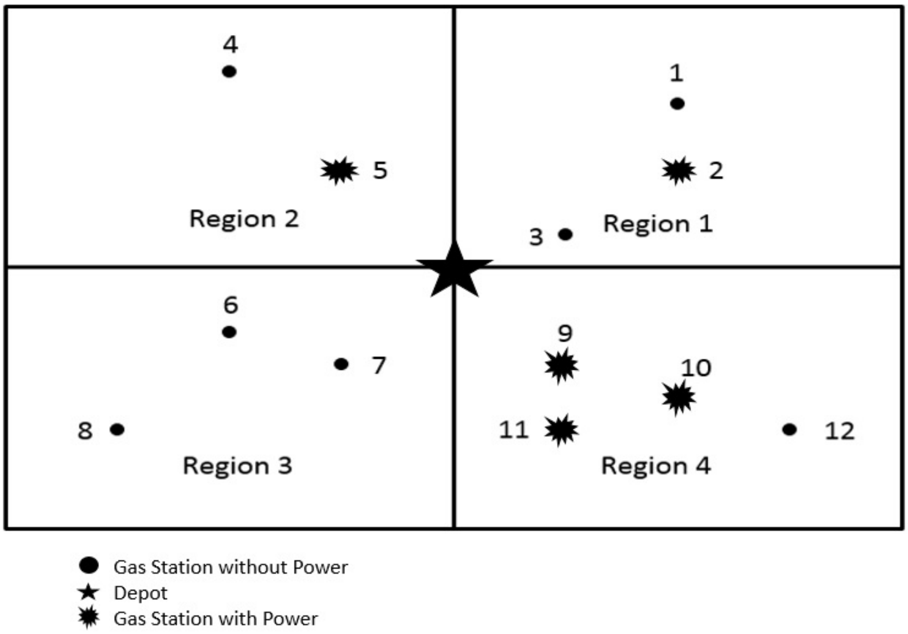


Figure 3: An Illustrative Example.

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

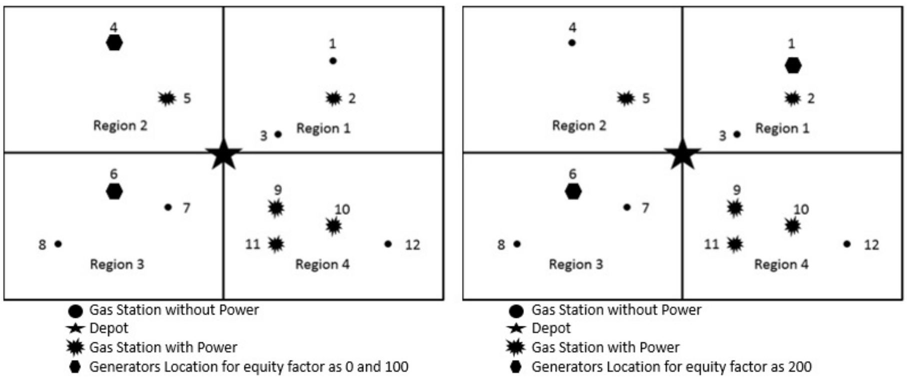


Figure 4: Generator Placement for Illustrative Example.

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

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. For scenario 2. 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, the solution changes, The model suggests placing 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.

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, the model assigns 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. For period 2, one type 1 truck is assigned to gas stations 1, 5 and 10. In period 3 we continue to assign two

