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The casualty transportation of Ebola outbreak in Liberia: A simulation study

Hyejin Cho
Purdue University

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Is approved by the final examining committee:

Seokcheon Lee
Co-chair

Yuehwern Yih
Co-chair

Mark Lehto

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Approved by Major Professor(s): Seokcheon Lee

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THE CASUALTY TRANSPORTATION OF EBOLA OUTBREAK IN LIBERIA: A SIMULATION STUDY

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ABSTRACT

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In this paper, we have solved the unique problem of casualty transportation problem under Ebola by developing dynamic policies for vehicle routing to provide practical decision support. The objective of the proposed model is to minimize the total transmission risk. We describe the problem with real-constraints based on the empirical data of the 2014 Ebola outbreak in Liberia. The casualty transportation problem is a variant of Dynamic Pick-up and Delivery Problems, in which a vehicle is dispatched to demand location in real time and it then transports the demands to the destination. DPDP integrates various sources of dynamic events as well as real-world aspects. All decision made in dynamic vehicle routing problems are taken in real-time. In same light, the casualty transportation problem is solved in real-time under infectious disease environment. Particularly in case of Ebola, the prompt burial or cremation of deceased Ebola victims would is critical in reducing the transmission of the virus thus casualty transportation problem should be considered mandatory to stop transmission. To solve the casualty transportation problem, our approach involves developing adequate policies for vehicle routing construction under Ebola situation, to evaluate those policies performance through simulations, and to recommend the best policy resulted from experimental results that can reduce the total transmission risk a lot.

Key words: Humanitarian logistics, Dynamic casualty transportation problem, Dynamic pickup and delivery problem, Ebola transmission rate, Real-time decision making

1. INTRODUCTION

1.1 Background

The worst-known Ebola epidemic in history infected 28,603 people and killed 11,301 people in 2014 to 2015 mostly in Liberia, Guinea, and Sierra Leone. Ebola is transmitted via physical contact with bodily fluids, secretions, tissues, or semen from infected individuals. Infected patients present flu-like symptoms which rapidly progress to extensive bleeding, and death frequently occurs within 10 days of initial infection (Chowell et al., 2004; Camacho et al., 2014; Chowell & Nishiura, 2014). World Health Organization (WHO) reports that the body is very contagious briefly after the person dies from Ebola (WHO, 2015). This is when the virus is overtaking the whole body and all bodily fluids come out the remains. Therefore, in order to stop the Ebola virus from spreading, rapid burial or cremation of the Ebola victims is one of the important intervention strategies to control the spread of Ebola.

In addition, under infectious disease environment, government and healthcare organizations try to reduce transmission by putting several strategies, say intervention, into the affected region. The intervention strategies to stop Ebola virus from spreading include surveillance, placement of suspected cases in quarantine for 3 weeks (the maximum estimated length of the incubation period), education of strict barrier nursing techniques (i.e. protective clothing and equipment and hygienic kits, patient management), and the rapid burial or cremation of infected remains. Among these, we focus on the distribution of protective clothing and equipment and hygienic kits and rapid burial. Through our research, we designed the casualty transportation problem under twelve scenarios in which either burial processes or education strategy or both of them exist and we developed six policies for solving the suggested problem so as to minimize the total transmission risk.

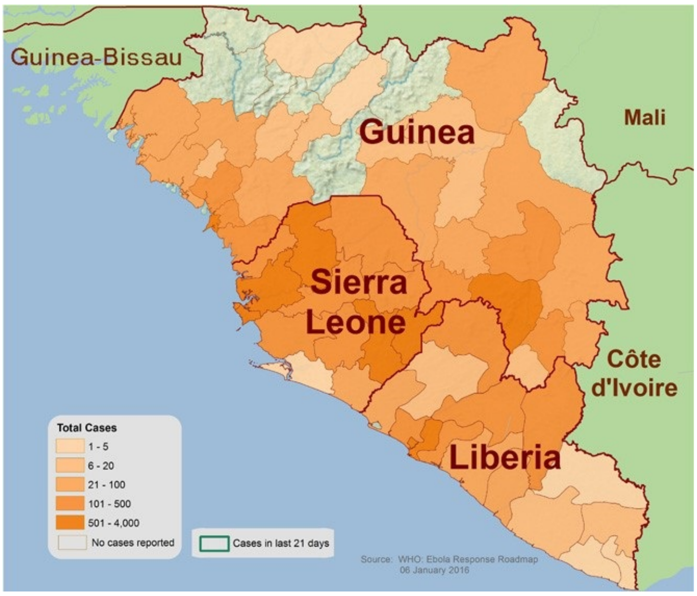
Currently there is little literature that considers the transmission rate of affected remains from Ebola. This is the motivation to examine the casualty transportation problem under Ebola environment. After reviewing previous literature, few researchers studied the transmission chain from remains and effect of the rapid burial and other intervention. Hence we studied the transmission model of Ebola affected remains and casualty logistics considering the significance of the rapid burial and the risk of Ebola affected remains.

In this research, we model the burial process under the community setting which is where the death occurs in the non-hospital setting. In the hospital setting burial process is undertaken in healthcare center environment, which minimizes improper handling and exposure to family members. On the other hand, the community burial process includes a burial team retrieving the body, disinfecting a whole place where the infected death lies on, packing the body, transporting it to a burial site, and burying it. This process is more complicated than the hospital one, because burial teams must be trained to follow the WHO burial process guideline, which takes a long time and the team members also have a risk of infection.

Throughout the research, we described the casualty transportation problem, constructed dynamic vehicle routing policies, and evaluated those policies using the vehicle routing simulation to minimize the transmission risk based on the empirical data from 2014 Ebola outbreak in Liberia.

1.2 West Africa Ebola Outbreak Case

The 2014 Ebola outbreak in West Africa mostly in Guinea, Liberia, and Sierra Leone (Figure 1.1) is recorded as the twenty-sixth known Ebola virus disease outbreak (Gray et al., 2015) and the worst Ebola outbreak in history (Eisenberg et al., 2015). The outbreak started in Guinea in December 2013. As of 25 September 2015, total Ebola cases of Guinea, Sierra Leone, and Liberia are 3804, 14124, and 10675 respectively (Figure 1.2). Figure 1.3 shows the infected cases and the accumulated deaths in Liberia as of 25 September 2015 (CDC, 2015; WHO, 2014a). During more than a year, Ebola virus swept across the countries.



-World Health Organization, 2016, Ebola response roadmap

Figure 1.1. Affected West Africa regions

One of the reason for this extraordinary crisis is the Zaire strain which is one of Ebola virus strains. It is one of the most fatal species which lead to the 2014 outbreak in West Africa (WHO, 2016). The other reason is West African funeral custom, that is to wash and kiss the body of person who died. Under chaotic epidemic situation, inadequate healthcare systems and lack of resources contributed to the delay in responding the outbreak and worsened the crisis (Gray et al., 2015).

