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Drones for disaster response and relief operations: A continuous approximation model

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ABSTRACT

This paper proposes a Continuous Approximation (CA) model that designs the potentiality of drones as a mode of transportation to supply emergency commodities in a disaster-affected region. The model determines the optimal distribution center locations and their corresponding service regions and ordering quantities to minimize the overall distribution cost for the disaster-relief operation. We propose a two-phase CA approach that solves the model efficiently. We conduct extensive sensitivity analysis to reveal insights into how system design varies with key drone design parameters. We use three disaster-prone coastal counties of Mississippi as a testbed to visualize and validate the modeling results.

1. Introduction

Between 1995 and 2015, *Emergency Events Database* (EM-DAT) of *The Center for Research on the Epidemiology of Disasters* (CRED) recorded a total of 6457 weather-related disasters, which claimed over 606,000 lives and left 4.1 billion people injured, homeless, and/or in need of emergency assistance. More specifically, between 2005 and 2014, EM-DAT recorded an average of 335 weather-related extreme events which is approximately 14% higher than the number recorded between 1995 and 2004 and twice the number between 1985 and 1995. Scientists predict that we will witness a continued upward trend in weather-related extreme events in the decades ahead (UNISDR, 2015).

Among all the countries in the world hit by the highest number of weather-related disasters, United States (US) comes first, with 472 disasters occurring over the past 20 years (Shaw, 2015). In recent years, natural disasters such as flooding, wildfire, hurricane, tornadoes, and many others hit frequently in different parts of the US and cause significant damages to both economy and human life. The most devastating natural disaster that shocked the entire country in recent years was Hurricane Katrina which rampaged the Gulf Coast of the US in the morning of August 29, 2005. It had a *Category 3* rating on the Saffir-Simpson Hurricane Scale and it brought sustained winds of 100–140 miles per hour.[1] The storm itself did a great deal of damage, but its aftermath was even more catastrophic. Many people charge that the federal government reacted slowly to meet the needs of the disaster affected people. The main reason behind this is that the government, particularly the federal government, seemed unprepared for the disaster. It took the Federal Emergency Management Agency (FEMA) days to establish operations in the disaster-affected regions, and even then did not seem to have a sound plan of action. People suffered significantly because of the scarcity of clean water, food, and medical aid. A proper plan regarding facility location and inventory policy of emergency products as well as deciding on which mode of transportation to use would have been much more beneficial during the recovery phase of the disaster and helped people in the affected region significantly.

Logistics activities in response to a disaster are commonly known as *humanitarian logistics*. Humanitarian logistics can be defined as the process of planning, implementing, and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from a point of origin to a point of consumption for the purpose of meeting the end beneficiaries requirements (Thomas and Mizushima, 2005). The aim is to deliver the right commodity at the right time, to the right place, and to the right people. Although the basic methodology behind humanitarian logistics is the same as classical logistics operation, the effect of decision making holds more significance for humanitarian logistics. Note that while planning a robust logistics network, decisions regarding where to place emergency

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[1] Available from: http://www.cnn.com/2005/WEATHER/12/21/katrina/.

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facilities from where all the commodities will be transported to the demand sites is of significant importance as it has a direct impact on how fast disaster-affected points can be served. Simultaneously, inventory policy decisions are equally important since they determine whether enough commodities are available to serve all the disaster affected regions.

In this study, we propose an integrated facility location-inventory allocation model for a disaster affected region where drones can be considered as a potential mode of transportation to transport emergency supplies to the demand points. Drones can become very useful as a mode of transportation in humanitarian logistics since they do not need any preexisting path to fly. Thus, if a natural disaster strikes and roads are blocked, drones can easily be used to serve a disaster affected region. Nowadays drones are used in a diverse range of civilian activities, primarily humanitarian aid and rescue actions in various natural disasters which include earthquakes, hurricanes, flooding, volcanic eruption, tsunamis, and many others. The crisis management of these natural disasters poses very critical decisions related to the well-being of the affected people. Integrating drones into emergency and disaster response protocols can be considered as an effective tool to provide immediate relief benefits needed by civilians, communities, and first responders. The disaster relief life cycle can be split into four major stages: prevention, preparation, response, and recovery (Center for Disaster, 2016). Drones have the potential to play a major role in all four stages, though currently are used overwhelmingly in the response stage. Unfortunately, even though they have the potential to respond quickly in a critical situation, drones are surprisingly under-utilized.

When a disaster strikes, drones are able to provide support with risk assessment, mapping, and planning for the affected region (Measure-Red cross, 2015). Al-Tahir et al. (2011) present an overview and assessment of the technology relevant to low cost cameras and platforms to acquire aerial photographs of a disaster-affected Caribbean region. The authors suggest that drones can be employed further to establish temporary communication structures, creating up-to-date maps of the affected region, and searching for hot spots where the rescue teams may have more chances of finding victims. There are a number of cases where drones have already been used in humanitarian settings. For instance, in 2013, a US start-up company called *Matternet* announced that it had tested humanitarian aid drone prototypes in Haiti and the Dominican Republic (Cohen, 2014). Drones were further used to create up-to-date maps of the devastated areas following Typhoon Haiyan in 2013 where the mapping efforts were coordinated between multiple aid and drone organizations (Greenwood, 2015). Similarly, when the earthquake and Tsunami hit the Fukushima area of Japan, the nearby nuclear power plant named *Fukushima Daiichi plant* was highly affected. A drone was launched to fly around the Fukushima plant to gauge the radiation levels. It took off around six kilometers away from the damaged power plant in Namie City. It had a flying time of 30 min and it was able to collect radiation levels in real-time and went back to the scientists safely (Pamintuan-Lamorena, 2014). Table 1 summarizes the application of drones in response to natural disasters in recent years between 2005 and 2015 (Murphy, 2014).

Table 1
Drones used in response to natural disasters between 2005 and 2015 (Murphy, 2014).

Year	Natural disaster	Name of drone	Application A	B	C	D
2005	Hurricane Katrina Response (USA)	AeroViroment Raven	✓	✓		
		Evolution	✓	✓		
		iSENSYS T-Rex	✓	✓		
		Silver Fox	✓	✓		
2005	Hurricane Katrina Recovery (USA)	iSENSYS IP3			✓	
2005	Hurricane Wilma (USA)	iSENSYS T-Rex		✓	✓	
2007	Berkman Plaza II	iSENSYS IP3			✓	
2009	Laquila Earthquake (Italy)	Custom		✓	✓	
2009	Typhoon Morakot (Taiwan)	Unknown		✓		
2010	Haiti Earthquake (Haiti)	Elbit Skylark		✓		
2011	Christchurch Earthquake (NZ)	Parrot AR. Drone			✓	
2011	Tohoku Earthquake (Japan)	Pelican			✓	
2011	Fukushima Nuclear Emergency (Japan)	Custom		✓		
		Honeywell T-Hawk		✓	✓	
2011	Evangelos Florakis Explosion (Cyprus)	AscTec Falcon		✓	✓	
		AscTec Hummingbird		✓	✓	
2011	Thailand Floods (Thailand)	FIBO UAV-1		✓		
		FIBO UAV Glider		✓		
		SIAM UAV		✓		
2012	Finale Emilia Earthquake (Italy)	NIFTi			✓	
2013	Typhoon Haiyan (Philippines)	unknown			✓	
2013	Lushan Earthquake (China)	HW18 (Ewatt HoverWings)	✓	✓		
2013	Boulder Colorado floods (USA)	Falcon Fixed		✓		
2014	SR350 Mudslides Response (USA)	DJI Phantom		✓		
		AirRobot 100		✓		
		Precision Hawk		✓		
2014	SR350 Mudslides Recovery (USA)	AirRobot 180				✓
		Precision Hawk				✓
2014	Balkans flooding (Serbia, Bosnia-Herzegovina)	ICARUS custom		✓		✓
2014	Collbran landside (USA)	Falcon Fixed	✓	✓		
		Falcon Hover	✓	✓		
2014	Yunnan China Earthquake (China)	Parrot AR Type 2		✓		

A=Search, B=Reconnaissance and mapping, C=structural inspection, and D=estimation of debris.

In situations, where transportation network is highly impacted by natural disasters, obvious mode of transportation e.g. trucks often can't be used in response operations. Despite high expectations of the role of drones to serve in humanitarian logistics, there is not yet a comprehensive design framework on how to economically deploy a drone that is capable of serving a disaster affected region considering the restrictions provided by Federal Aviation Administration (FAA)[2] (Federal Aviation, 2016) and the technological limitations (e.g., limited battery and weight carrying capacity) that the existing drones hold. This paper proposes a continuous approximation (CA) model for determining the optimal configuration of a humanitarian logistics system, including the location of distribution centers and the corresponding emergency supply inventories at these centers under stochastic demand and drone flying range constraints. This optimal configuration shall minimize the overall system cost including the costs of opening distribution centers, ordering and holding costs of emergency supplies, and the expected transportation costs of using trucks and drones to serve a disaster affected region. We approximate the nonlinear drone transportation cost by considering a number of routing specific factors such as climbing, hovering, descending, turning, acceleration and deceleration, rotational, and constant speed cost into account. We then propose a two-phase continuous approximation approach to solve this nonlinear programming problem efficiently. Finally, we apply this model to three disaster prone coastal counties of Mississippi i.e., Hancock, Harrison, and Jackson counties and draw interesting managerial insights into the optimal system design and the total system cost (Table 2).

[2] In the United States, Federal Aviation Administration (FAA) requires UAVs to be operated under a ceiling of 400ft which will severely limit the effective range of utilizing drones for disaster relief operation (Federal Aviation, 2016)

Table 2
Summary of key parameters and variables used in this study.

	Notes	unit
Set		
I	Set of clusters (i.e. i = 1, 2, …, 12)	
Symbol		
N_{r_i}	Total number of distribution centers	–
Decision variables		
A_{r_i}	Influence area	mile^2
Q_{r_i}	Ordering quantity	–
Parameters		
f_r	Cost of opening a refueling station for trucks and battery charging station for drones	$
g_r	Constant scalar	–
γ_i	Discrete demand points in each cluster C_i expressed as a spatial density slow varying function	–
θ_i	Customer demand for each cluster C_i expressed as a spatial density slow varying function	–
δ	Planning horizon	days
p	Probability of using truck to transport emergency supplies	–
q	Probability of using drone to transport emergency supplies	–
α_p	Transportation cost per mile per item using truck	$
α_q	Transportation cost per mile per item using drone	$
P_{cl}	Required power of the motor while climbing	watt
v	Speed of drone while climbing	miles/h
k	Altitude of drone	mile
C_c	Cost per unit of energy consumed	$
β	Minimum power needed to hover over the ground	watt
λ	Motor speed multiplier	–
t_h	Hovering time	s
$P_{ds}v'$	Required power of the motor while descending	watt
	Speed of drone while descending	miles/h
P_{acc}	Required power of drone during acceleration	watt
P_{vc}	Required power of drone while maintaining constant speed	watt
P_{dec}	Required power of drone during deceleration	watt
T_1	Time spent during acceleration phase	s
T_2	Time spent during constant speed phase	s
T_3	Time spent during deceleration phase	s
m	Total payload of a drone including its own weight	kg
d	Distance covered with acceleration a_{cc}	mile
T	Time taken to cover distance d covered with acceleration a_{cc}	s
w	Percentage of total distance covered during acceleration phase	–
b	Percentage of total distance covered during constant speed phase	–
y	Percentage of total distance covered during deceleration phase	–
P_{turn}	Required power of drone during turning	watt
$\eta_t\Delta\theta$	number of turns a drone takes in a given time period	–
	Angle covered during turning	radian
w_{turn}	Angular rotation speed	rad/s
R_r	Reorder cost	$
μ_r	Mean lead time	days
σ_r^2	Variance of lead time	days
α_r	Service level at distribution center	–
h_r	Holding cost	$
R_d	Range of drone	miles

In summary, the main contributions of this paper are as follows:

- As far as the author's know, this study is the first work that addresses design of a humanitarian logistics system by considering drone as a viable mode to transport emergency supplies to the disaster affected regions.
- The nonlinear drone transportation cost along with the inventory cost decisions are effectively modeled. We then employ a two-phase continuous approximation approach to solve the nonlinear distribution problem.
- Provided a real life application to visualize and validate the modeling results and deduced a number of managerial insights about different key drone parameters (e.g., drone flight height, speed), road access availability following a natural catastrophe, and how inventory holding and reordering cost impact the humanitarian logistics system performance.