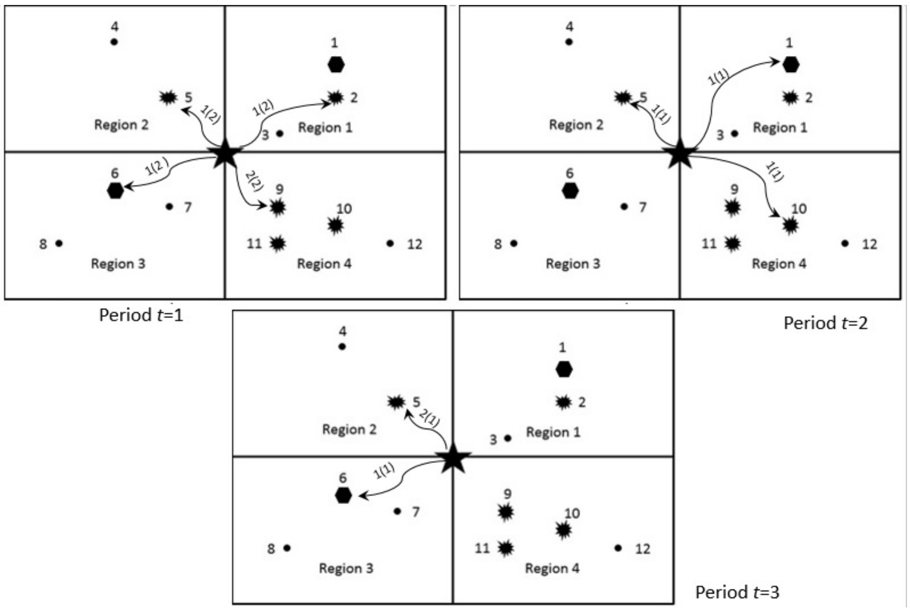


Figure 5: Truck Assignments for Scenario 3.

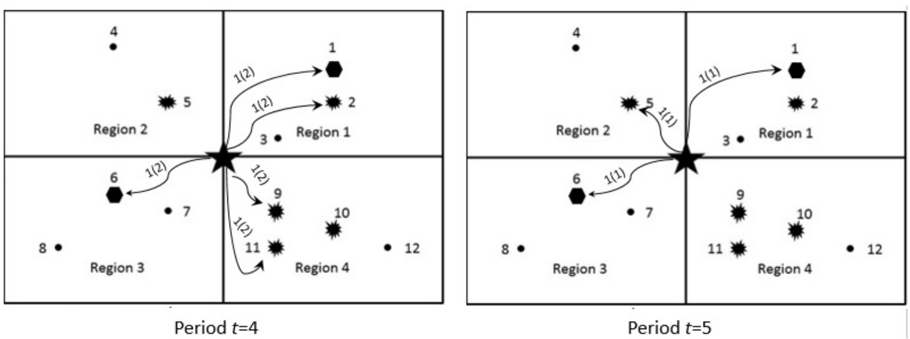


Figure 6: Truck Assignments for Scenario 3 (continued).

type 1 trucks to gas station 5 and one type 1 truck to gas station 6. The model then assigns 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 $\lambda = 200$ and an equity variable value as 0.1. Our finally objective is 224 which includes both, the total sale quantity and the equity weight. From this numerical case study we can see that our model is quite flexible, effective and sensitive in maximizing sale quantity while at the same time incorporating the important equity weight consideration. We can see that as the value of parameter λ increases, the equity variable z gets larger, and the objective value increases. 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 equity, we tend to evenly distributed generators to regions so as to improve the equity value.

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

This project specifically considers Superstorm Sandy as a case 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 bore the brunt of the impact of this storm (Aon Benfield, 2013). 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. 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).

Among counties in the state of New Jersey, we chose Monmouth and Ocean Counties for this initial two-county case study since these two counties are the most impacted counties