Consequently, the case fatality ratio, which is the proportion of the number of deaths among the total number of Ebola cases, of the 2014 outbreak was estimated as 70.8% (Chowell & Nishiura, 2014). Furthermore, healthcare workers were at risk of transmission due to their frequent contact with patients and body fluid, and burial rituals (Eisenberg et al., 2015). To mitigate the outbreak, intervention efforts were undertaken in West Africa. The efforts included restriction of individual mobility and border crossings, distribution of home health kits containing gloves, gowns, disinfectants, and other supplies (Eisenberg et al., 2015). Eventually WHO declared Ebola free in Liberia, Guinea, and Sierra Leone on September 3, December 29, and November 7 2015 respectively.

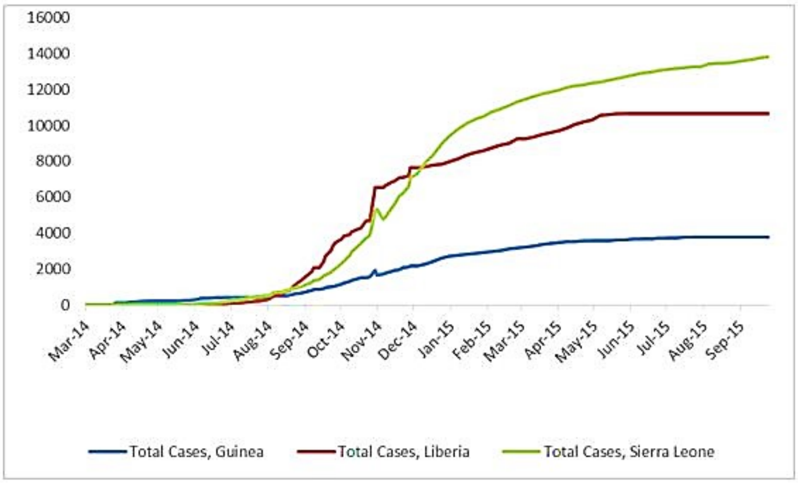


Figure 1.2. The total Ebola cases in West Africa

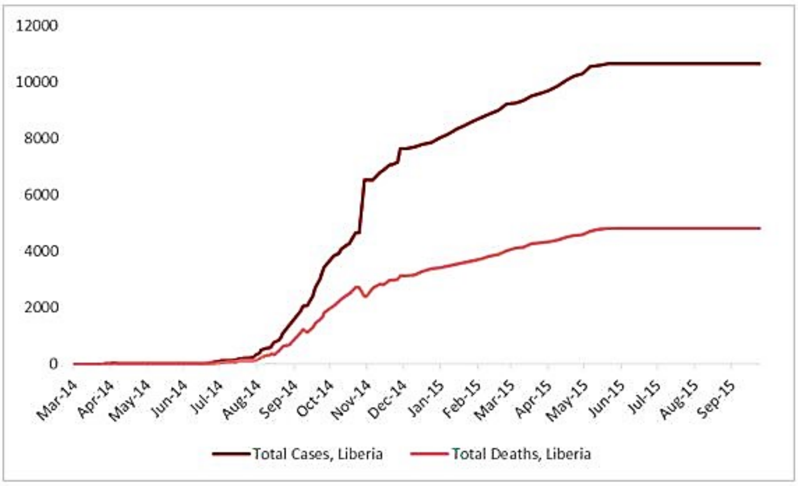


Figure 1.3. The total Ebola cases and death tolls in Liberia

1.3 Burial Process

The casualty transportation problem indicates how to determine the priority of deceased people from Ebola to retrieve and bury them. This problem considers not only burial process time but also other realistic parameters such as trucks travel time. We clarify, however, the burial processes step by step and the time of each step is recorded in Table 1.1 (Roselim, 2014) because these processes are the core logic to define the problem.

By analyzing the burial processes based on the 2014 outbreak, we partition the burial processes into two stages: retrieval process and burial process. The retrieval process starts after the truck arrives at the affected site and it includes disinfection and pickup activity. After the retrieval process, the truck travels to the burial region and the burial process begins after the truck arrives at the destination. The burial process comprises digging the ground and burying the body. The process time of the retrieval and burial process are obtained based on articles (Helene, 2015; Nielsen et al., 2015; Roselim, 2014). Throughout the paper, when we use the term, burial process, it encompasses the retrieval process as well as burial process.

Step 1: A death occurs

When an infected death occurs in a community, the death is notified to the healthcare center immediately and placed in the waiting list, called Request Truck Queue, to be assigned by a burial team if there are no available vehicles. If there are available vehicles, one of them will be chosen and dispatched to the Ebola remains' location. Initially, trucks are located at different healthcare centers, which are uniformly distributed across the country.

Step 2: Dispatch a vehicle to the death

Once a vehicle becomes available, a healthcare worker allocates it to the infected remains by following a rule (e.g., chronological order, nearest distance). Then the truck is dispatched to the location of the infected remains. The vehicle carries a burial team, which comprises five workers.

Step 3: Retrieval Process

Once the vehicle reaches the affected area, the disinfection activity starts. The burial team members are in their protective suits and then the team leader, who carries the sterilizer sprayer, begins disinfecting the entry door

Next, the burial team gets into the place and lay two double strength body bags on the ground near the infected remain. The team lifts the body into the bag safely and zips it up. Before leaving, the team leader disinfects the entire area thoroughly and the other members pack anything that can be contaminated, for instance, a blanket and pillows, into the other body bag. The burial team members excluding the leader carry the bags with great care to the waiting truck.

Finally, the bags are safely loaded into the truck and the leader disinfects the truck thus completing the retrieval process. This whole retrieval process, which takes about 40 to 50 minutes (Xinhua, 2014).

In some cases, the truck heads to the Ebola center to test if the virus was in fact the cause of the death. Once this is confirmed, the body is transported to the burial or cremation site. Otherwise, the body is returned to their families for burial. We do not consider this procedure in the model because we assume all bodies are contaminated by the Ebola virus.

Step 4: Burial process

After retrieving the the body of the infected deceased, the vehicle departs to the burial site. Once the vehicle arrives at the aimed place, team members prepare the burial process. First they carry body bags to a grave, dig the ground about 2m deep to prevent body fluids from coming out of ground, and have a brief ritual with the surrounding people before burying the bags. Eventually the team buries the bags and the burial process is completed. The burial process takes about 1 hour on average

Step 5: Heading back to depot

After finishing retrieval and burial process, the vehicle heads back to any healthcare center. The vehicle needs not to head back the same depot where it departed from at the Step 1.