The exposition of this paper is as follows. In Section 2 we review the literatures that are most pertinent to this research. In Section 3, we present a continuous approximation model to supply emergency commodities in a disaster affected region. In Section 4, we outline the developed two-phase continuous approximation approach to solve our optimization model. We then present the model input parameters in Section 5 and a series of experimental results in Section 6. Lastly, we conclude and present avenues for future research in Section 7.

2. Literature review

The proposed research is built upon existing studies on facility location and inventory allocation problems which researchers have attempted to solve over the years. Nozick and Turnquist (1998) perform regression analysis to approximate the safety stock cost of a distribution center and incorporate the inventory decisions in a fixed-charge facility location model. Nozick and Turnquist (2001) extend their prior work by developing a model that simultaneously integrates facility costs, inventory costs, transportation costs, and service responsiveness by borrowing ideas from queuing theory, discrete choice location analysis, and multi-objective decision-making. Erlebacher and Meller (2000) propose a two-stage heuristic procedure to identify the interactions that exist between location and inventory in designing distribution system. Shen et al. (2003) propose a formulation to integrate facility location and inventory allocation decisions under the same decision making framework to minimize the overall system cost. Note that the formulation incorporates a nonlinear inventory and safety stock cost. Miranda and Garrido (2004) propose a non-linear mixed-integer programming model that incorporates inventory control decisions, i.e., economic order quantity and safety stock decisions into typical facility location models. The authors employ a Lagrangian relaxation approach to solve their proposed nonlinear optimization problem. Teo and Shu (2004) study a distribution network design problem integrating transportation and an infinite horizon multi-echelon inventory cost function. The authors consider the trade-off that exists between inventory, direct shipment, and facility location cost for such a system. Romeijn et al. (2007) propose a framework for the two-echelon supply chain design problem that incorporates location decisions as well as location-specific transportation and inventory decisions. Fairly recently, Tsao et al. (2012) have developed a detailed non-linear cost model where the authors propose a solution technique that preserves the interrelations between facility location and inventory management decisions.

Disaster preparedness and response has been studied extensively by many researchers in recent years. Ozdamar and Ertem (2015) have reviewed different logistics models developed for the response and recovery planning phases considering their modeling and formulation characteristics. They also investigate the technological advances that facilitate the execution of proposed models and solutions on various types of information systems. This in turn leads to the conclusion in order to achieve unobstructed international humanitarian cooperation, standard software that integrates different planning phases is highly needed. Luis et al. (2012) propose an analysis of the use of operations research models in transportation of relief goods from the perspective of both practitioners and academics. Authors conclude in this study that, if models are flexible enough to address the high level of uncertainty in modeling disasters, the same framework can also be carried over into other areas with similar challenges. A novel framework is proposed by Sahebjamnia et al. (2015) that is developed for integrated business continuity and disaster recovery planning for efficient and effective resuming and recovering of critical operations after being disrupted. In this study, at the strategic level, the context of the organization is first explored and primary features of the organizational resilience are recognized. Afterwards, a new multi-objective mixed integer linear programming model is formulated to allocate internal and external resources to both resuming and recovery plans simultaneously. Finally, hypothetical disruptive events are investigated to evaluate the applicability of the plans at the operational level. A stochastic linear mixed-integer programming model with integrated decision considering facility and stock pre-positioning, evacuation planning, and relief vehicle planning is proposed by Manopiniwes and Irohara (2016). In this work, authors suggest a compromise between the cost and equity of relief victims. Ransikarbum and Mason (2016) propose a goal programming-based multiple-objective integrated response and recovery model to investigate strategic supply distribution and early-stage network restoration decisions. Given limited capacity, budget, and available resources, this model prescribes equity- or fairness-based compromise solutions for user-desired goals. Numerical experiments in this study shows that goal programming based model provides a compromise solution when no solution exists that satisfies hard or real constraints. Tofighi et al. (2016) propose a two-stage scenario-based possibilistic-stochastic programming approach for designing a relief network in Tehran in preparation for potential earthquakes to cope with the main logistical problems before and after disaster strikes. During the first stage, the locations for central warehouses and local distribution centers are determined along with the pre-positioned inventory levels for the emergency supplies. In the second stage, a relief distribution plan is developed based on various disaster scenarios with the objective of minimizing total distribution time, the maximum weighted distribution time for the critical items, total cost of unused inventories, and weighted shortage cost of unmet demands. A tailored differential evolution algorithm is also developed to find feasible solutions within a reasonable CPU time. Jia et al. (2007) create models and solution approaches for determining the facility locations of medical supplies in response to large-scale emergencies. The authors include the uncertainty in demand and insufficient medical supply by ensuring each demand point receives services from multiple facilities located at different distances from the demand points. Using a maximal covering problem, they incorporate both the quantity-of-coverage and quality-of-coverage. They develop three different heuristic approaches to determine the best facility locations. Considering various factors such as demand locations, the transportation network condition after a disaster, the locations of existing hospitals, and the number of available temporary facility locations, Chen et al. (2016) propose an integer programming model to improve the effectiveness of emergency medical service after a disaster by determine the locations for EMS facilities. They use Lagrangian relaxation to enable the ability to solve large, realistic sized problems. A two-stage stochastic mixed integer program (SMIP) is presented by Rawls and Turnquist (2010) for an emergency response pre-positioning strategy for different disasters. The authors investigate effect of uncertainty in the inventory level and transportation network availability after a disaster strikes in a mathematical model. This model is then solved using a customized Lagrangian L-shaped method. Noyan (2012) has developed a risk-averse two-stage stochastic programming model for disaster management. Here, the author has specified the conditional-value-at-risk as the risk measure and has developed two decomposition algorithms based on the generic Benders-decomposition approach to solve such problems. Both the concepts of the value of perfect information and the value of the stochastic solution are utilized for the proposed framework.

Transportation of emergency supplies to a disaster affected region has been an area of interest among researchers for many years. Different researchers have explored this area considering a vast array of factors. Ben-Tal et al. (2011) propose a robust optimization model for dynamically assigning emergency response and evacuation traffic flow problems with time dependent demand uncertainty. Hamedi et al. (2012) propose a genetic algorithm-based heuristic to solve a humanitarian response planning problem for a fleet of vehicles with reliability considerations. Yuan and Wang (2009) present two mathematical models where the first model is a single-objective path selection model that minimizes the total travel time along a path. The travel speed on each arc is modeled as a continuous-time decreasing function. The second model extended the first model to consider a case where chaos, panic, and congestion in the time of a disaster are taken into consideration. The authors propose an ant colony algorithm to solve their proposed optimization models. Yan and Shih (2009) developed a multi-objective, mixed-integer, multiple-commodity network flow problem that minimizes the length of time required for both emergency roadway repair and relief distribution. Oran et al. (2012) present novel formulations of the facility location problem and vehicle routing problem with time windows with priority considerations. This means that the proposed models ensure that higher priority locations are considered first, and then lower priority ones are considered. This goes for both facility and routing decisions. The facility location problem is solved using an MIP solver, while a tabu search based metaheuristic is developed for the solution of the vehicle routing problem with time windows. Yi and Özdamar (2007) propose an integrated location-routing model for coordinating logistics support and evacuation operations after emergencies and natural disasters. The objective of this study is to maximize response service level by enabling quicker transportation to affected areas and locating temporary emergency units in potential locations. The resultant model generates queues in a minimized way through the full utilization of facility capacities achieved by the interaction of the routing problem with service rate equilibrium and location. Ji and Zhu (2012) present an optimization framework that quantifies the risk of disasters as well as the support mechanisms for the disaster relief logistics. Interested readers can review the studies of Abounacer et al. (2014), Sheu et al. (2005), Sheu (2007), Zhang et al. (2012), Balcik and Beamon (2008), Lin et al. (2009), and Rath and Gutjahr (2014) for a detailed discussion about the different variants of location-routing problems applied to a disaster relief operation.

Another stream of research focuses on locating facilities in different disaster response problems. Ahmadi et al. (2015) propose a multi-depot location-routing model to solve a last mile delivery problem for serving a disaster affected region. A novel Variable Neighborhood Search (VNS) algorithm is developed to solve large instances of the proposed model. Khayal et al. (2015) propose a location-allocation model that transfers excess resources between temporary facilities operating in different time periods with the goal of minimizing deprived victims affected by disasters. One uniqueness of this model is that it allows delayed satisfaction of demand when resources in a planning period are not enough to fulfill the customer demand. Salman and Yücel (2015) study the problem of locating emergency response facilities in such a way that majority of the demand can be satisfied in a reasonable amount of time. The authors developed a tabu search heuristic to solve the proposed optimization model. Afshar and Haghani (2012) propose a mathematical model in response to natural disasters that controls the flow of several relief commodities from multiple sources to demand points. The model further considers various level of details such as vehicle routing schedules for relief commodities and the optimal locations of temporary facilities. Kılcı et al. (2015) propose a mixed-integer linear programming model that simultaneously controls the utilization of the shelters and assigns population to operating shelter areas. This model has been primarily designed to assist the planning phase for a possible disaster recovery process. Rennemo et al. (2014) propose a three-stage stochastic programming model that considers the opening of local distribution facilities, initial allocation of supplies, and last mile distribution of aid. The model further captures multi-commodity flows and transportation modes while explicitly considers different vehicle types. The authors use utility as a measure to achieve a fair distribution of aid to serve a disaster affected region.

The majority of the studies discussed above use discrete models to formulate the integrated network design problem. These models often provide unrealistic solutions when the availability of data is limited. Further, the increased volume of data will add computational complexity for the discrete models. A Continuous Approximation (CA) approach can be employed to overcome this problem since the method requires less data to approximate solutions. This approach defines decision variables in terms of continuous functions which in turn reduces the complexity of the model. Newell (1973) has demonstrated the idea of applying continuous techniques to finite-dimensional operational research problems. Daganzo (1996) has addressed a number of different transportation-related problems using a CA approach. Blumenfeld and Beckmann (1985) have developed an analytical framework for estimating the cost of distributing freight from one origin to many destinations. The analysis uses a continuous space modeling approach, which requires only the spatial density of destinations and the average and variance of demand. Langevin et al. (1996) present an overview of CA models that have been developed for freight distribution problems. Geoffrion (1976) has developed a continuous model to serve warehouse demands which are distributed uniformly over a plane. Erlenkotter (1989) has developed a model to determine the optimal area served by a single production unit where demand is assumed to be distributed uniformly over a market area. Rutten et al. (2001) have extended the model proposed by Erlenkotter (1989) to develop a more precise model by approximating accurately the fixed location, inventory, and transportation costs. The aim is to determine the optimal number of depots serving a set of uniformly distributed customers in a given area.

An analytic method is developed by Burns et al. (1985) that uses the spatial density of customers to minimize the freight transportation and inventory costs. This study analyzes and compares two distribution strategies: direct shipping (i.e., shipping separate loads to each customer) and peddling (i.e., dispatching trucks that deliver items to more than one customer per load). Dasci and Verter (2001) present a CA framework to represent spatial distributions of cost and customer demand. The proposed CA model provides a number of insights about the impact of problem parameters on facility design decisions. Wangand and Lu (2006) have studied spatial modeling and proposed smoothing techniques for non-homogenous processes by considering details at different levels of the distribution network. Further, this study has proposed fine refinements to the approximation model based on the level of details captured by the data. A CA framework is developed by Murat et al. (2010) where the market demand is modeled as a continuous density function. This methodology prioritizes the allocation decisions rather than the location decisions and a local search heuristic (steepest-descent algorithm) is employed to solve the optimization model. Pujari et al. (2008) have implemented a CA approach to determine the optimal number of shipments along with their sizes while location, production, inventory, and transportation decisions are taken into consideration. Different from other works, our approach provides a first comprehensive design framework on how to economically deploy drones to serve a disaster affected region. The model provides numerous managerial insights which allow the decision makers to understand how different key drone specific parameters (e.g., drone flight height, speed), road access availability following a natural catastrophe, and inventory holding and reordering cost impact the overall system design performance.

3. Problem description and model formulation

3.1. Problem description

In this section, we develop an integrated mathematical model of a logistics network for a disaster affected region that employs drones and trucks as the potential modes of transportation to transport emergency supplies from multiple source points (e.g., distribution centers) to destination points (e.g., customer demand points). The objective is to minimize the expected overall cost which includes the cost of locating facilities(i.e. distribution centers), allocating inventories, and transporting emergency supplies using trucks and drones. The proposed model and the solution approach have been designed for the disaster preparedness phase. Fig. 1 illustrates the service area of the proposed logistics network for a distribution center.