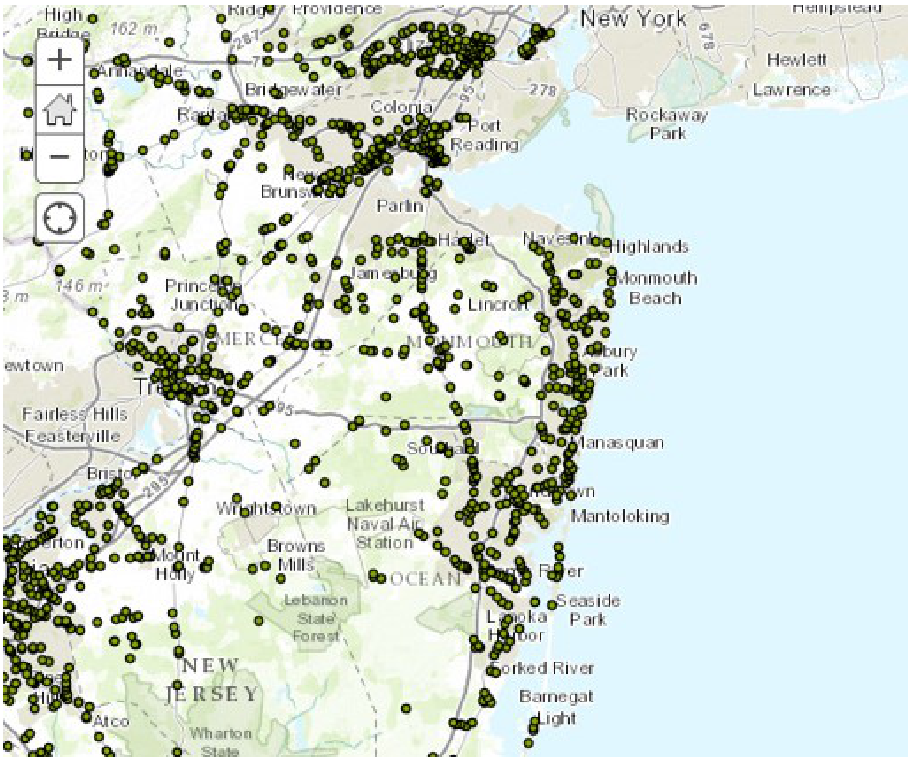


Figure 7: Gas Station Map for Monmouth and Ocean Counties in New Jersey

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 capture severe gasoline demand crisis and consider a "stress-test" of the system, we assume our demand is three times of maximum gasoline outputs for all gasoline stations within the region. We consider that 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 that region.

Since we only have the gas station location information, it is impossible to get all the parameters for each of the gas stations. Additionally, to put the system through some systematic testing, 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 are 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 an allowance of 5

As mentioned above, 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 impacts the result significantly. 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 is more. 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 compromising the objective function value and equity. 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 without sacrificing on equity and objective function 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

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)

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 averaged across 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 only marginally affected although the solution solving time improves significantly. 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 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 minimally. 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 could have been utilized twice in each period. This implies that we have effectively reduced the total number of available trucks. We see that the solution time is reduced but other values e.g. objective function 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 execute 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 Comprehensive Case Study for All Counties in the State of New Jersey

We follow the same underlying processes as the previous 2-county 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). 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 8 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. 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 in case 4 to 20,000 in case 5 to 200,000,000 in case 2. We see that for this large data set, in order to achieve a better equity value, we have to use a very large value for equity weight parameter. Now let's 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 have much of an impact on the results. 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 function value significantly. When we get more available gasoline resources, 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 and total delivery values. From this large case study, we conclude that our model is, indeed, both effective and efficient.

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)

6 Report's Conclusions

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 this project, we consider a single depot and two types of delivery trucks with limited gasoline resource in a limited time period. We utilize the limited supply of back up generators and optimize the generators' assignments and truck deliveries to the gas stations to achieve maximum gasoline delivery. Concurrently, this work incorporates a critical equity factor across the different regions. We utilize an illustrative numerical example to validate the model and show 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. A two-county New Jersey case study showed that different combinations of two types of trucks can affect the performance significantly. Different input parameters, e.g. available resource, number of generators, equity parameter affect the deliverable results. From the comprehensive all-county New Jersey 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 further enhance the model we need to study human behavior that models demand in a gas shortage situation. A combination of analytical and simulation models could be useful in expanding the modeling framework. The development of such models and their interaction with the basic model proposed in this project can be treated as future work.

In summary, this project utilized sophisticated mathematical techniques to model a resource constrained, demand driven "balanced objective function that concurrently optimizes gasoline supply with equity considerations in the aftermath of a natural disaster. The New Jersey case studies showed the value of this model in deploying critical resources equitably and effectively. A rigorous and robust investigation of this important problem, in our opinion, is a valuable contribution of this work.

References

Altay, N., Green, W.G.(2006). OR/MS Research in Disaster Operations Management. European Journal of Operational Research, 175(1), 475-493.doi:10.1016/j.ejor.2005.05.016

Benfield, A.(2013). Hurricane Sandy Event Recap Report http://thoughtleadership.aonbenfield.com/Documents/20130514_if_hurricane_sandy_event_recap.pdf

Barbarosoglu, G., Arda, Y.(2004). A Two-Stage Stochastic Programming Framework for Transportation Planning in Disaster Response, Journal of the Operational Research Society, 55(1): 43-53.

Campbell, A.M., Vandenbussche, D., Hermann,W.(2008). Routing for Relief Efforts. Transportation Science,42(2),127-145.doi:10.1287/trsc.1070.0209.

Caunhye, A.M., Nie, X., Pokharel, S.(2012). Optimization Models in Emergency Logistics: A Literature Review, Socio-Economic Planning Sciences, 46(1): 4-13.