Table 1.1.
Burial Processes Time (hours)

Process	Retrieval process	Burial process
Time	Normal (0.75, 0.1)	Normal (1, 0.2)

(Roselim, 2014; World Health Organization, 2014)

1.4 Organization

The remainder of this paper is organized as follows. Section 2 reviews related literature. Section 3 describes the proposed Ebola casualty transportation problem including its characteristics. Section 4 presents six policies which construct vehicle routing for collecting casualties and simulation study which consists of twelve scenarios to examine the performance of suggested policies. In Section 5, generated test instances and simulations results are presented. The paper closes with a conclusion and an outlook on future work in Section 6.

2. LITERATURE REVIEW

2.1 Humanitarian Logistics

Disaster logistics is usually referred as humanitarian logistics. It includes prepositioning relief supplies stocks, rescuing victims from disaster, and providing the relief supplies to victims affected by disasters so as to minimize human suffering and death and to maximize the number of survivors (Balcik et al., 2008).

As the term humanitarian implies, the objective of the logistics differs drastically from commercial logistics (Beamon & Fernandes, 2004; Beamon & Kotleba, 2006; Van Wassenhove, 2006; Holguín-Veras et al., 2007). Commercial logistics usually deals with a predetermined suppliers, manufacturing sites, and a predictable and stable demand, whereas, humanitarian logistics do not obtain even predict suppliers, demands, and sites (Jahre et al., 2007).

Furthermore, since the key objective of commercial logistics to either minimize the cost of transportation or logistics, most methodologies and operational management have been developed to lower the cost.

Whereas, humanitarian logistics objective does not simply focus on the cost but focusses on the response time, the socioeconomic cost, the served affected area. Also since humanitarian logistics include a wide range of operations under great uncertainty, it may fail in applying pre-developed mathematical model that helps decision process of regular commercial logistics to humanitarian logistics. Alternatively, methodologies for humanitarian logistics should incorporate externalities such as human suffering level.

Logistics has always been a chief element in humanitarian aid operations, which results in the logistics efforts account for 80 percent of disaster relief (Jahre et al., 2007). Notwithstanding researchers have viewed humanitarian logistics as the strikingly different from commercial logistics, they acknowledge similarity between humanitarian and commercial logistics (Glenn Richey Jr et al., 2009; Balcik et al., 2008).

Although the environments where humanitarian logistics operate are different from the commercial setting, the basic activities within humanitarian supply chains are not extremely different from commercial logistics (Glenn Richey Jr et al., 2009). Similar to commercial supply chains, stocks flow through the relief chain via a series of long-haul and short-haul shipments (Balcik et al., 2008). This suggests that analyzing the supply chain actors and activities in the commercial situation might enable humanitarian logistics problems to have proper methodologies.

There are four phases of disaster management: mitigation, preparedness, response, and recovery. Some literature combines mitigation and preparedness stage into one (Özdamar & Ertem, 2015).

Mitigation and preparedness activities, for instance, building re-enforcement, inventory and equipment pre-positioning, are operated before the disaster to amplify safety and to weaken the potential impact on population and infrastructure (Özdamar & Ertem, 2015; Holguín-Veras et al., 2012)(FEMA IS-1, 2010).

Whereas, post disaster activities include response and recovery operations, for example, the transportation of supplies to affected area and of equipment for repairs to rebuild the infrastructure, and rescue activities (Holguín-Veras et al., 2012).

Furthermore, the recovery process is categorized into two sub-phases, which are short-term and long-term recovery. Short-term recovery practices consist of the distribution of medicines, the transportation of victims and search aids. On the other hand, long term operations involve restoring the infrastructure and treating human mental illness affected by disaster. Thus the main operational decisions in short-term recovery activities are relief supply allocation, vehicle delivery scheduling, and vehicle routing (Balcik et al., 2008).

Short-term recovery practices occur under chaotic and arduous environments, however long-term recovery operations occur in more calm circumstances. Considering the urgency and the high uncertainty, short-term recovery processes have further priority and dynamics than the other one (Holguín-Veras et al., 2012). Balcik et. al., 2008 referred the short-term recovery activity as last mile distribution (Balcik et al., 2008). The authors defined the last mile distribution as to delivery of relief supplies from local or temporary distribution centers to the victims. They also realized the most compelling logistical problems in the short-term recovery rise from the deficiency of transportation resources and emergency supplies, damaged transportation infrastructure, and lack of coordination among relief actors (Balcik et al., 2008).

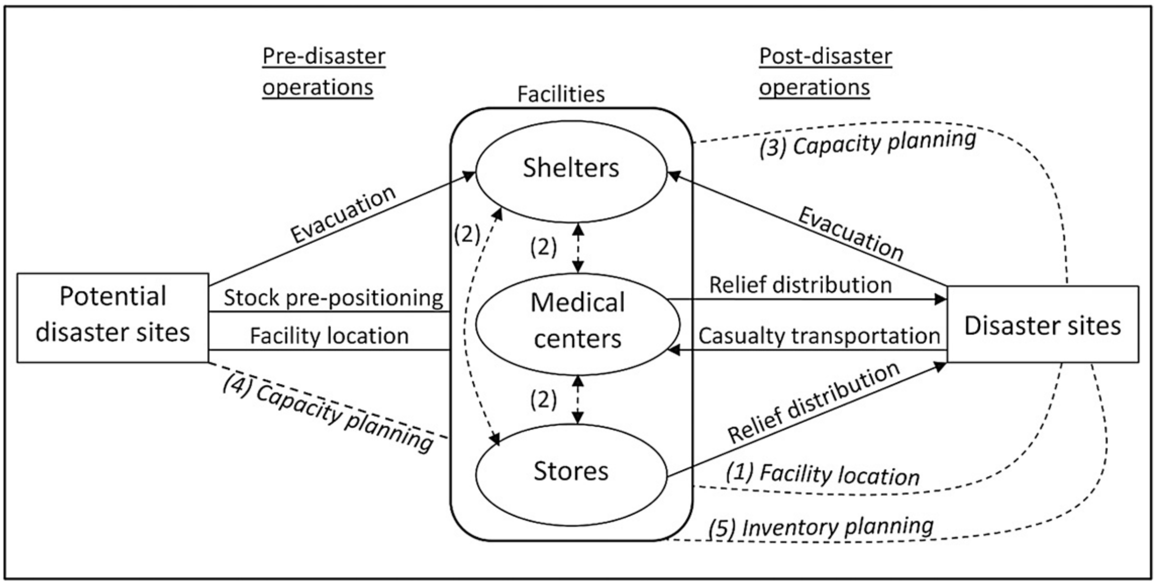
Although the characteristics of importance and necessity of humanitarian logistics, research in this area has not been performed much (Liberatore et al., 2014) and methodologies for short-term recovery has been developed little as well. Furthermore, the transportation of casualty under infectious disease problem has been also barely studied (Caunhye et al., 2012). The term of casualty transportation problem was devised by Caunhye et. al., 2012 (Figure 2.1) (Caunhye et al., 2012). Therefore, our suggested problem has both uniqueness and significance.