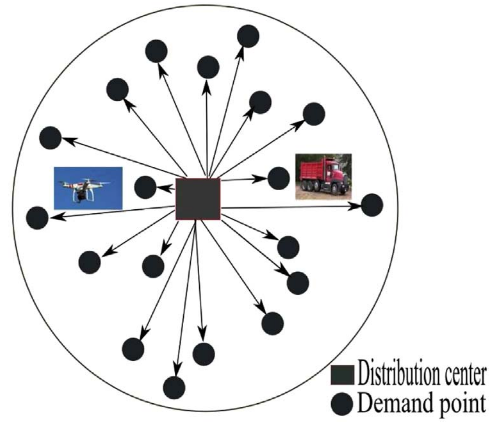


Fig. 1. Service area of the proposed logistics network.

3.2. Model assumptions

Before we present our logistics network design problem, let us first introduce a number of assumptions that we made related to the network structure, demand pattern for emergency commodities, availability of modes of transportation, and inventory replenishment policies at the distribution centers. Note that developing a humanitarian logistics network is a challenging job in itself, and incorporating drones as a potential mode of transportation further complicates the modeling efforts. These assumptions help to simplify the logistics model without sacrificing our understanding of the problem. Most of the assumptions made in this study are influenced by the works of Ganeshan (1999), Dasci and Verter (2001), Teo and Shu (2004), and Tsao et al. (2012). The assumptions are stated as follows: (*i*) we consider an "*arborescent network*" where each distribution center can serve multiple customer demand points but the opposite is not allowed. This assumption is common for any transportation network (e.g., see Melo et al. (2006)). The assumption is even more significant for the case of a disaster where a fixed distribution center is assumed to serve emergency supplies to multiple customer demand points. (*ii*) demand at each distribution center follows a Poisson process as it is generated by the demand originating from customer demand points in its influence area (service area); (*iii*) demand per unit time for customer demand points in cluster C_i is an independent and identically distributed Poisson process with rate θ_i (cluster C_i groups customers with similar demand). Assumptions (*ii*) and (*iii*) are complementary; thus, we have explained them together. It is prevalent in literature to model demand by Poisson process (see Melo et al. (2011), Araman and Caldentey (2011), McCarthy et al. (2008)). Consequently, if demands at customer demand points are generated via a Poisson process, demand at each distribution center will also be generated via a Poisson process as distribution centers will be used to serve the customer demand points. (*iv*) Lateral shipment of products among distribution centers and customer demand points is not allowed in the model. All the shipments from the distribution centers to the customer demand points are via direct shipment. Lateral shipments, through extensively used in the supply chain literature, are typically ignored in humanitarian logistics literatures due to their impracticability in real life disaster-specific applications. Therefore, in this study we assume no lateral shipments between the distribution centers and customer demand points. (v) The Euclidean distance measure is used to calculate the distance between a distribution center and a customer demand point. For the target area that has a sparse transportation network, we understand that Euclidean distance is not a good choice. Therefore, we have multiplied the Euclidean distance with a factor (e.g., 1.2) to approximate realistic travel distances. (vi) Dasci and Verter (2001) have shown that the irregular shapes of the service region (i.e., circular, hexagon, square, diamond, triangle) has little effect on the optimal solution. Based on this result, we assume that the influence area of each distribution center to be almost circular. Moreover, we assume that each distribution center is located at the center of the influence areas. Note that, in our study $g_r\sqrt{A_{r_i}}$ represents the average distance from a distribution center to the demand points in the service region, provided that the facility is located at the center of the region. This is a well-known result used by many authors in the CA literature (e.g., Newell, 1973; Erlenkotter, 1989). These prior studies have experimentally validated that the optimal solution has little effect based on the type of shape (e.g., circular, hexagon, square, diamond, triangle) considered for the service region. (vii) the capacity limitation of the facilities are ignored at all network levels; ($viii$) a sufficient number of drones and trucks are available at all times to serve the demand points; (ix) customers within an influential area of a distribution center will only be served by that specific center and the probability of facility failure is not considered; and (x) drones always carry loads with full capacity. The last four assumptions are in alignment with a number of such assumptions made in prior disaster-specific application studies (e.g., Yushimito et al., 2012; Eksioglu et al., 2009; Moshref-Javadi and Lee, 2016).

3.3. Model

To formulate the cost functions, the entire logistics network is expressed in terms of smooth continuous functions. In a two dimensional space $\mathbb{S}^2$, let the integrated network be represented by a continuous service area denoted by R where $R \subseteq \mathbb{S}^2$. All the demand points occupy a discrete position in this service area R and for each cluster C_i, these discrete demand points can be expressed as a spatial density slow varying function $\gamma_i(x)$, where $x:=\{x_1, x_2, \ldots, x_N\} \in R$. Similarly, the customer demand for each cluster C_i can be expressed as a spatial density slow varying function $\theta_i(x)$; $x \in R$. Thus, the customer demand at each point $x \in R$ can be expressed as a product of the customer density and the customer demand, and is given by $\gamma_i(x)\theta_i(x)$; $x \in R$. Let $A_{r_i}(x)$ be the influence area associated with each distribution center in cluster C_i. If we cover the entire area R with influence areas of size $A_{r_i}(x)$, then the total number of distribution centers $N_{r_i}(x)$ needed at each cluster C_i is given by[3]

$$N_{r_i}(x) = \frac{R}{A_{r_i}(x)} \tag{1}$$

In our model, three cost functions are considered; namely, total facility cost, total transportation cost, and average inventory holding cost for the distribution centers. Note the fixed cost of purchasing trucks and drones are not considered while calculating the total transportation cost. A brief discussion on how to calculate these costs are provided as follows:

- *Total facility cost*, $TF(x)$: A fixed cost is incurred for establishing and running a distribution center. The *total facility cost* can be obtained by multiplying the fixed cost of opening a distribution center f_r with the total number of distribution centers $N_{r_i}(x)$. Note that f_r consists of opening a refueling station for trucks and a battery charging station for drones. Thus, the total facility cost can be expressed as follows:

$$TF(x) = f_r N_{r_i}(x) \tag{2}$$

- *Total transportation cost*, $TOT(x)$: It has already been discussed that both drones and trucks will be made available to transport emergency supplies from multiple distribution centers to demand points. Let δ be the length of the planning horizon and let α_p and α_q be the unit transportation cost (\$/mile/unit) of transporting emergency supplies via truck and drone, respectively. Taking N as the total demand points in the disaster affected region, the euclidean distance between a distribution center j and a demand point at $x \in R$ is taken as $\| x - x_j \|$ where $j = 1, 2, \ldots, N$. Since the impact of disaster can not be predicted accurately in advance, let $p(x|\mathbf{x})$ be the probability that a demand point $x \in R$ can still be served via truck after a natural catastrophe (e.g., hurricane, tornado). This implies that some roads are still accessible (with a probability $p(x|\mathbf{x})$) for trucks to transport emergency supplies to the customers (e.g., disaster affected zones). In case of the unavailability of road access, the demand points $x \in R$ can be served by drones with a probability $q(x|\mathbf{x})$ where $p(x|\mathbf{x}) + q(x|\mathbf{x}) = 1$. Note that, the average travel distance from the distribution center, located at the center of the influence area, to the customers is proportional to $A_{r_i}(x)$. This average distance can be denoted by $g_r\sqrt{A_{r_i}(x)}$ where g_r is a constant scalar. The value of g_r is approximated by simple geometry given by Li and Ouyang (2010) as follows:

$$g_r \approx \frac{2}{3\sqrt{\pi}} \tag{3}$$

Let $\mathbb{E}[D_{r_i}(x)]$ be the expected demand per unit time experienced by each distribution center in cluster C_i and

$$\mathbb{E}[D_{r_i}(x)] = \gamma_i(x)\theta_i(x)A_{r_i}(x);\ x \in R \tag{4}$$

Thus, the total transportation cost, $TOT(x)$ can be expressed as follows:

$$TOT(x) = \underbrace{p(x|\mathbf{x})\alpha_p g_r\sqrt{A_{r_i}}\,\delta\mathbb{E}[D_{r_i}(x)]N_{r_i}(x)}_{\text{truck transportation cost}} + \underbrace{q(x|\mathbf{x})\alpha_q g_r\sqrt{A_{r_i}}\,\delta\mathbb{E}[D_{r_i}(x)]N_{r_i}(x)}_{\text{drone transportation cost}} \tag{5}$$

Note that the total customer demand during the planning horizon δ in whole service area R is given by $\int_{\mathbb{R}} \gamma_i(x)\theta_i(x)dx$. Since $\gamma_i(x)\theta_i(x)$ is a slow varying function of $x \in R$, it can be argued that $\int_{\mathbb{R}} \gamma_i(x)\theta_i(x)dx = \delta\gamma_i(x)\theta_i(x)R$. Therefore, the total transportation cost can be rewritten as follows:

$$TOT(x) = \underbrace{p(x|\mathbf{x})\alpha_p g_r\sqrt{A_{r_i}}\,\delta\gamma_i(x)\theta_i(x)R}_{\text{truck transportation cost}} + \underbrace{q(x|\mathbf{x})\alpha_q g_r\sqrt{A_{r_i}}\,\delta\gamma_i(x)\theta_i(x)R}_{\text{drone transportation cost}} \tag{6}$$

where R can also be expressed as $R = A_{r_i}(x)N_{r_i}(x)$.

Approximation of α_p: Determining unit transportation cost (\$/mile/unit) for trucks has been studied in detail in literature. Interested readers are encouraged to read works done by Gonzales et al. (2013), Barnes and Langworthy (2003), and Marufuzzaman et al. (2015).

Approximation of α_q: Drone transportation cost needs to be estimated in such a way that resembles drone behavior in a real world scenario. In this study, drone transportation cost is estimated by considering different stages of a drone flight such as climbing, hovering, descending, turning, acceleration and deceleration, rotational, and constant speed. Moreover, total flight time of drone is also considered in this study. For each of these stages, the amount of battery charge depleted and its associated cost is estimated. For calculation of service time, we incorporate this component into the hovering time calculation. Considering all these factors into equations is nontrivial

[3] Eq. (1) is valid under the assumption that the customer demand is a slow varying function of x and thus the influence area of each distribution center can be approximated by a circular region as described by Daganzo (1996)

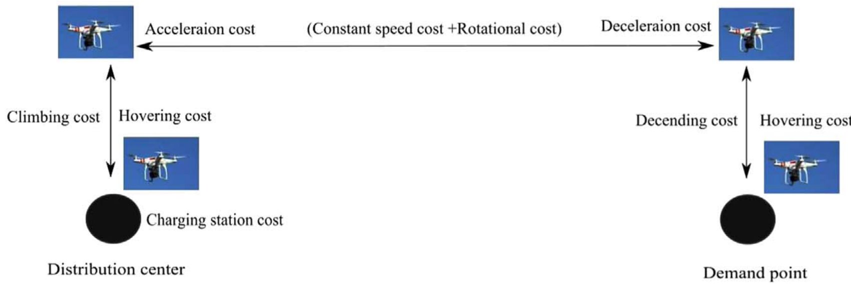


Fig. 2. Cost components of drone transportation.

and so a non-linear cost function has been developed to represent them in a realistic manner.

As stated, calculating the unit transportation cost, α_q ($/mile/unit) using drones is not straightforward. A number of factors (e.g., weight, carrying capacity, types of power supply, propellers, flight time) govern this cost; thus, it becomes very difficult to derive and predict an exact energy consumption model. In this study, we represent the energy consumption of a drone as a function of its speed and operating condition(see Franco and Buttazzo (2015)).