Caunhye, A.M., Li, M., Nie, X.(2015). A Location-Allocation Model for Casualty Response Planning during Catastrophic Radiological Incidents, Socio-Economic Planning Sciences, 50: 32-44.

Caunhye, A.M., Zhang, Y., Li, M., Nie, X.(2016). A Location-Routing Model for Prepositioning and Distributing Emergency Supplies, to appear in Transportation Research Part E: Logistics and Transportation Review.

Cozzani, V., Campedel, M., Renni, E., & Krausmann, E.(2010). Industrial Accidents Triggered by Flood Events: Analysis of Past Accidents, Journal of Hazardous Materials, 175(1-3),501-509.

CNN (2012). Gas shortage continues in areas hit by Sandy http://money.cnn.com/2012/11/02/news/economy/gas-shortage-sandy/

Huffington Post (2012). Hurricane Sandy Gasoline Shortage: Dry Pumps Could Last For Days. Retrieved September, 2013 http://www.huffingtonpost.com/2012/11/01/sandy-gasoline-shortage_n_2059651.html

PHMSA (Pipeline and Hazardous Materials Safety Administration, U.S. Department of Transportation) (2013). Hazardous Materials Table (HMT), Title 49 CFR 172. 101 Table (List of Hazardous Materials). Retrieved September, 2013 (http://www.phmsa.dot.gov/hazmat/library).

Galindo, G., Batta, R. (2013). Review of Recent Developments in OR/MS Research in Disaster Operations Management. European Journal of Operational Research, 230(2), 201-211. doi:10.1016/j.ejor.2013.01.039

Galindo, G., Batta, R. (2013). Prepositioning of Supplies in Preparation for a Hurricane under Potential Destruction of Prepositioned Supplies, Socio-Economic Planning Sciences, 47(1): 20-37.

Gong, Q., Batta R. (2007). "Allocation and Reallocation of Ambulances to Casualty Clusters in a Disaster Relief Operation." IIE Transactions 39.1: 27-39.

Haghani, A., Oh, S.C. (1996). Formulation and Solution of a Multi-Commodity. Multi-Modal Network Flow Model for Disaster Relief Operations, Transportation Research Part A: Policy and Practice, 30(3): 231-250.

Huang, M., Smilowits, K., Balcik, B.(2012). Models for Relief Routing: Equity,Efficiency and Efficacy. Transporation Research Part E: Logistics and Transportation Review, 48(1),2-18.doi:10.1016/j.tre.2011.05.004

Lodree, E.J., Ballard, K.N., Song, C.H. (2012). Pre-Positioning Hurricane Supplies in a Commercial Supply Chain, Socio-Economic Planning Sciences, 46(4): 291-305.

Maskrey, A. (1989). Disaster mitigation: A Community Based Approach. Oxfam Professional, Oxford, England.

Mete, H.O., Zabinsky, Z.B. (2010). Stochastic Optimization of Medical Supply Location and Distribution in Disaster Management, International Journal of Production Economics, 126(1):76-84.

New Jersey Office of GIS Open Data `http://njogis.newjersey.opendata.arcgis.com/datasets/d511b06f89cb48dc903e59cf4f346dda_2`

Ozdamar, L., Ekinci, E., Kucukyazici, B. (2004). Emergency Logistics Planning in Natural Disasters, Annals of Operations Research, 129(1-4): 217-45.

Pacheco, G.G., Batta, R. (2016). Forecast-driven Model for Prepositioning Supplies in Preparation for a Foreseen Hurricane, Journal of the Operational Research Society, 67(1): 98-113.

Rawls, C.G., Turnquist, M.A. (2010). Pre-Positioning of Emergency Supplies for Disaster Response, Transportation Research Part B: Methodological, 44(4): 521-534.