We will propose six dynamic policies for vehicle routing for infected remains from Ebola with the empirical data of the 2014 outbreak in Liberia thereby we expect the proposed route construction policies to enable post-disaster operations to be more effective and fast.

2.2 Dynamic Pickup and Delivery Problem

To understand related studies and methodologies for the suggested problem, we reviewed traditional vehicle routing problems (VRP). In general, vehicle routing problems can be classified into four types (Table 2.1) (Pillac et al., 2013). General features related to demand or input data, such as single or multi-period (static/dynamic) and deterministic versus stochastic are factors in VRP category.

A routing problem is said to be static when all the input data of the problem are known before routes are constructed. Whereas, in a dynamic routing problem, some of the input data are revealed or updated during the execution of routing.



(Caunhye et al., 2012)

Figure 2.1. Humanitarian logistics research areas

Usually dynamic modeling can adjust to frequent information updates and to vehicle re-routing and re-allocation of service capacities (Yi & Özdamar, 2007). Thus real-time communication between the vehicles are required so as to reveal routing information dynamically during the execution of the routes.

Different from the dynamic information, stochastic input data partially known as random variables which realizations are only revealed during the execution of the routes, which means that we do not know demand at the beginning because of its highly probabilistic nature. Stochastic property also needs real-time communication but we can apply probabilistic distribution to the routing problem so as to generate the routing for the time window. In general, input data in dynamic problems is estimated by analyzing historical data and assumed to follow proper probabilistic distribution.

Researchers have concentrated on solving dynamic problems by developing heuristic algorithms such as insertion heuristics, deletion heuristics, and interchange moves, and Tabu search. Even though dynamic problems are solved by rigorous mathematical programming or even heuristics with lots of assumptions, the solution does not guarantee to solve real-world problem because of uncertainty properties of practical environment. Therefore, dynamic vehicle routing problem should be researched more and it is one of the important and necessary research area in vehicle routing problem category.

Table 2.1.
Classification of Vehicle Routing Problems

	Deterministic	Stochastic
Static	All input is known beforehand Routes do not change	Input data partially known as random variable which realizations are only revealed during the execution of the routes
Dynamic	Part or all input is unknown revealed dynamically during the execution of the routes Input is unknown Whenever making a solution, new input occurs Need to update real-time data and to communicate between vehicles	Same to the dynamic deterministic problem Stochastic knowledge is available on the dynamically revealed information

Regarding the retrieval and burial processes for the infected deceased under Ebola circumstances, the suggested problem can be considered as the application of dynamic pickup and delivery problem (DPDP). DPDP is a well-studied class of the Vehicle Routing Problem (VRP), which consists in finding a set of routes for the vehicles which satisfies a variety of constraints and so as to achieve the goal (Toth & Vigo, 2002; Ferrucci & Bock, 2014). A key property of DPDP is that dynamically arriving demands must be transported from pickup locations (origin) to delivery locations (destination) within given time windows (Berbeglia et al., 2010).

The term dynamic implies the input data such as the information of the arrival of new demands is not known beforehand, instead it is released during the execution of the routing. With respect to the dynamic characteristic, the problem consists of designing the vehicle routes in an online fashion, communicating to the vehicle which customer to serve next as soon as it becomes available (Pillac et al., 2013; Novoa & Storer, 2009; Secomandi & Margot, 2009; Secomandi, 2001).

The objective varies in different DPDP applications, for example, it can be to minimize the total cost and to minimize the response time. In our problem, it is to minimize the total transmission risk of remains.

The response time is the total time the customers spend waiting to be served (Bertsimas & Van Ryzin, 1991). In the same light, the response time can be interpreted as the duration from the time an emergency call arrives at the station to the time an emergency vehicle arrives at the affected site under disaster environment (S. Yang et al., 2005) in which the response time plays a critical role.

In a DPDP, the input data which are generally user requests are revealed over time. In contrast to a static problem, the planning horizon of a dynamic problem may be unbounded. Therefore, a solution to a dynamic problem cannot be a static output, but rather a solution strategy which using the revealed information, specifies which actions must be performed as time increases.

From this perspective, we suggest proper policies for vehicle routing construction so that healthcare workers can achieve rapid burial with the lowest total transmission risk. Table 2.2 summarizes the comparison between the casualty transportation problem and a typical DPDP.

The DPDP differs from the dynamic traveling repairman problem (DTRP) which is another application of VRPs in term of the chance of changing vehicle location. In the DPDP the vehicle changes location in the model during service, whereas, in the DTRP the vehicle spends time at the service location of each demand to complete serving the demand and does not transport the demand to the designated site. That is, in the DPDP, the vehicle changes location, on the other hand, in the DTRP the vehicle does not change location while servicing a demand.

One of variants of the DPDP is the stacker crane problem (SCP), which encompasses our problem. When vehicles go to a pick-up location, it must immediately go to the delivery location for that demand. This is an asymmetric TSP by considering each pick-up and delivery pair as a single point. Since the stacker crane problem is a NP-hard problem, the method to solve this problem include simulation study (Swihart & Papastavrou, 1999).

Thus, the casualty transportation problem is the application of the DPDP as the stacker crane problem because a vehicle should retrieve Ebola infected remains and transport them to the burial site immediately.

2.3 Ebola

Ebola hemorrhagic fever is a severe viral disease of which fatality rate of 20 to 90%, depending on the virus species (Baize, et al., 2014). There are five species of Ebola virus: Sudan ebolavirus, Zaire ebolavirus, Tai Forest ebolavirus, Bundibugyo ebolavirus, and Reston ebolavirus (Beeching et al., 2014). Among ebolaviruses, Zaire and Sudan strain has been discovered as the most fatal to human. These Zaire and Sudan ebolavirus' case-fatality rate ranges from 60% to 90% and the rest has a case-fatality rate of 40 to 60% (De Wit et al., 2011).

By tracking Ebola outbreaks in history, Zaire ebolavirus infected Democratic Republic of Congo in 1976 and concurrently but unrelated outbreak that occurred in Sudan was caused by Sudan ebolavirus (De Wit et al., 2011). Reston ebolavirus was discovered in 1989 originated from Philippines. It caused outbreaks in US and Italy in 1990, 1992, and 1996 but Reston virus has caused disease in nonhuman primates, but not in humans. Tai Forest ebolavirus is also referred as Cote Divoire ebolavirus and the name implies the location of outbreak in 1994. Tai Forest virus causes non-fatal human case, which is similar to Reston virus. Bundibugyo ebolavirus was identified in Uganda in 2007 to 2008 (De Wit et al., 2011).