There are a number of significant factors that contribute to the unit cost calculation of drones such as climbing, hovering, descending, turning, acceleration and deceleration, rotational, and constant speed cost. A pictorial representation of all the costs associated with drones are illustrated in Fig. 2. To represent these costs, let us assume that each drone can be located in a three-dimensional space (i, j, k) where i and j are the component on the X-Y plane and k represents it's altitude. Let β be the minimum power needed to hover over the ground and χ be a motor speed multiplier. Note that both β and χ are constants that depend on the weight of the drone as well as on certain characteristics of it's motor/propeller. We further denote P_{cl} to be the power of the motor, v to be the speed of drone while climbing, and t_h to be the hovering time. If C_c is the cost per unit of energy consumed, then climbing cost (CC) of drone can be approximated as follows:

$$CC = P_{cl}\left(\frac{k}{v}\right)C_c \tag{7}$$

where $P_{cl}(\frac{k}{v})$ is the power consumption of the drone that is needed to climb at altitude k with speed v. Subsequently, the hovering cost (HC) of a drone is given by

$$HC = (\beta + \chi k)t_h C_c \tag{8}$$

Pugliese et al. (2016) presume that this estimate of the hovering cost is almost the same as in real case. Now, it is natural to assume that descending speed as well as motor power needed while descending will always be lower than the climbing speed and power consumption while climbing. Thus, define v' to be the descending speed where $v' < v$ and P_{ds} to be the power consumption of the drone while descending from altitude k with speed v' where $P_{ds} < P_{cl}$, the descending cost (DC) can now be approximated as follows:

$$DC = P_{ds}\left(\frac{k}{v'}\right)C_c \tag{9}$$

We now calculate the transportation cost of drone due to moving from the distribution center to the destination points. We assume that the trajectories consist of three phases, i.e., an acceleration phase where the drone gains speed from zero, an intermediate phase in which the drone has a constant speed, and a final deceleration phase when the drone reaches close to its destination point (shown in Fig. 2). Note that from the distribution center, which is the center of each A_{r_i}, the total distance covered after these three phases will be on average equal to $g_r\sqrt{A_{r_i}(x)}$. Let us divide the overall time to cover $g_r\sqrt{A_{r_i}(x)}$ into three time periods, i.e., t_1, t_2, and t_3. Acceleration occurs to reach speed v_c from zero during time interval $[0, t_1]$. This constant speed v_c is maintained by the drone during time interval $[t_1, t_2]$. Finally, the drone decelerates to zero again in time interval $[t_2, t_3]$ from constant speed v_c. These variable speed costs(VC) can be approximated as follows:

$$\begin{aligned} VC &= \left(\int_0^{t_1} P_{acc}dt + \int_{t_1}^{t_2} P_{vc}dt + \int_{t_2}^{t_3} P_{dec}dt\right)C_c \\ &= (P_{acc}T_1 + P_{vc}T_2 + P_{dec}T_3)C_c \end{aligned} \tag{10}$$

where P_{acc}, P_{vc}, and P_{dec} denote the power consumption during acceleration, maintaining constant speed, and deceleration, respectively and $T_1 = t_1 - 0$, $T_2 = t_2 - t_1$, and $T_3 = t_3 - t_2$. Now, the power required by the drones can be computed as follows:

$$P = \left(\frac{\text{Work done by the drone}}{T}\right) = \left(\frac{m^*a_{cc}^*d}{T}\right) \tag{11}$$

where m is the total payload a drone can carry including its own weight, a_{cc} is the acceleration in which drone covers a distance, d is the covered distance whose value can be taken as $g_r\sqrt{A_{r_i}(x)}$, and T is the total time it takes to cover $g_r\sqrt{A_{r_i}(x)}$ with full payload. Using Eq. (11), a_{cc} can be calculated as follows:

$$a_{cc} = \left(\frac{P^*T}{m^*d}\right) \tag{12}$$

As explained before, a drone spends time T_1 to reach from zero velocity to v_c, then flies for time T_2 with constant speed v_c, and at the end spends time T_3 during deceleration where it reduces down its speed from v_c to zero (shown in Fig. 3). From the law of motion we know that

$$v_c = u + a_{cc}^*T \tag{13}$$

where u is the initial velocity, a_{cc} is the acceleration, v_c is the final velocity, and T is the total time spent by the drone. In this case, the initial velocity can be taken as zero i.e., u=0. Thus, Eq. (13) becomes

$$v_c = a_{cc}^*T \tag{14}$$

Let us assume that a certain percentage of the drones covered region is attributed to accelerating, maintaining constant speed, and decelerating the drones. In other words, a drone covers w% of the total distance during acceleration phase, b% during constant speed, and the remaining y% during deceleration phase (shown in Fig. 3). Thus, using

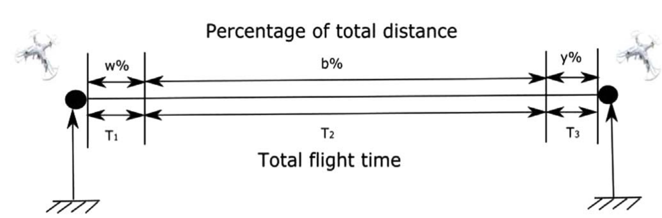


Fig. 3. Approximate distribution of flight times with distance in drone transportation.

Eqs. (11)–(14), we can calculate the time spent at different stages of the drone's flight as follows:

$$T_1 = \sqrt{\frac{v_c{*}m{*}w\%{*}g_r\sqrt{A_{r_i}(x)}}{P_{acc}}} \tag{15}$$

$$T_2 = \frac{b\%{*}g_r\sqrt{A_{r_i}(x)}{*}2}{v_c} \tag{16}$$

$$T_3 = \sqrt{\frac{v_c{*}m{*}y\%{*}g_r\sqrt{A_{r_i}(x)}}{P_{dec}}} \tag{17}$$

Finally, while traveling from one point to another, motor power is also required for providing the rotational movement of the drones. Let w_{turn} be the angular rotational speed, p_{turn} be the power needed per turn, and n_t be the number of turns a drone takes in a given time period. With this, the rotational cost (*RC*) incurred to cover an angle $\Delta\theta$ can be computed as follows:

$$RC = p_{turn}\left(\frac{n_t\Delta\theta}{w_{turn}}\right)C_c \tag{18}$$

We are now ready to approximate the unit cost incurred by drone α_q (\$/mile/unit) for the entire traveling distance as follows:

$$\begin{aligned}\alpha_q &= CC + HC + DC + VC + RC\\ &= \underbrace{P_{cl}\left(\frac{k}{v}\right)C_c}_{\text{climbing cost}} + \underbrace{(\beta+\chi k)t_h C_c}_{\text{hovering cost}} + \underbrace{P_{ds}\left(\frac{k}{v'}\right)C_c}_{\text{descending cost}}\\ &+ \underbrace{\left(\int_0^{t_1}P_{acc}dt + \int_{t_1}^{t_2}P_{vc}dt + \int_{t_2}^{t_3}P_{dec}dt\right)C_c}_{\text{variable speed cost}} + \underbrace{p_{turn}\left(\frac{n_t\Delta\theta}{w_{turn}}\right)C_c}_{\text{rotational cost}}\end{aligned} \tag{19}$$

Replacing α_q in Eq. (6), we obtain the following total transportation cost *TOT*(*x*) to serve disaster affected zones using trucks and drones:

$$\begin{aligned}TOT(x) = p(x|\mathbf{x})\alpha_p g_r\sqrt{A_{r_i}}\delta\gamma_i(x)\theta_i(x)R + C_c\Bigg\{P_{cl}\left(\frac{k}{v}\right) + (\beta+\chi k)t_h + P_{ds}\left(\frac{k}{v'}\right)\\ + \left(\int_0^{t_1}P_{acc}dt + \int_{t_1}^{t_2}P_{vc}dt + \int_{t_2}^{t_3}P_{dec}dt\right)\\ + p_{turn}\left(\frac{n_t\Delta\theta}{w_{turn}}\right)\Bigg\}q(x|\mathbf{x})g_r\sqrt{A_{r_i}}\delta\gamma_i(x)\theta_i(x)R\end{aligned} \tag{20}$$

For notation convenience, from now on we will use p and q to represent $p(x|\mathbf{x})$ and $q(x|\mathbf{x})$, respectively.

- *Average inventory cost for distribution center*, *TOI*(*x*): Each distribution center orders emergency supplies in batches of $Q_{r_i}(x)$ and with each batch ordered incurs a reorder cost $R_r(x)$. Therefore, the total reorder cost, *TR*(*x*), for all the distribution centers can be expressed as follows:

$$TR(x) = N_{r_i}(x)R_r(x)\left(\frac{\delta\mathbb{E}[D_{r_i}(x)]}{Q_{r_i}(x)}\right) \tag{21}$$

Now, the average inventory at each distribution center is given as the sum of cycle inventory, $\frac{Q_{r}(x)}{2}$ and safety stock (Graves and Willems, 2003; Schmidt et al., 2012), $z_{\alpha_r}\sqrt{Var[D_{r_i,LT}]}$, where $Var[D_{r_i,LT}] = \mu_r Var[D_{r_i}] + \sigma_r^2\mathbb{E}[D_{r_i}]^2$ and $Var[D_{r_i}] = \gamma_i(x)\theta_i(x)A_{r_i}(x)$. Here, μ_r and σ_r^2 are the mean and variance of the lead time, *LT*, respectively and α_r is defined as the service level at each distribution center.

To calculate the average inventory cost, we further need inventory holding cost at the distribution centers. Let h_r be the inventory holding cost of a distribution center for each item over the planning horizon, δ. Therefore, the total average inventory holding cost, *TOI*(*x*), can be expressed as follows:

$$TOI(x) = \underbrace{h_r N_{r_i}(x)\left(\frac{Q_{r_i(x)}}{2} + z_{\alpha_r}\sqrt{Var[D_{r_i,LT}]}\right)}_{\text{inventory holding cost}} + \underbrace{N_{r_i}(x)R_r(x)\left(\frac{\delta\mathbb{E}[D_{r_i}(x)]}{Q_{r_i}(x)}\right)}_{\text{reorder cost}} \tag{22}$$

With this, we are now ready to calculate the total location-routing cost to serve a disaster affected zone using trucks and drones. Note that all the cost terms derived in this section are in terms of each point x in the service region R. The problem of minimizing the total cost for the entire region R can be expressed as follows:

$$Minimize \quad \int_R (TF(x) + TOT(x) + TOI(x)) \tag{23}$$

subject to

$$N_{r_i}(x)A_{r_i}(x) = R \tag{24}$$

$$g_r\sqrt{A_{r_i}} \le R_d \tag{25}$$

$$Q_{r_i}(x) \in \mathbf{Z}^+ \tag{26}$$

$$A_{r_i}(x) \in \mathbf{R}^+ \tag{27}$$

where $Q_{r_i(x)}$ and $A_{r_i}(x)$ are the decision variables. Constraints (24) are the area coverage constraints which ensure that the entire service region is covered by the sum of the distribution centers influence area. Constraints (25) indicate that the average distance between the distribution center and customer demand points should never be more than the range of drone R_d. Constraints (26) and (27) guarantee integer and continuous values for $Q_{r_i(x)}$ and $A_{r_i}(x)$, respectively.

4. Solution methodology

To minimize the total network cost, we have used a two-phase continuous approximation technique developed by Tsao et al. (2012), which in it's essence is a basic extension of the work conducted by Daganzo (1996). The three coastal counties of Mississippi i.e., Harrison, Hancock, and Jackson counties are used to visualize and validate the modeling results. This is shown in Fig. 4. However, from Fig. 4 it is clear that the customer demand density does not follow a homogeneous Poisson process. As a result, the two-phase continuous approximation method cannot be applied directly to this case since the input function violates the slow varying property which is essential for the analysis using the continuous approximation technique. However, a more detailed analysis of the region considered in the study reveals that there are smaller areas where these functions can be considered as slow varying i.e., the functions are smooth. Thus, to apply the two-phase approximation method in this study, we first divide the entire region into smaller sub-regions over which the functions maintain the slow varying property (phase-I). In phase-II of the solution methodology, the problem is modeled over the sub-regions using the cost functions described in Section 3 and later solved using a continuous approximation approach.

4.1. Phase-I approximation: a grid cover-couple approach:

In phase-I, a *grid cover-couple* approach is used to divide the entire studied coastal region into sub-regions with slow varying functions. To do this, a mesh of equal sized squares needs to be designed to cover the entire region R. However, while designing this mesh, within each grid, demand must be slow varying. A trial and error method is utilized to determine the feasible shape of the grid. Based on this method, we determine the grid size by taking the variability of demand in the grids into account. Based on our experimentation, we set a 5×5 square mile grid since we observed that within this grid size the demand is found to be slow varying. This idea is illustrated in Fig. 4. In doing so, each grid can be attributed a density level that can be easily measured.

Now, the grids with similar densities can be clustered together to form areas over which the customer demand point function is slow varying. To partition the region into clusters ($C_1, C_2, \ldots, C_N$), a *tolerance limit* ϵ is specified that measures the similarity among grids. The tolerance limit defines the amount of variability in the demand density for each grid that is acceptable while treating them as similar. In other words, grids with density at most ϵ apart are considered similar. However, choice of the value of ϵ depends on the customer demand point density pattern of the existing network. Fig. 5 illustrates this process, where in Fig. 5a we divide the three coastal counties of MS into seven clusters based on the ϵ value. After applying this process, it becomes apparent that approximately 70–80% of the population in the three studied counties are concentrated within four of these clusters. Thus, we repeat the same clustering procedure inside these four clusters, however we use a smaller ϵ value to obtain a larger number of clusters. Throughout this process, a total of twelve clusters are made available from these four initial clusters. We proceed by using these twelve clusters and discard the rest. Note, almost all the clusters are located close to the coastal region which is highly prone to natural disasters, and a majority of the people in these counties live within these clusters. Fig. 5b illustrates this process of coupling.