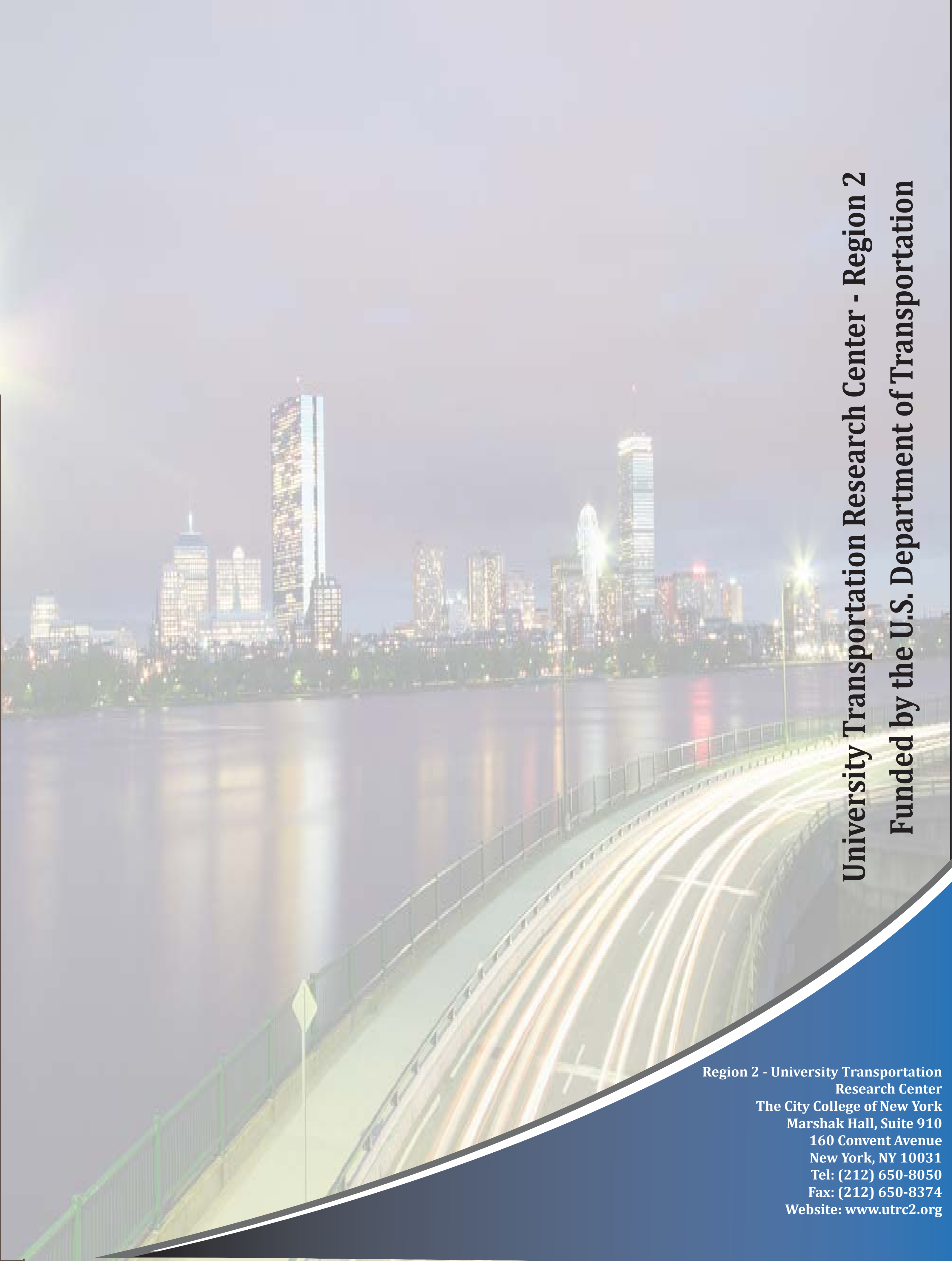
Rawls, C.G., Turnquist, M.A. (2012). Pre-Positioning and Dynamic Delivery Planning for Short-Term Response Following a Natural Disaster, Socio-Economic Planning Sciences, 46(1): 46-54.

Rennemo, S.J., Ro, K.F., Hvattum, L.M., Tirado, G. (2014). A Three-Stage Stochastic Facility Routing Model for Disaster Response Planning, Transportation Research Part E: Logistics and Transportation Review, 62(2): 116-135.

Sheu, J.B. (2007). An Emergency Logistics Distribution Approach for Quick Response to Urgent Relief Demand in Disasters, Transportation Research Part E: Logistics and Transportation Review, 43(6): 687-709.

Sheu, J.B. (2010). Dynamic Relief-Demand Management for Emergency Logistics Operations under Large-Scale Disasters, Transportation Research Part E: Logistics and Transportation Review, 46(1): 1-17.

Van Wassenhove, L.N. (2005). Humanitarian Aid Logistics: Supply Chain Managment in High Gear. Journal of the Operational Research Society, 57(5),475-489.



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