Ebola viral disease (Ebola) symptoms are the sudden onset of fever and malaise, accompanied by myalgia, headache, vomiting, and diarrhea. The initial symptoms are nonspecific, which makes early clinical diagnosis difficult (Dixon et al., 2014; Beeching et al., 2014). In calamitous forms, referred as the second stage, multi-organ dysfunction, including hepatic damage, renal failure, and central nervous system involvement occur, leading to shock and death (Dixon et al., 2014). Recovery is more likely from the initial stage, with much higher fatality rates in the second stage (Eisenberg et al., 2015).

The natural reservoir of Ebola and mode of transmission to humans has not been ascertained, however, laboratory testing of reservoir competence supports that three species of fruit bats can be possible Ebola virus reservoir (Leroy et al., 2005). The virus which is transmitted from Animal to human is thought to occur during hunting and consumption of the reservoir species or infected non-human primates (Beeching et al., 2014) and when the human population contacts with infected wildlife (Dixon et al., 2014).

On the other hand, human to human transmission results from direct contact with body fluids, for instance, blood, vomit, saliva, urine, sweat, semen, and breast milk (Breman et al., 1978; Beeching et al., 2014; Dixon et al., 2014) of infected individuals during the stages of illness or after death (Nielsen et al., 2015; Dowell et al., 1999). Infection through inhalation is possible in non-human primates, but there is no evidence for airborne transmission in humans (Beeching et al., 2014).

The 2014 Ebola outbreak in west Africa was affected by Zaire ebolavirus, which historically has demonstrated the highest case-fatality rate (up to 90%) since the virus was discovered in 1976 (Beeching et al., 2014; Baize et al., 2014; Dixon et al., 2014). Two vaccine candidates have been developed and demonstrated completely in studies in nonhuman primates, however, it remains still unknown that both vaccine candidates will translate to human population (Kanapathipillai et al., 2014; Stanley et al., 2014; Geisbert et al., 2009).

Besides Ebola vaccines, several control measures (e.g., isolation of patients, safe patient and body transfer systems, safe and rapid burial, environmental and household decontamination, quarantines and cordons sanitizes, travel restrictions, distribution of protective kits, education for community members, and so on) are put in the affected region to curtail the outbreak (Gray et al., 2015).

To understand the Ebola transmission dynamics and to develop proper intervention strategies to mitigate the disease, it is crucial to construct the transmission model of Ebola. By using a compartmental model of infection, which is SEIR, Camacho et al., unearthed the temporal dynamics of Ebola. Furthermore, the authors suggested person-to-person transmission model from different sources, which are an infectious host in the community, at rate $\beta_i(t)$ and a deceased but not buried patient at rate $\beta_d(t)$ (Camacho et al., 2014). The transmission rate follows time-dependent smooth decreasing functions (Equation (3.1)) (Camacho et al., 2014; Lekone & Finkenstädt, 2006; Ndanguza et al., 2013):

$$\beta_d(t) = \beta_d(1 - \delta_{pp}\sigma(t, \alpha_{pp}, \tau_{pp})) \tag{2.1}$$

where σ is the following sigmoid function:

$$\sigma(t, \alpha, \tau) = \frac{1}{1 + exp(-\alpha(t - \tau))}$$

Based on the 2014 reported cases of Ebola in West Africa, Lewnard et al., 2014 estimated the effectiveness of protective kit allocation. The authors simulated the transmission model with protective kit allocated under different scenarios, which had different start date of allocating kits (Lewnard et al., 2014).

Pandey et al., 2014 also access the effectiveness of several strategies for curtailing Ebola with a stochastic model of Ebola disease transmission that takes into account different environment (e.g. community, hospitals, and funerals) (Pandey et al., 2014). The authors emphasized non-pharmaceutical interventions such as quarantine, case isolation, contact precautions, and rapid and safe burial (Pandey et al., 2014).

Moreover, Pandey et al., 2014 calculated R_0 for Ebola in partitioned transmission routes of which results for R_0 imply that reducing transmission in hospitals and the community is insufficient to stem the exponentially growing epidemic. Since West African funeral custom has touching and kissing to deceased person, it is imperative to simultaneously restrict traditional burials to hinder Ebola transmission in West Africa (Pandey et al., 2014). Also, the author claims that rapid burial is one of the required factor to stop Ebola transmission.

Accordingly, we solve the casualty transportation problem by showing how rapid burial can be achieved by establishing dynamic policies and demonstrating the effectiveness of the suggested policies through simulation under different intervention strategies.

Table 2.2.
Comparison of casualty transportation problem and DPDP

	The casualty transportation problem	Dynamic pickup and delivery problem
Common properties	Some of the input data which are generally the user requests are revealed or updated during the period of time in which operations take place The planning horizon of a dynamic problem may be unbounded A solution to a dynamic problem cannot be a static output but rather a solution strategy which, using the revealed information, specifies which actions must be performed a time goes by Some information about future requests is known as a probability distribution Because of the problem complexity, the exact probability distribution of future events is not always known but can be approximated through the use of historical data is known as a probability distribution.	
Problem classes	dynamic stacker crane problem	dynamic vehicle routing problem with pickups and deliveries (D-VRPPD) dynamic stacker crane problem (D-SCP) dynamic dial-a-ride problem (D-DARP)
Related research in D-SCP	N/A	
Approach	Suggest adequate policies for vehicle routing construction	Adapt a static algorithm that solves the static version of the problem The static algorithm is applied only once at the beginning of the planning horizon. Then update the current solution with heuristic methods (e.g., insertion heuristics, deletion heuristics, interchange moves, and a local search algorithm) Agent-based simulation Tabu search
Algorithmic performance assessment	simulation	competitive analysis, less strict analysis (i.e., analyzed the performance of a dynamic algorithm over a fixed (and finite) set of instances

(Berbeglia et al., 2010; Hentenryck & Bent, 2009; Hvattum et al., 2006, 2007; Roselim, 2014; World Health Organization, 2014; Powell et al., 2003; J. Yang et al., 1999, 2004; Mes et al., 2007; Gutenschwager et al., 2004; Mitrović-Minić et al., 2004; Mitrović-Minić & Laporte, 2004)

3. PROBLEM DESCRIPTION

3.1 Problem Definition

The casualty transportation problem is the variation of the DPDP with multiple vehicles with unit capacity which is classified in the one-to-one pick-up and delivery problem. Also the suggested problem is referred as a casualty logistics problem. We define the problem with unit capacity vehicles because of the Ebola transmission characteristic. The burial team takes just one Ebola remains to the designated area at the same time (Nielsen et al., 2015) in order to disinfect the vehicles as well as healthcare workers. Thus in this problem the vehicles capacity is considered to be one.