4.2. Phase-II approximation: distribution center influence area using continuous approximation (CA) approach:

Phase-I approximation divides the total service region, R, into a number of clusters (e.g., $C_1, C_2, \ldots, C_N$ where $N \in \mathbf{Z}^+$) with slow varying demand. Within the boundary of each cluster, the *Continuous Approximation* (CA) technique can be used to formulate the integrated facility location and inventory allocation model for the disaster affected scenarios. The optimization model developed in Section 3 is used for modeling the total logistic costs in each cluster. After solving the optimization model by CA, the solution will give the optimal service region $A_{r_i}(x)$ and order quantity $Q_{r_i}(x)$ for each distribution center. Note that for each cluster $\{C_i\}_{\forall i \in N}$, the size of the influential area $A_{r_i}(x)$ is the same, but varies for a different cluster. Moreover, the optimal value of reorder quantity $Q_{r_i}(x)$ can also be approximated for each distribution center. Using the influence area of each distribution center, we can easily calculate the total number of distribution centers $N_{r_i}(x)$ needed in each cluster $\{C_i\}_{\forall i \in N}$. The total number of distribution centers needed for the total affected region can be obtained by summing up all the distribution centers in each and every cluster.

4.3. Continuous approximation model

Each cluster in the service region, R, has a slow varying property. Therefore, we can ignore the dependence of all continuous functions on parameter x. Let A_{r_i} be the size of the influence area and Q_{r_i} be the optimal reorder quantity for each distribution center in cluster $\{C_i\}_{\forall i \in N}$. Let $\mathbf{TNC}(A_{r_i}, Q_{r_i})$ be the total network cost and is given by the sum of the facility, transportation, and inventory cost functions. The integrated logistics model now becomes:

Minimize:

$$\begin{aligned}\mathbf{TNC}(A_{r_i}, Q_{r_i}) = &\sum_{i=1}^{N} f_r\left(\frac{C_i}{A_{r_i}}\right) + \sum_{i=1}^{N} \left(p\alpha_p g_r\sqrt{A_{r_i}}\delta\gamma_i\theta_i C_i\right) + \sum_{i=1}^{N} qC_c\left\{P_{cl}\left(\frac{k}{v}\right) + (\beta + \chi k)t_h + P_{ds}\left(\frac{k}{v'}\right)\right.\\ &\left. + \left(\int_0^{t_1} P_{acc}dt + \int_{t_1}^{t_2} P_{vc}dt + \int_{t_2}^{t_3} P_{dec}dt)\right) + p_{turn}\left(\frac{n_t\Delta\theta}{w_{turn}}\right)\right\} g_r\sqrt{A_{r_i}}\delta\gamma_i\theta_i C_i\\ &+ \sum_{i=1}^{N} h_r\left(\frac{Q_{r_i}}{2} + z_{\alpha_r}\sqrt{\gamma_i\theta_i\mu_r A_{r_i} + \sigma_r^2(\gamma_i\theta_i A_{r_i})^2}\right)\left(\frac{C_i}{A_{r_i}}\right) + \sum_{i=1}^{N} R_r\left(\frac{\delta\gamma_i\theta_i C_i}{Q_{r_i}}\right)\end{aligned} \tag{28}$$

subject to

$$g_r\sqrt{A_{r_i}} \leq R_d \tag{29}$$

$$Q_{r_i} \in \mathbf{Z}^+ \tag{30}$$

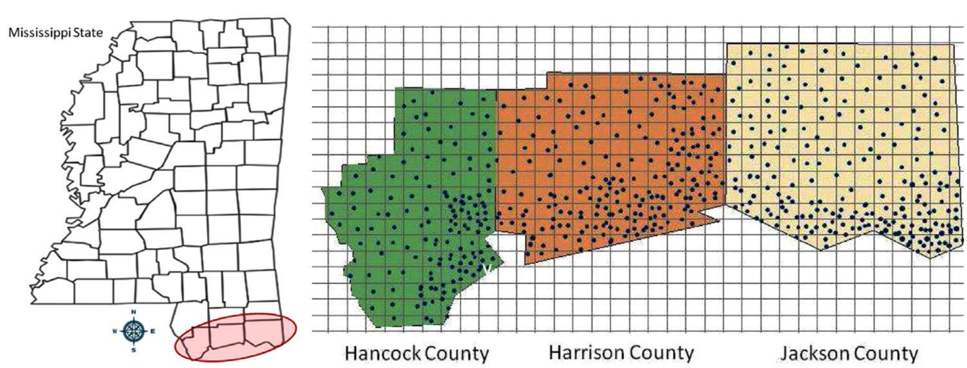
$$A_{r_i} \in \mathbf{R}^+ \tag{31}$$

where C_i is the area of cluster i in service region $\mathbb{R}$ and $N_{r_i} = \left(\frac{C_i}{A_{r_i}}\right)$, which denotes the number of distribution centers in cluster i. The decision variables are A_{r_i} and Q_{r_i} for $i = 1, 2, \ldots, N$.

4.4. Solution approach

As described previously, $\mathbf{TNC}(A_{r_i}, Q_{r_i})$ contains two decision variables for each cluster: the optimal influence area of each distribution center, A_{r_i} and the ordering quantity for each distribution center, Q_{r_i}. The optimal values of A_{r_i} and Q_{r_i} minimize the total network cost $\mathbf{TNC}(A_{r_i}, Q_{r_i})$ of the system. The objective function of the optimization model, defined by (28)–(31), is a non-linear function containing $2N$ variables (A_{r_i} and Q_{r_i} for $i = 1, 2, \ldots, N$). As a result, this model is very challenging to solve. Furthermore, the direct evaluation of the convexity property of the objective function is not straightforward and hence requires a sound methodological approach. To solve this problem, we use the following solution approach that provides optimal values of the decision variables of the problem. The detailed procedure to determine the optimal solution of $\mathbf{TNC}(A_{r_i}, Q_{r_i})$ is outlined below.

Let us assume that A_{r_i} is known. Given A_{r_i}, the first and second order derivative of $\mathbf{TNC}(A_{r_i}, Q_{r_i})$ with respect to Q_{r_i} are $\frac{d\mathbf{TNC}(Q_{r_i} \mid A_{r_i})}{dQ_{r_i}}$ and $\frac{d^2\mathbf{TNC}(Q_{r_i} \mid A_{r_i})}{dQ_{r_i}^2}$. We know that if the second derivative of a function is greater than zero, the function is convex. Simple algebraic calculation indicates that



(a) County Locations in MS (b) Grid Cover of Counties

Fig. 4. Customer density in grid for Hancock, Harrison, and Jackson counties in MS.

$$\frac{d^2\mathbf{TNC}(Q_{r_i}|A_{r_i})}{dQ_{r_i}^2} = \frac{2R_r\delta\gamma_i\theta_i C_i}{Q_{r_i}^3} > 0, \quad i = 1, 2, \ldots, N \tag{32}$$

This means $\mathbf{TNC}(Q_{r_i}|A_{r_i})$ is a convex function of Q_{r_i}. The optimal Q_{r_i} of the model $\mathbf{TNC}(Q_{r_i}|A_{r_i})$ can be obtained by equating the first order derivative to zero and solving for Q_{r_i}. This means that $\frac{d\mathbf{TNC}(Q_{r_i}\,|\,A_{r_i})}{dQ_{r_i}} = 0$:

$$Q_{r_i}(A_{r_i}) = \sqrt{\frac{2A_{r_i}R_r\delta\gamma_i\theta_i}{h_r}} \tag{33}$$

Substituting the value of Q_{r_i} into Eq. (30) yields

$$\begin{aligned}\mathbf{TNC}(A_{r_i}, Q_{r_i}) = {} & \sum_{i=1}^{N} f_r\left(\frac{C_i}{A_{r_i}}\right) + \sum_{i=1}^{N}\left(p\alpha_p g_r\sqrt{A_{r_i}}\,\delta\gamma_i\theta_i C_i\right)\\ & + \sum_{i=1}^{N} qC_c\left\{P_{cl}\left(\frac{k}{v}\right) + (\beta + \chi k)t_h\right.\\ & + P_{ds}\left(\frac{k}{v'}\right) + \left(\int_0^{t_1} P_{acc}dt + \int_{t_1}^{t_2} P_{vc}dt + \int_{t_2}^{t_3} P_{dec}dt\right)\\ & \left. + p_{turn}\left(\frac{n_t\Delta\theta}{w_{turn}}\right)\right\}g_r\sqrt{A_{r_i}}\,\delta\gamma_i\theta_i C_i\\ & + \sum_{i=1}^{N} h_r\left(\frac{\sqrt{\frac{2A_{r_i}R_r\delta\gamma_i\theta_i}{h_r}}}{2} + z_{\alpha_r}\sqrt{\gamma_i\theta_i\mu_r A_{r_i} + \sigma_r^2(\gamma_i\theta_i A_{r_i})^2}\right)\left(\frac{C_i}{A_{r_i}}\right)\\ & + \sum_{i=1}^{N} R_r\left(\frac{\delta\gamma_i\theta_i C_i}{\sqrt{\frac{2A_{r_i}R_r\delta\gamma_i\theta_i}{h_r}}}\right)\end{aligned} \tag{34}$$

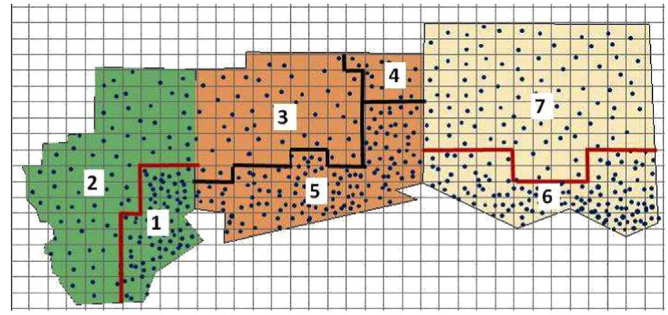
Based on the above discussion, the following algorithm (Algorithm 1) determines the optimal value of Q_{r_i} and A_{r_i}.

Algorithm 1.

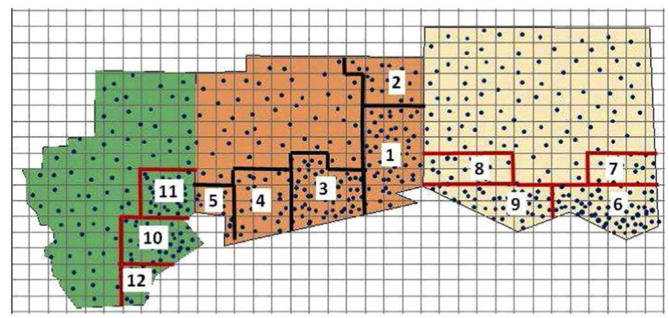
Step 1. Verify $\frac{d^2\mathbf{TNC}(A_{r_i})}{A_{r_i}^2} > 0$ to ensure the convexity of the function.
Step 2. Solve for $\frac{d\mathbf{TNC}(A_{r_i})}{A_{r_i}} = 0$ and determine the local minimum points.
Step 3. Based on the local minimum points calculate $\mathbf{TNC}(A_{r_i})$ and pick the one with the smallest value.
Step 4. Determine the value of Q_{r_i}, $Q_{r_i}(A_{r_i}) := \sqrt{\frac{2A_{r_i}R_r\delta\gamma_i\theta_i}{h_r}}$ by Eq. (33).
Step 5. Adjust Q_{r_i} for $i = 1 \sim N$ to get the nearest integer values.
Step 6. Calculate $\mathbf{TNC}(A_{r_i}, Q_{r_i})$ with optimal values of Q_{r_i} and A_{r_i}.

5. Data description

In this section, we provide a detailed description of the data collection procedure undertaken by this study. Historically, the coastal regions of Mississippi are impacted by various types of natural disasters such as hurricanes, tornadoes, and flooding. Among them, hurricanes affect the coastal regions of Mississippi far worse than any other type of disaster. Therefore, in this study we develop the logistics network keeping this disaster type in mind. Three coastal counties of Mississippi have been considered as potential test beds, i.e., Hancock, Harrison, and Jackson counties. Note that whenever a hurricane hits a region, the coastal areas are the one which is usually impacted the most. For instance, when Hurricane Katrina hit in the morning of August 29, 2005 and began its rampage for two days in Mississippi, the most impacted regions were the three coastal counties, although several other counties also experienced significant damage. Keeping that in mind, we collected data from Hancock, Harrison, and Jackson counties for use in this study. Fig. 6 illustrates the effect of Hurricane Katrina in these three counties compared to hurricane Camille that hit Mississippi in 1969. It is observed that Hurricane Katrina had a more devastating effect, because Katrina's surge was higher and covered a wider range as compared to Camille's. The major point here is that in both cases the highly impacted counties in Mississippi were Hancock, Harrison, and Jackson county.



(a) Original clusters



(b) Revised number of clusters

Fig. 5. Original and revised number of clusters for our studied region.

Based on the above discussion, we are now ready to fix a set of parameters that can be used as base parameters while determining the optimal values for A_{r_i}, Q_{r_i}, and **TNC**. We begin by setting the base case values for p and q equal to 0.7 and 0.3, respectively. This implies that in the aftermath of a disaster there is a 70% chance that trucks can be used for relief efforts given the road conditions, while the remaining percentage indicates that trucks are not capable of distributing goods to certain regions and thus drones must be used to serve these regions. We assume that only fuel cost is incurred during transportation via trucks, and this cost increases linearly as more distance is covered. We set α_p=\$0.40/mile/unit while transporting the emergency commodities via truck (http://www.fedex.com/ratefinder/home). We further set the fixed cost for opening a refueling station for both trucks and drones f_r=\$140,000 (Rocky Mountain Institute, 2014), Hall (2016) and inventory holding cost h_r=\$1.0/unit for our base case experimentations.

In this study we considered an EHANG-184 drone (http://www.ehang.com/ehang184/) to transport emergency commodities (e.g., medicines, first-aid, dry food) from multiple distribution centers to the demand points. This drone has a wingspan of 3401 mm. This is one of the largest and heaviest drones available in the market weighing

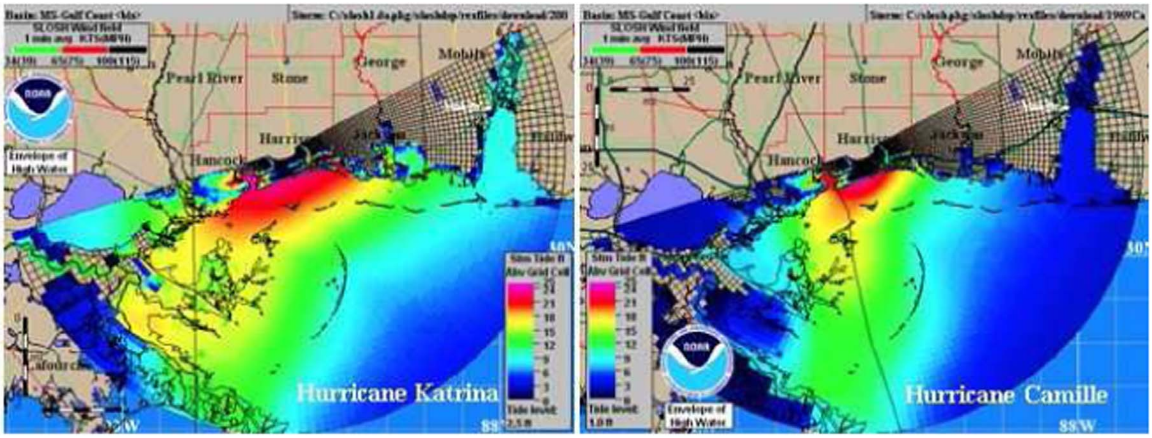


Fig. 6. The affected region caused by Hurricane Katrina and Camille (Masters, 2016).

approximately 200,000 g. In addition to the weight of its built-in components, EHANG-184 can carry up to 99,700 g for a period of 23 min.[4] Note that EHANG-184 can carry more weight, but because of this flight time will reduce significantly. It has a maximum flying altitude (k) of 2.17 miles (Specout, 2016) and contains up to eight motors that put out 142 hp or 106 kW to eight propellers. Charging of its battery pack takes up to four hours in trickle mode and two hours in fast charge mode (Coxworthe, 2016). EHANG-184 can cover up to 10. 52 miles round trip in each flight with a fully charged battery. This means that the drone can cover up to 5.26 miles of distance one way before returns back to the distribution center (Dronethusiast, 2015). To calculate the drone transportation cost, we set the climbing (v), descending (v'), and constant speed (v_c) equal to v=55 m/s, v'=20 m/s, and v_c=25 m/s, respectively. The power required for climbing (P_{cl}), acceleration (P_{acc}), constant speed (P_{cc}), deceleration (P_{dec}), and descending (P_{ds}) by a drone is set to be equal to P_{cl}=12,000 W, P_{acc}=90,000 W, P_{cc}=85,000 W, P_{dec}=70,000 W, and P_{ds}=5000 W, and respectively. The power needed to hover close to the ground is β=90,000 W while the motor speed multiplier χ is set to 1.0. To calculate the rotating cost, we set the angular rotation speed as w_{turn}=2.1 rad/s, the power needed to turn as p_{turn}=1000 W and the covered angle during turning as $\Delta\theta$=1.0 rad. Finally, while covering a distance, it is assumed that drones cover 5% of the distance during the acceleration phase (w), 90% of it during constant speed phase (x), and the rest of it during deceleration phase (y). Table 3 summarizes the key input parameters used in this study.

6. Numerical experiments

This section presents the key lessons learned from solving our proposed model **TNC**(A_{r_i}, Q_{r_i}). We use the three disaster prone counties in Mississippi i.e., Hancock, Harrison, and Jackson counties as a test bed to visualize and validate our modeling results and provide managerial insights under different realistic settings.

6.1. Base case results

We first conduct numerical experiments of the base case scenario to determine the optimal values of service area A_{r_i}, ordering quantity Q_{r_i}, and total network cost **TNC**. Table 4 presents the computed results after applying the two-phase continuous approximation method proposed in Section 4. Results show that for the base case scenario, we obtain total facility cost TF=\$6,716,592, total delivery cost TOT=\$10,003,838, total inventory cost TOI=\$422,741, and total network cost **TNC**=\$17,143,168 to serve the disaster affected region. Table 4 further provides the optimal values of A_{r_i} and Q_{r_i} for the clusters $\{C_i\}_{i\in N}$ depicted in Fig. 5. Based on our observation, clusters with higher demand densities generate lower A_{r_i}. Thus, we experimentally validate the finding that the influence area of a distribution center A_{r_i} is highly correlated with the demand density of that region. Fig. 7 provides the graphical illustration of **TNC** versus decision variables A_{r_i} and Q_{r_i} for the twelve clusters depicted in Fig. 5. It is clear from the figure that the two-phase continuous approximation method is capable of determining the optimal system cost **TNC** under different values of A_{r_i} and Q_{r_i} (Table 4).

6.2. Impact of drone flying altitude k on disaster relief operation:

We now analyze the impact of drone flying altitude k on disaster relief operation. In the United States, Federal Aviation Administration (FAA) requires UAVs to be operated under a ceiling of 400 ft which will severely limit the effective range of utilizing drones for disaster relief operation (Federal Aviation, 2016). However, increasing the flying altitude k for drones will add additional cost in the relief operation. Therefore, we now conduct sensitivity analysis by varying the drone altitude k between 200 and 800 ft and observe its impact on disaster relief operation. Table 5 reports how A_{r_i}, Q_{r_i}, and **TNC** are impacted by different values of k. Clearly, increasing the k value decreases the average service area A_{r_i} provided by drones during the disaster relief operation and we observe the same trend in all the clusters $\{C_i\}_{i\in N}$

Table 3
Key input parameters used in this study (Coxworthe, 2016; Specout, 2016).

Input Parameter	Symbol	Value
Unit truck transportation cost	α_p	\$0.40/mile/unit
Motor speed multiplier	χ	1.0
Climbing power	P_{cl}	12,000 W
Descending power	P_{ds}	5000 W
Acceleration power	P_{acc}	90,000 W
Constant speed power	P_{cc}	85,000 W
Deceleration power	P_{dec}	70,000 W
Turning power	p_{turn}	1000 W
Hover power	β	90,000 W
Maximum altitude	k	2.17 miles
Constant speed	v_c	55 miles/h
Climbing speed	v	55 miles/h
Descending speed	v'	45 miles/h
Angular rotation speed	w_{turn}	2.1 rad/s
Hovering time	t_h	20 s

[4] This is the only drone available in the market that can carry approximately 100kg in one trip while the closest one is XactSense Titan (http://drones.specout.com/l/144/XactSense-Titan) which can carry only 26kg. This is one of the reasons to consider EHANG type drones in this study.

Table 4
Optimal decision variables and cost components for different clusters.

Cluster C_i	A_{r_i} (mile[2])	Q_{r_i} (units)	**TNC** ($)	TF ($)	TOT ($)	TOI ($)	NDI
1	7.38	1135	3,366,995	1,400,000	1,885,444	81,551	10
2	6.45	1194	638,928	280,000	342,774	16,154	2
3	7.04	1155	4,822,130	1,960,000	2,740,011	122,119	14
4	6.13	1216	960,646	420,000	515,568	25,078	3
5	14.33	878	590,461	280,000	301,983	8478	2
6	10.06	1008	1,659,982	700,000	927,141	32,841	5
7	10.78	982	1,305,184	560,000	720,770	24,414	4
8	6.76	1173	1,268,408	560,000	677,446	30,962	4
9	5.92	1232	1,683,744	700,000	937,154	46,590	5
10	11.01	974	879,013	420,000	444,177	14,836	3
11	7.83	1109	883,269	420,000	444,758	18,511	3
12	27.35	675	207,819	140,000	66,612	1207	1
Total			18,266,579	7,840,000	10,003,838	422,741	56

depicted in Fig. 5. Since the average service area A_{r_i} drops due to the increase in k values, the average relief ordering quantity Q_{r_i} also drops to serve those reduced areas. This in turn increases the overall system cost **TNC** for the disaster relief operation Table 7. It is observed that on average the total system cost **TNC** increases by 4.9% if the drone altitude k increases from 200 to 800 ft.[5] Fig. 8 provides a detailed view as how different cost components (e.g., total ordering cost (TOI), total transportation cost (TOT)) vary with the corresponding k values. We see that in Fig. 8(a), as k increases, both TOI and TOT increases. We further show the distribution of TOT cost between drones and trucks in Fig. 8(b). It is observed that as the value of k increases, both the contribution of costs in TOT for drones and trucks also increases. On average, the total transportation cost via drone increases by 20.1% as the value of k increases from 200 to 800 ft. Overall, the A_{r_i} and Q_{r_i} decreases but **TNC** increases as k increases.

6.3. Impact of drone speed v_c on disaster relief operation:

We now study the impact of drone velocity v_c on disaster relief operation. Table 6 reports how A_{r_i}, Q_{r_i}, and **TNC** are impacted by different values of v_c. Clearly, if the drone speed v_c increases, the average service area A_{r_i} and average relief ordering quantity Q_{r_i} both increase. These results are obvious since drones can now cover more area due to their improved speed capabilities. On average, the drone service area increases by 32.2% if the drone speed v_c increases from 35 miles/h to 75 miles/h. This further increases the average relief ordering quantity Q_{r_i} by 13.6% since the distribution centers now require additional supplies to support the increased areas of A_{r_i}. Since A_{r_i} increases, the system now requires fewer number of distribution centers N_{r_i} to satisfy the customer demands. Thus, the overall system cost **TNC** for the disaster relief operation drops as the value of v_c increases. Fig. 9 further depicts this relationship along with the cost components TOI and TOT. Note that we observe a significant drop in total transportation cost TOT (especially drone transportation cost) as the value of v_c increases from 35 miles/h to 75 miles/h. In summary, we conclude that the disaster relief operation can be conducted in a much cheaper way if the technology of drone speed v_c improves in coming years.