Furthermore, there are two decision types in this problem. The first one is that there are more waiting Ebola remains than the number of available vehicles. In this case, the vehicle decides which demand should be served first. The second one is when more vehicles than the number of waiting Ebola remains are available. In this case, the closest vehicle to the remains is sent to that body. The former case is more usual under emergency situation due to the resource deficiency. Therefore we suggest six policies for the former situation and for the latter condition, we just fix the nearest neighbor policy.

Our contribution is to solve the variant of the DPDP with the unique objective function referred to the total transmission risk function, which has not been handled before. The total transmission risk function consists of not only the total response time (which is usually the traditional objective in the previous DPDP problems) but also the transmission rate of infected remains of Ebola.

Camacho et al, 2004 suggested the person-to-person transmission rate function $\beta_d(t)$ from the unburied infected remains. The authors used the time-dependent smooth decreasing function for $\beta_d(t)$ (Equation (3.1)) (Chowell & Nishiura, 2014; Chowell et al., 2004; Lekone & Finkenstädt, 2006; Ndanguza et al., 2013). We use parameter estimates done in literature (Chowell & Nishiura, 2014; Lewnard et al., 2014; Althaus, 2014)(Equation (3.2)).The transmission routine from infected remains occurs only during the time between after death and before burial.

$$\beta_d(t) = \beta_d \mathbb{1}_{(t<\tau)} + \beta_d e^{-\alpha(t-\tau)} \mathbb{1}_{(t\geq\tau)} \tag{3.1}$$

$$\beta_d(t) = 0.78\mathbb{1}_{(t<\tau)} + 0.78e^{-0.015(t-\tau)} \mathbb{1}_{(t\geq\tau)} \tag{3.2}$$

where τ is the time at which intervention put in, t is the time when the bodies are buried completely.

We assume τ is the time when burial team arrives at the place where body of died person lies. From the transmission rate function, we can get the transmission risk function at time t per body (Equation (3.3)). It is achieved by integrating $\beta_d(t)$ over the time that an infected patient deceases to the time that the body is buried comprehensively.

$$Transmission\ risk\ of\ the\ infected\ remains\ over\ time\ t = \int_t \beta_d(t)dt \tag{3.3}$$

To get the total transmission risk, we sum the person to person transmission risk among the total remains. We call it as the total transmission risk function, $B(t)$ (Equation (3.4)).

$$B(t) = \sum_D \int_t \beta_d(t)dt \tag{3.4}$$

where D represents the total number of the infected deceased.

The objective of the casualty transportation problem is to minimize the total transmission risk, $B(t)$ to minimize the number of infected population, to maximize the number of survivors, and to minimize Ebola lasting period.

We make an assumption on some of the parameters. Arrival rates and the number of vehicles (denoted as v and the value of v is from 27 to 53 in the 2014 outbreak in Liberia) are attained from CDC and articles connected to the 2014 Ebola outbreak (CDC, 2015; Al-Varney, 2015).

3.2 Assumptions

- We assume bodies of the deceased people from Ebola occur in the community setting and not in the hospital setting
- Person to person contact behavior changes once intervention strategies (e.g., retrieve and bury processes, education) starts
-Traffic condition (heavy/low) is not considered. (i.e. ignore traffic jams and their resulting delays)

4. METHODOLOGIES

To solve the casualty transportation problem, we suggest six policies for vehicle routing, which enables real-time decision making to minimize the total transmission risk. An available vehicle is dispatched to the Ebola remains which contains the highest priority resulted from the determined policy among the suggested policies.

The six policies that affect the decision of vehicle routing to the Ebola deceased victims are: 1) nearest neighbor (NN), 2) first come first served (FCFS), 3) last come first served (LCFS), 4) lowest transmission risk (LTR), 5) highest transmission risk (HTR), and 6) the highest transmission rate combined with nearest neighbor (HRATE). The suggested policies are summarized in Table 4.1.

Table 4.1.
Six Policies

Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
NN	FCFS	LCFS	LTR	HTR	HRATE

As explained in Table 4.2, the suggested policies determine the priority of remains to be served when the number of requests exceeds the number of available vehicles exist. If there are no available vehicles to transport the arrived request, the request is put in the waiting list, called Request Truck Queue. Then the healthcare worker allocates the truck once available to the remains which has the highest priority by the policy. If multiple remains are waiting and multiple vehicles are available, the decision maker picks the remains with the highest priority which is decided by the policy and then dispatch the closest truck to that remains. In case when higher number of vehicles than the number of demands are waiting, simply the closest truck to the demand is dispatched.

In general, there are limited number of vehicles in disaster. Considering this aspect, the suggested policies guide healthcare workers to determine the priority of demands to be served rather than the priority of vehicles. Vehicles are always picked by the closest distance between them and demands.

Since the first three policies would be familiar to all readers we will not explain them thoroughly. The fourth and the fifth policy consider the transmission rate with the response time. Among arrived demands we will find one that has the minimum or the maximum transmission risk at the time when truck arrives at the place then dispatch the nearest vehicle to it. Basically those two policies consider the waiting time of demands at Request Truck queue, transmission risk, and the distance between demands and available vehicles. The sixth policy considers the transmission rate and the distance.

Table 4.2.
Decision Types and Policies

vehicles / demands	1	N
1		Closest vehicle
M	Closest demand First come demand served first Last come demand served first Lowest transmission risk of demand Highest transmission risk of demand Highest transmission rate divided by vehicle's traveling time of demand	Combine

4.1 Policy 1 - Nearest Neighbor

All infected remains will be retrieved and buried by a burial team depending on the distance between a body and a truck. No matter when a death occurs, at the time when a vehicle becomes available, the closest demand to the vehicle among waiting bodies at the Request Truck Queue will be served first.

The nearest neighbor policy overlaps with the decision type which is there are higher number of available vehicles than the number of demands in which the closest truck will be dispatched to the demand. Hence, the nearest neighbor policy implies that there is only the shortest distance rule exists in the system thereby the total transmission risk function relies on only distance. Although this rule is simple, it is intuitively adopted by healthcare workers in real world.

When looking at the transmission risk function closer, it can be interpreted as the function of the response time. Thus, if the nearest neighbor policy reduce the response time strikingly, the total risk would be much lowered under this policy.

We randomly generated distances between demands and trucks in the range of 60 to 180 miles. This range is achieved by calculating the Euclidean distance among the centers of the Liberian counties.

4.2 Policy 2 - First Come First Served

All requests arrived at the healthcare center are recorded in chronological order. According to the first come and first served (FCFS) policy, once a vehicle is available, it is dispatched to the first arrived demand no matter how the distance between the available vehicle and the fist come demand is.