6.4. Impact of road access probability p on disaster relief operation:

In this experiment, we analyze the impact of road access probability p on disaster relief operation. Results reported in Table 7 shows that if the road access drops after a disaster (i.e., the value of p decreases), then the value of A_{r_i} and Q_{r_i} decreases but the total network cost **TNC** increases. The results are obvious due to the fact that drones are still hindered by limited technological capabilities and thus can not carry much weight or fly longer. In other words, the area A_{r_i} covered by drones are much smaller than trucks. An example of this can be shown for *cluster 1* (i.e., C_1 in Table 7) where it is observed that the service area A_{r_1} for drones and trucks are 5.99 and 9.32 miles, respectively. Thus, if the road condition deteriorates after a natural catastrophe, meaning that trucks can no longer serve the demand points, then customer demands will primarily be served by drones at a higher cost. Fig. 10 further illustrates this phenomenon and showed how sensitive different cost components (e.g., TOT, TOI) are against different p values. It is observed that when p=0.0, meaning that all the customer demands will be served by drones, incurs a transportation cost of $14.9 million. On the other hand, when we assume that all the road conditions are still accessible even after a massive disaster strikes in Hancock, Harrison, and Jackson counties of Mississippi (i.e., p=1.0), then the overall transportation cost to serve those counties becomes $13.4 million. Therefore, compared to trucks, drone transportation adds an additional $1.5 million to serve the customer demands based on a condition when the road access completely ruins after a massive disaster.

6.5. Impact of emergency commodities holding cost h_r and reordering cost R_r on disaster relief operation

In this experiment, we analyze the impact of emergency commodities holding cost h_r and reordering cost R_r on disaster relief operation. Holding emergency commodities during disaster costs more than the regular operations. Thus, we first conduct sensitivity analysis on holding cost h_r and analyze its impact on disaster relief operation. Table 8 reports how A_{r_i}, Q_{r_i}, and **TNC** are impacted by different values of h_r. Clearly, h_r significantly impacts the ordering quantities Q_{r_i} for all the clusters $\{C_i\}_{i\in N}$ depicted in Fig. 5. It is observed that if h_r increases from $1.0/unit to $20.0/unit, then on average Q_{r_i} drops by approximately 346.0% and thus adds an additional 45.1% system cost for the disaster relief operation. In the next experiment, we investigate whether increasing reorder cost R_r has any impact on decision variables and total network cost. We have conducted experiments with five experimental instances where R_r is varied from $3/order to $40/order. Table 9 reports how A_{r_i}, Q_{r_i}, and **TNC** are impacted by different values of R_r. The results show that when R_r increases, the distribution centers increase their ordering quantities Q_{r_i} to reduce ordering frequencies. Note that in both instances (i.e., cases with h_r and R_r),

[5] Note that in our calculation we have used the equivalent number in *miles* since the rest of our units are in *miles*

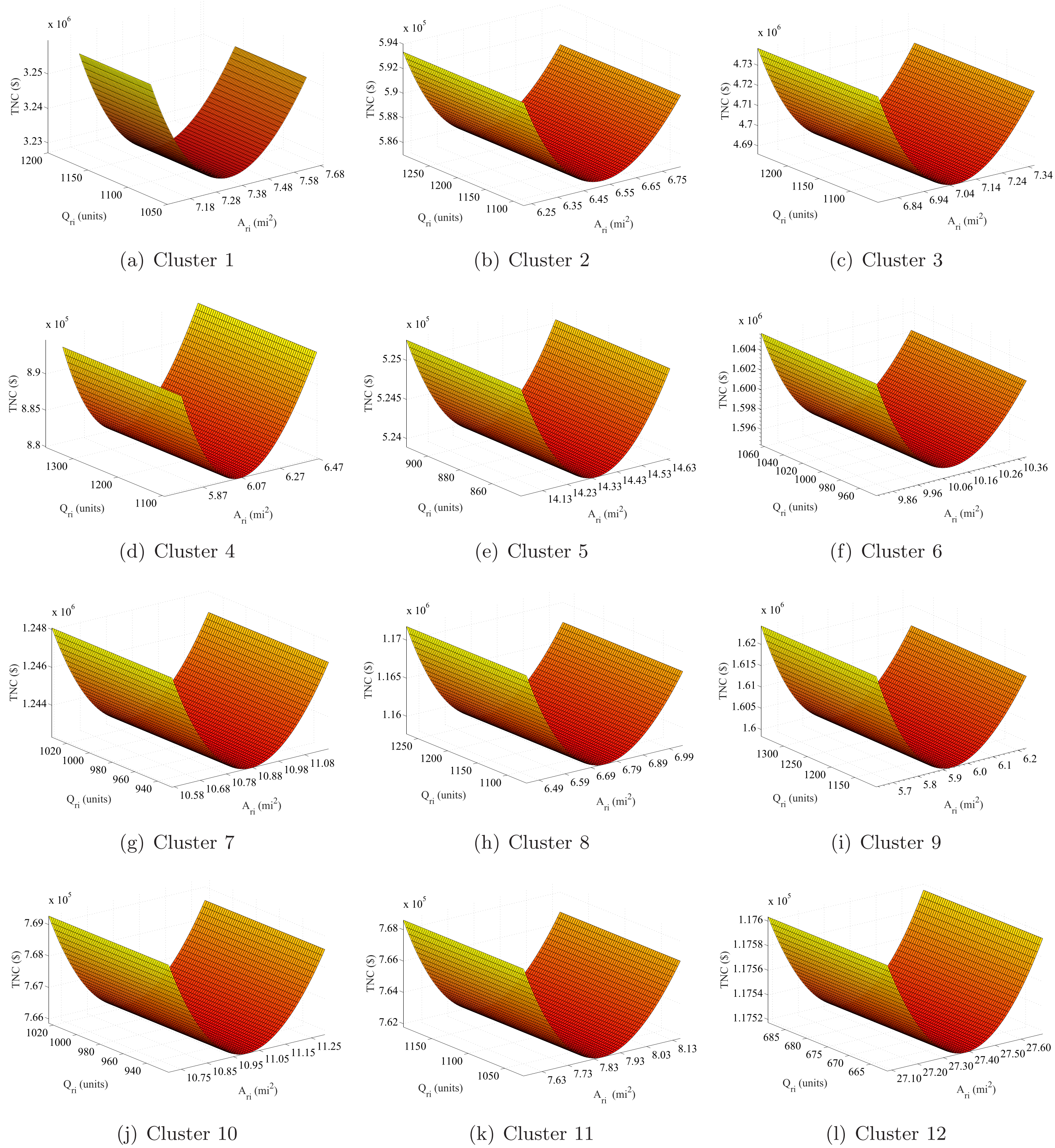


Fig. 7. Graphical illustrations of **TNC** vs. A_{r_i} and Q_{r_i}.

influence area A_{r_i} increases slightly to cover more region so as to ensure that a fewer number of distribution centers are needed to minimize the holding and reordering costs for the centers.

7. Conclusion

This paper provides a first comprehensive design framework on how to economically deploy drones to serve a disaster affected region. The study determines the optimal locations for the distribution centers with their corresponding emergency supply inventories and service regions under stochastic demand and drone routing constraints so that the overall system cost (including distribution center opening, inventory, and transportation cost) can be minimized. We approximate drone transportation cost by considering a number of routing specific factors such as climbing, hovering, descending, turning, acceleration and deceleration, rotational, and constant speed cost. The model will

Table 5
Impact of A_{r_i}, Q_{r_i}, *NDI*, and **TNC** under different values of *k*.

		k (ft)					*k* (f)			
		200	400	600	800		200	400	600	800
	Cluster									
	1	7.99	7.92	7.84	7.38		9	9	9	10
	2	6.79	6.66	6.52	6.46		2	2	2	2
	3	7.39	7.24	7.09	7.04		13	13	14	14
	4	6.52	6.43	6.24	6.13		2	2	3	3
	5	14.79	14.62	14.51	14.33	NDI	2	2	2	2
A_{r_i}	6	10.48	10.26	10.12	10.06		4	4	4	5
	7	11.46	11.21	10.94	10.78		3	3	4	4
	8	7.28	7.1	6.94	6.76		3	3	4	4
	9	6.43	6.21	6.04	5.92		5	5	5	5
	10	11.58	11.39	11.24	11.01		2	2	3	3
	11	8.23	8.08	7.96	7.83		2	3	3	3
	12	27.84	27.58	27.42	27.35		1	1	1	1
	1	1186	1174	1161	1135		3.123	3.195	3.21	3.277
	2	1259	11,236	1208	1194		0.531	0.568	0.575	0.585
	3	1243	1221	1202	1155		4.103	4.319	4.592	4.686
	4	1274	1261	1241	1216		0.802	0.823	0.865	0.879
	5	940	921	899	878		0.501	0.513	0.514	0.523
Q_{r_i}	6	1053	1039	1021	1008	TNC	1.522	1.535	1.586	1.595
	7	1033	1011	997	982		1.215	1.222	1.23	1.242
	8	1204	1191	1186	1173		0.981	0.985	1.001	1.157
	9	1280	1259	1248	1232		1.486	1.502	1.512	1.598
	10	1018	1004	999	974		0.701	0.733	0.748	0.766
	11	1129	1121	1118	1109		0.683	0.705	0.712	0.761
	12	696	689	684	675		0.101	0.102	0.104	0.117

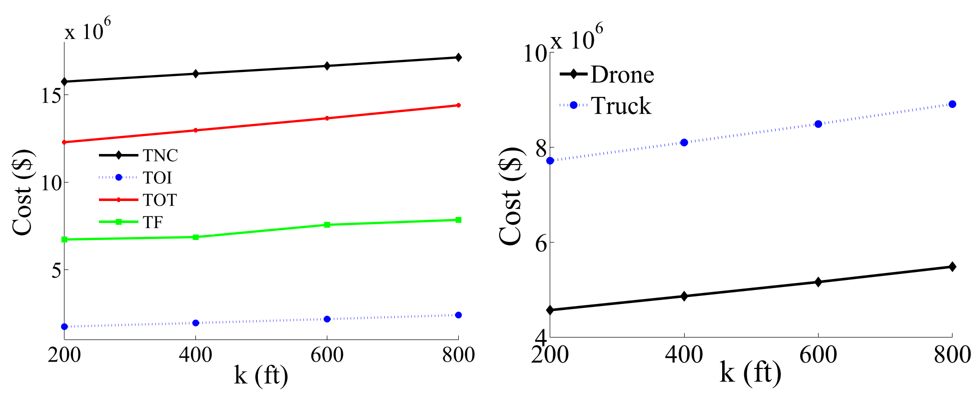
provide a tool for the decision makers to use for fast deployment of emergency supplies following a natural catastrophe. This problem is $\mathcal{NP}$-hard and deals with densely distributed customer demand points and non-linear drone transportation and emergency supply inventory cost functions. Therefore, we formulate this problem in a continuous model and propose a two-phase continuous approximation approach to solve this model. We decompose the entire studied region into subregions with slow varying functions and propose a continuous approximation approach to determine the optimal influence area, ordering quantity, and system cost to serve the disaster affected region.