When we look at the transmission risk function, it increases logarithmically (at rate 0.0125 or 0.025 dependent on the scenarios) as time increases, which means that the initial stage of responding is critical to lower the transmission risk. That is to say, through the FCFS policy, the risk of the first come remains would reaches almost the convergent point of the transmission risk function if the remains waits for being retrieved for a long time.

4.3 Policy 3 - Last Come First Served

The last come first served policy (LCFS) is the reverse case of the first come and first served policy. All the arrived notifications of occurrence of infected remains are recorded in decreasing chronological order. Similar to the FCFS policy, the last come first served policy does not rely on the distance when there are more number of remains than the number of available trucks.

It, however, differs significantly from FCFS policy despite of the fact that it does not involve the distance like the FCFS policy does. By the last come first served rule, the last come remains will be retrieved first and has the lowest transmission risk among waiting bodies at that moment. Then the reducibility of the total transmission risk is greater than that of the first come first served policy because the risk of the first served remains is much lower than the convergent value of the transmission risk function. Again, this aspect is obtained from the logarithmic property of the transmission risk function.

4.4 Policy 4 - Lowest Transmission Risk

remains

Among waiting requests, we can find one which has the expected lowest transmission risk. Expected lowest transmission risk states the transmission risk in the future when the burial team will arrive at the location of deceased victim. In other words, the lowest transmission risk policy includes the notion of the nearest neighbor and last come first serve policy.

However, in some cases where the distance between the last come demand and the available vehicle is very large, the LTR rule guides another demand which arrived earlier than the last come demand. Since the burial processes begin after the truck arrives at the location of the infected remains, the starting time of person to person contact behavior change is exactly when the truck arrives at the affected place. As a result, the transmission risk of waiting demands at the Request Truck Queue is not same with the risk at the time when the burial team starts burial processes.

With the transmission risk function for each remains at time t when a truck becomes available, we can find the remains that has the minimum transmission risk at time $t + \alpha$, where α implies the expected travel time of truck to the remains' place. Thus the lowest transmission risk policy includes distance concept, which improves the last come first served approach.

All distances between the waiting demands and the available vehicle are different to each other, which is reflected in the simulation models by using the triangular distribution in range of 60 to 180 miles.

Basically we compare all transmission risk among arrived demands, find one with the expected minimum transmission risk at Request Truck Queue, and dispatch the nearest vehicle to it. Once the vehicle arrives at the demand, the increasing rate of the transmission risk starts to decrease because the intervention affects the person to person contact behavior. After retrieval process, the vehicle heads toward the burial site and after completion burial, eventually transmission rate becomes zero and the transmission risk stops increasing.

4.5 Policy 5 - Highest Transmission Risk

The highest transmission risk (HTR) policy is opposite to the LTR policy. It picks the demand which possesses the highest expected transmission risk among the waiting requests. The highest transmission risk policy is the combination of LCFS, FCFS, and farthest distance rule. Suppose there are three waiting demands at the Request Truck Queue, say D_1, D_2, and D_3 in chronological order. A vehicle becomes available and the distances between the vehicle and D_1, D_2, and D_3 are 50mi, 80mi, and 100mi respectively. It can be expected that the vehicle will be dispatched to D_1 and D_3 under the FCFS policy and LCFS rule respectively. Whereas, under the HTR policy, we can not simply predict the routing result. The expected transmission risk of D_3 can be higher than that of the rest and vice versa because we do not know how long the waiting time of each demand is and how far the demand from the vehicle is before executing the vehicle routing. Hence, the highest transmission risk mixes up the LCFS, FCFS, and the furthest distance rule and the consequent priority of demands would count on the given situation.

4.6 Policy 6 - Highest Transmission Rate Combined with Nearest Neighbor

The highest transmission rate combined with nearest neighbor (HRATE) policy can be achieved by dividing the transmission rate by the trucks travel time to the place where the remains lies. While this policy looks analogous to the HTR policy, under this policy, a truck is dispatched to a demand with the highest value of transmission rate and the closest distance between the available truck.

Next, considering the form of the total transmission risk function, the HRATE policy looks similar to the LTR rule. However, the transmission rate is instantaneous thus it does not provide the information about the risk. That is to say, the highest transmission rate can not be considered as the highest transmission risk.

5. EXPERIMENTAL DESIGN

Through simulation, the best policy which reduces the total transmission risk further across the scenarios will be selected among the proposed six policies and all experiment results are statistically analyzed. To develop simulation models, we design the experiments with real data, which is resulted from the 2014 Ebola outbreak studies.

5.1 Input Data

Our model is designed to address the realistic aspects as many as possible. Based on the empirical data from the 2014 Ebola outbreak, we can obtain arrival rates, the approximated number of burial teams, and the approximated number of operated vehicles. To design the simulations, we assume that Ebola victims' arrival follows the exponential distribution, and the number of resources is constant within the scenarios.

Arrival rates

The arrival rates are obtained from the empirical data of the 2014 Ebola outbreak in Liberia (Appendix A). Since daily death rates vary over time (WHO, 2014a; CDC, 2015; Caitlin, 2015), we designed the model to have different arrival rates of demands along with the simulation time horizon. We sectored the epidemic time horizon into three phases and obtained arrival rates respective to each phase as described in Table 5.1.

Burial teams

According to the safe burial guideline, the number of burial teams should be operated as minimum to avoid the secondary transmission (CDC, 2014). Red Cross declared the burial team started with three teams with seven members each and later increased to five. Later, the team increased to twelve with 150 burial team members as Ebola remains increased.

Table 5.1.
Ebola Remains Arrival Rates

Contents \ Phase	Phase 1	Phase 2	Phase 3
Period	3/25 - 8/28 2014	8/29 2014 - 3/18 2015	3/19/2015 -
Arrival Rates	0.2468	0.9000	0.2124

- arrival rates per hour in each Ebola outbreak phase

From April 27, 2014 to April 29, 2015 it is reported that the teams collected 3,684 deceased victims from Montserrado and its surroundings (Massa, 2015; Anita et al., 2015). In addition, based on the WHO report, US established and operated about 50 teams in Liberia as of February 2015 (Office of the Press Secretary, 2015). Integrating all articles related to the burial teams, we assume 40 to 50 burial teams on average were managed in the 2014 Ebola outbreak in Liberia (Xinhua, 2014).

Vehicles

Logisticians have managed a fleet of about 100 vehicles and countless motorcycles and bikes, which have been critical in surveillance, contact tracing, response, and burial activities in Liberia (WHO, 2014b; Anita et al., 2015) in the 2014 outbreak. The actual number of vehicles, however, are less than the reported number due to technical issues (Al-Varney, 2015; Frontieres, 2014; Russell & Seble, 2014; Antoinette, 2015; Automotive Fleet, 2015). Since the number of available vehicles is up to the number of burial teams, we consider only forty to fifty trucks were available in the 2014 Ebola outbreak in Liberia. Yet, we define the scenarios to have different number of vehicles to explore the effect of policies under various setting.