Table 6
Impact of A_{r_i}, Q_{r_i}, *NDI*, and **TNC** under different values of v_c.

		v_c (miles/h)						v_c (miles/h)				
		35	45	55	65	75		35	45	55	65	75
	Cluster											
	1	6.3	6.9	7.3	7.7	8.1		11	10	10	9	9
	2	5.5	6.1	6.4	6.7	7		2	2	2	2	2
	3	6	6.6	7.1	7.3	7.7		11	10	10	9	9
	4	5.2	5.7	6.1	6.4	6.6		3	2	2	2	2
	5	12	13.3	14.3	15.1	15.8	NDI	2	2	2	2	1
A_{r_i}	6	8.5	9.3	10	10.6	11.1		4	4	4	4	3
	7	9.1	10	10.7	11.3	11.8		3	3	3	3	3
	8	5.8	6.3	6.7	7	7.3		3	3	3	3	3
	9	5	5.5	5.9	6.1	6.4		4	4	4	3	3
	10	9.3	10.2	11	11.6	12.1		2	2	2	2	2
	11	6.6	7.3	7.8	8.2	8.5		2	2	2	2	2
	12	22.6	25.2	27.3	29.1	30.6		1	1	1	1	1
	1	1050	1099	1135	1163	1185		3.605	3.375	3.227	3.123	3.046
	2	1106	1157	1194	1222	1245		0.651	0.611	0.585	0.567	0.554
	3	1069	1119	1155	1183	1206		5.227	4.898	4.686	4.537	4.427
	4	1128	1179	1216	1245	1268		0.977	0.918	0.879	0.853	0.833
	5	804	846	878	903	923		0.597	0.553	0.523	0.503	0.487
Q_{r_i}	6	928	974	1008	1035	1056	TNC	1.8	1.676	1.595	1.539	1.497
	7	903	948	982	1008	1029	($\times 10^6$)	1.405	1.306	1.242	1.197	1.163
	8	1086	1136	1173	1201	1223		1.29	1.209	1.157	1.121	1.094
	9	1143	1195	1232	1261	1284		1.773	1.667	1.598	1.55	1.515
	10	895	940	974	1000	1021		0.866	0.805	0.766	0.738	0.717
	11	1025	1074	1109	1137	1159		0.852	0.797	0.761	0.736	0.718
	12	614	648	675	697	714		0.136	0.125	0.117	0.112	0.107

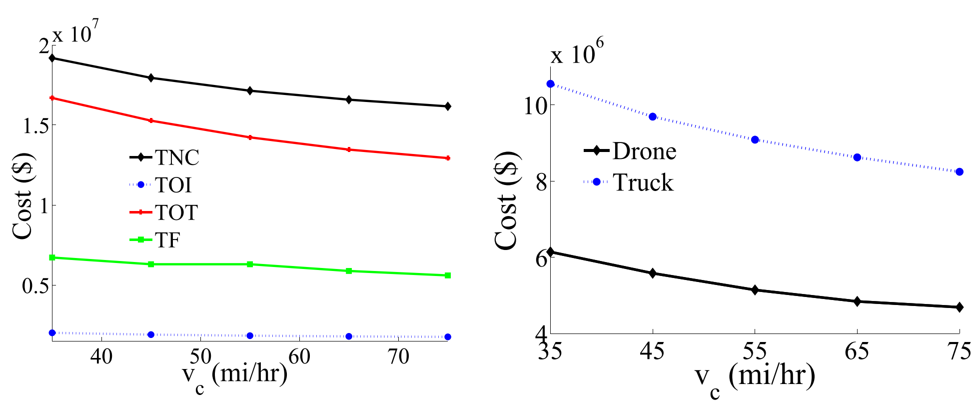
Table 7
Impact of A_{r_i}, Q_{r_i}, *NDI*, and **TNC** under different values of p.

		p						p				
		0	0.25	0.5	0.75	1.0		0	0.25	0.5	0.75	1.0
	Cluster											
	1	5.99	6.62	7.17	8.01	9.32		12	11	10	9	8
	2	5.11	5.84	6.29	7.01	7.96		2	2	2	2	1
	3	6.04	6.32	6.85	7.6	8.82		11	11	10	9	8
	4	5.29	5.58	5.98	6.61	7.51		2	2	2	2	2
	5	12.01	12.32	13.74	15.91	20.42	NDI	2	2	2	1	1
A_{r_i}	6	8.36	8.86	9.72	10.99	13.41		4	4	4	3	3
	7	9.01	9.42	10.39	11.96	14.55		3	3	3	3	2
	8	5.89	6.11	6.59	7.32	8.42		3	3	3	3	2
	9	5.11	5.42	5.78	6.32	7.21		4	4	4	3	3
	10	9.22	9.62	10.61	11.99	14.92		2	2	2	2	2
	11	6.36	7	7.61	8.56	9.99		2	2	2	2	2
	12	22.05	22.89	25.9	30.99	44.56		1	1	1	1	1
	1	1054	1071	1113	1173	1269		3.305	3.274	3.244	3.194	3.112
	2	1111	1129	1173	1232	1320		0.591	0.588	0.587	0.583	0.573
	3	1076	1089	1134	1192	1286		4.754	4.749	4.706	4.645	4.543
	4	1139	1152	1196	1253	1339		0.882	0.881	0.881	0.877	0.866
	5	801	811	855	919	1042		0.581	0.558	0.535	0.505	0.463
Q_{r_i}	6	921	942	986	1059	1158	TNC	1.699	1.665	1.616	1.581	1.481
	7	896	911	959	1031	1135	($\times 10^6$)	1.391	1.298	1.26	1.211	1.143
	8	1086	1111	1151	1212	1301		1.171	1.168	1.162	1.149	1.128
	9	1152	1171	1212	1262	1353		1.591	1.596	1.599	1.594	1.579
	10	876	905	951	1016	1128		0.823	0.801	0.777	0.746	0.702
	11	1028	1042	1088	1189	1247		0.785	0.785	0.767	0.752	0.729
	12	598	611	654	714	857		0.146	0.136	0.123	0.112	0.096



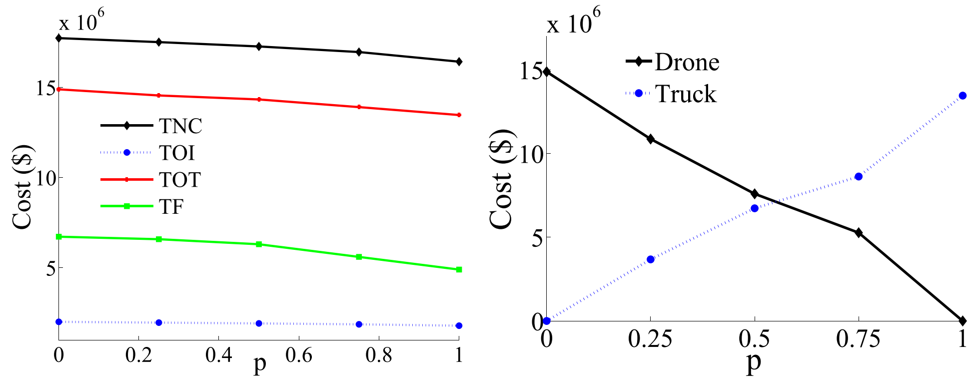
(a) Cost components vs. k (b) Truck and drone cost vs. k

Fig. 8. Cost components under different k values.



(a) Cost components vs. v_c (b) Truck and drone cost vs. v_c

Fig. 9. Cost components under different v_c values.



(a) Cost components vs. p (b) Truck and drone cost vs. p

Fig. 10. Cost components under different p values.

Table 8
Impact of A_{r_i}, Q_{r_i}, NDI, and **TNC** under different values of h_r.

		h_r ($/unit)						h_r ($/unit)				
		1.00	5.00	10.00	15.00	20.00		1.00	5.00	10.00	15.00	20.00
	Cluster											
A_{r_i}	1	7.38	7.39	7.41	7.42	7.42	NDI	8	8	8	8	8
	2	6.46	6.46	6.47	6.48	6.49		7	7	7	7	7
	3	7.04	7.05	7.07	7.07	7.08		8	8	8	8	8
	4	6.13	6.14	6.15	6.16	6.17		7	7	7	7	7
	5	14.33	14.36	14.37	14.39	14.4		15	15	15	15	15
	6	10.06	10.08	10.09	10.11	10.11		11	11	11	11	11
	7	10.78	10.8	10.81	10.82	10.83		11	11	11	11	11
	8	6.76	6.78	6.79	6.8	6.8		7	7	7	7	7
	9	5.92	5.93	5.94	5.95	5.96		6	6	6	6	6
	10	11.01	11.03	11.04	11.05	11.06		12	12	12	12	12
	11	7.83	7.85	7.86	7.87	7.88		8	8	8	8	8
	12	27.35	27.38	27.41	27.42	27.44		28	28	28	28	28
Q_{r_i}	1	1135	508	360	294	254	TNC ($\times 10^6$)	3.227	3.533	3.912	4.289	4.665
	2	1194	534	378	309	268		0.585	0.646	0.721	0.796	0.871
	3	1155	517	366	299	259		4.686	5.145	5.713	6.278	6.842
	4	1216	545	385	315	273		0.879	0.974	1.091	1.208	1.324
	5	878	393	278	227	197		0.523	0.555	0.593	0.632	0.671
	6	1008	451	319	261	226		1.595	1.718	1.869	2.02	2.17
	7	982	439	311	254	220		1.242	1.333	1.445	1.557	1.668
	8	1173	525	371	303	263		1.157	1.274	1.418	1.562	1.705
	9	1232	552	390	319	276		1.598	1.774	1.992	2.208	2.425
	10	974	436	308	252	218		0.766	0.821	0.889	0.957	1.024
	11	1109	497	351	287	249		0.761	0.831	0.917	1.002	1.087
	12	675	302	214	175	151		0.117	0.121	0.127	0.132	0.137

We use three disaster prone coastal counties of Mississippi i.e., Hancock, Harrison, and Jackson counties as a test bed to visualize and validate our modeling results. Managerial insights are drawn to determine how different key drone parameters (e.g., drone flight height, speed), road access availability following a natural catastrophe, and inventory holding and reordering cost impact the overall system performance. Some key insights gained from this study are summarized below:

- Influence area A_{r_i} of distribution centers to serve a disaster affected region is highly correlated with the demand density of that region.
- Increasing the drone flight height k drastically reduces their service area A_{r_i} and thus increases the overall system cost **TNC** for the disaster relief operation (shown in Table 5 and Fig. 8).
- Increasing the drone speed v_c drastically increases their service area A_{r_i} and thus can reduce the overall system cost **TNC** for the disaster relief operation (shown in Table 6 and Fig. 9).
- Unit transportation cost for drones is more expensive than trucks and thus adds an additional cost in the system if the road access p drops significantly after a natural catastrophe (shown in Table 7 and Fig. 10).
- Ordering quantity Q_{r_i} drops with increasing holding cost h_r but increases with increasing reorder cost R_r to offset the overall system cost (shown in Tables 8 and 9).

This research also opens up a number of future research opportunities. Note that the solution obtained from Algorithm 1 does not guarantee optimality. Future research will devote to this research direction by finding high quality solution approaches for our proposed optimization model. This study ignores wind factors in approximating the routing cost for drones. It will be interesting to see how the inclusion of wind factors in the optimization framework impact the overall delivery performance of drones. Moreover, in real settings when a set of drones will be deployed to serve a disaster affected region then it will be interesting to see how their scheduling and routing mechanisms will be coordinated. In this work, although the model has been

Table 9
Impact of A_{r_i}, Q_{r_i}, *NDI*, and **TNC** under different values of R_r.

		R_r ($/unit)						R_r ($/unit)				
		0	0.25	0.5	0.75	1		0	0.25	0.5	0.75	1
	Cluster											
Ari	1	5.99	6.62	7.17	8.01	9.32		12	11	10	9	8
	2	5.11	5.84	6.29	7.01	7.96		2	2	2	2	1
	3	6.04	6.32	6.85	7.6	8.82		11	11	10	9	8
	4	5.29	5.58	5.98	6.61	7.51		2	2	2	2	2
	5	12.01	12.32	13.74	15.91	20.42	NDI	2	2	2	1	1
	6	8.36	8.86	9.72	10.99	13.41		4	4	4	3	3
	7	9.01	9.42	10.39	11.96	14.55		3	3	3	3	2
	8	5.89	6.11	6.59	7.32	8.42		3	3	3	3	2
	9	5.11	5.42	5.78	6.32	7.21		4	4	4	3	3
	10	9.22	9.62	10.61	11.99	14.92		2	2	2	2	2
	11	6.36	7	7.61	8.56	9.99		2	2	2	2	2
	12	22.05	22.89	25.9	30.99	44.56		1	1	1	1	1
Qri	1	1054	1071	1113	1173	1269		3.305	3.274	3.244	3.194	3.112
	2	1111	1129	1173	1232	1320		0.591	0.588	0.587	0.583	0.573
	3	1076	1089	1134	1192	1286		4.754	4.749	4.706	4.645	4.543
	4	1139	1152	1196	1253	1339		0.882	0.881	0.881	0.877	0.866
	5	801	811	855	919	1042		0.581	0.558	0.535	0.505	0.463
	6	921	942	986	1059	1158	TNC	1.699	1.665	1.616	1.581	1.481
	7	896	911	959	1031	1135	($\times 10^6$)	1.391	1.298	1.26	1.211	1.143
	8	1086	1111	1151	1212	1301		1.171	1.168	1.162	1.149	1.128
	9	1152	1171	1212	1262	1353		1.591	1.596	1.599	1.594	1.579
	10	876	905	951	1016	1128		0.823	0.801	0.777	0.746	0.702
	11	1028	1042	1088	1189	1247		0.785	0.785	0.767	0.752	0.729
	12	598	611	654	714	857		0.146	0.136	0.123	0.112	0.096

developed with utilitarian policy, some aspects of egalitarian policy (e.g., fairness and time) can still be satisfied as long as enough trucks and drones are available and the demand points fall within drone range. In future work, we will try to understand how limiting the availability of trucks and drones and incorporating both densely and sparsely population centers will affect the results. We also do not consider battery costs for the replacement right after trips. We assume enough fully charged batteries will be available in the distribution centers for drones. In future studies, we also want to incorporate this factor into a mathematical model.

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