5.2 Scenarios

We developed continuous simulation models that is, the change of the system is smooth in time (Wang & Wang, 2013) and the developed models continuously track system response according to the total transmission risk function. The starting time of simulations is March 25, 2014 when the initial Ebola remains occurred and each scenario was simulated for a hundred replications. We have twelve scenarios (Table 5.2) to delve into the suggested policies' performance. Different types of intervention is included in each scenario in which the number of trucks is set as different as well.

5.2.1 Scenario 1 - burial without intervention

There is no intervention strategy in the scenario 1. Only burial team's retrieving and burying action enables the Ebola remains' transmission rate to decrease. Once a deceased victim is picked up, the transmission rate function starts decreasing exponentially at the rate of 0.0125 per hours (Equation (5.1)) (Camacho et al., 2014).

$$\beta_d(t) = 0.78\mathbb{1}_{t<\tau_b} + 0.78e^{-0.0125(t-\tau_b)}\mathbb{1}_{t\geq\tau_b} \tag{5.1}$$

where t implies the simulation system time at which the deceased victim in the system and τ_b implies the time when the burial team arrives at the remains' place.

As long as the body is safely buried, the transmission rate becomes zero and transmission risk does not increase any longer. We set the different number of vehicles in burial without intervention environment.

5.2.2 Scenario 2 - burial with global intervention - March 25 2014

The global intervention includes distribution of flyers, personal protective equipment (PPE), and sterilizer, and campaign to a whole affected region at the same time. In the 2014 Ebola outbreak, protective kits were provided to households in an attempt to reduce the household transmission. These kits include soap, bleach, PPE including gloves and masks, and sanitary containers for disposal of contaminated materials. In reality, Liberian government and international healthcare organizations strove to distribute protective kits to all Liberian counties on September 15 to October 3, 2014 by researching various articles and papers (Crowe et al., 2014; Frontieres, 2014). We call it as the global intervention.

As the term of global implies, the global intervention put in the system at the same time, which affects the all community members' person to person contact behavior simultaneously. Within scenario 2, the global intervention is put in the system on March 24. 2014 at which the simulation starts. This is the extreme case of the scenario 3 because the global intervention begins in a whole affected region right after the infectious decease outbreaks.

Considering the transmission rate function, the control level of the global intervention is 0.0125 per hour (Equation (5.2)) (Camacho et al., 2014).

$$\beta_d(t) = 0.78e^{-0.0125t}\mathbb{1}_{t<\tau_b} \tag{5.2}$$

where t implies the simulation time at which the request is in the system and τ_b is the arrival time of truck at the demand.

All arrived requests follow the Equation (5.2) before being retrieved. Once an available vehicle arrives at the requested location, the burial processes start. Then the transmission rate of the remains changes to Equation (5.3).

$$\beta_d(t) = 0.78e^{-0.025(t-\tau_b)}\mathbb{1}_{t\geq\tau_b} \tag{5.3}$$

where t implies the simulation system time at which the demand is in the system and τ_b is the burial team's arrival time at the affected place.

The value of control level is 0.025 once the burial processes begin. This value is obtained by multiplying the effects of the burial and the global intervention. Under this settings, Scenario_{21}, Scenario_{22}, and Scenario_{23} have 27, 40, and 53 trucks respectively.

5.2.3 Scenario 3 - burial with global intervention - September 24 2014

Since Liberian relief teams distributed protective kits on September 15 to October 3, we estimated the mid time of that period, which is September 24, 2014 (Crowe et al., 2014; Frontieres, 2014). Therefore, the scenario 3 reflects the 2014 outbreak well.

Before September 24, only the burial activity is operated as in scenario 1 (Equation (5.4))and on September 24 (the time interval between the simulation starting time and September 24 is 183 days, which is 4392 hours) the global intervention begins and the transmission rate starts decreasing at value of 0.0125 per hour. And the transmission rate is once again decreased after the truck arrives at the deceased victim(Equation (5.5)).

$$\beta_d(t) = 0.78\mathbb{1}_{(t<\tau_b<\tau_g)} + 0.78e^{-0.0125(t-\tau_b)}\mathbb{1}_{(t\geq\tau_b,\ t<\tau_g)} \tag{5.4}$$

$$\beta_d(t) = 0.78\mathbb{1}_{(t<\tau_g<\tau_b)} + 0.78e^{-0.0125(t-\tau_g)}\mathbb{1}_{(t\geq\tau_g,\ t<\tau_b)} + 0.78e^{-0.025(t-\tau_b)}\mathbb{1}_{t\geq\tau_b} \tag{5.5}$$

where t is the simulation system time at which the remains is in the system, τ_b is the starting time of the burial processes and τ_g is the starting time of the global intervention, which is 4392. Let us refer this environment with different number of trucks as: Scenario$_{31}$, Scenario$_{32}$, and Scenario$_{33}$ with 27, 40, and 53 trucks respectively.

5.2.4 Scenario 4 - burial with local intervention

The local intervention is derived from the fact that some people of the affected region can not obtain protective supplies due to the deficiency of supplies. Alternatively, when a call that notices a remains occurs arrives at the healthcare office, healthcare workers inform the caller about how to prevent from being transmitted by the body, for instance, warning for direct touch to the deceased victim's body. We consider this type of intervention as the local education intervention.

Since an emergency call arrives individually and dynamically, the local education strategy starts depending on the arrival time of requests. We assume once the request call arrives at the healthcare center, the worker immediately notify the prevention strategy to the caller, which is considered as the local intervention starts. Therefore, the starting time of the local intervention is exactly the time when the request arrives at the healthcare center.

Since we assume the local intervention strategy has the same effect with the global intervention, the control level is also same at value 0.0125 per hour. After the burial team arrives at the affected place, the transmission rate is decreasing exponentially at the rate of 0.025 (Equation (5.6)). This environment with different number of trucks are referred as: Scenario_{41}, Scenario_{42}, and Scenario_{43} with 27, 40, and 53 trucks respectively.

$$\beta_d(t) = 0.78\mathbb{1}_{(t<\tau_l<\tau_b)} + 0.78e^{-0.0125(t-\tau_l)}\mathbb{1}_{(t\geq\tau_l,\ t<\tau_b)} + 0.78e^{-0.025(t-\tau_b)}\mathbb{1}_{(t\geq\tau_b,)} \quad (5.6)$$

where t is the simulation system time at which the remains is in the system, τ_b is the starting time of the burial processes and τ_l is the starting time of the local intervention, which is dependent on the request's arrival time.

Table 5.2.

Scenarios

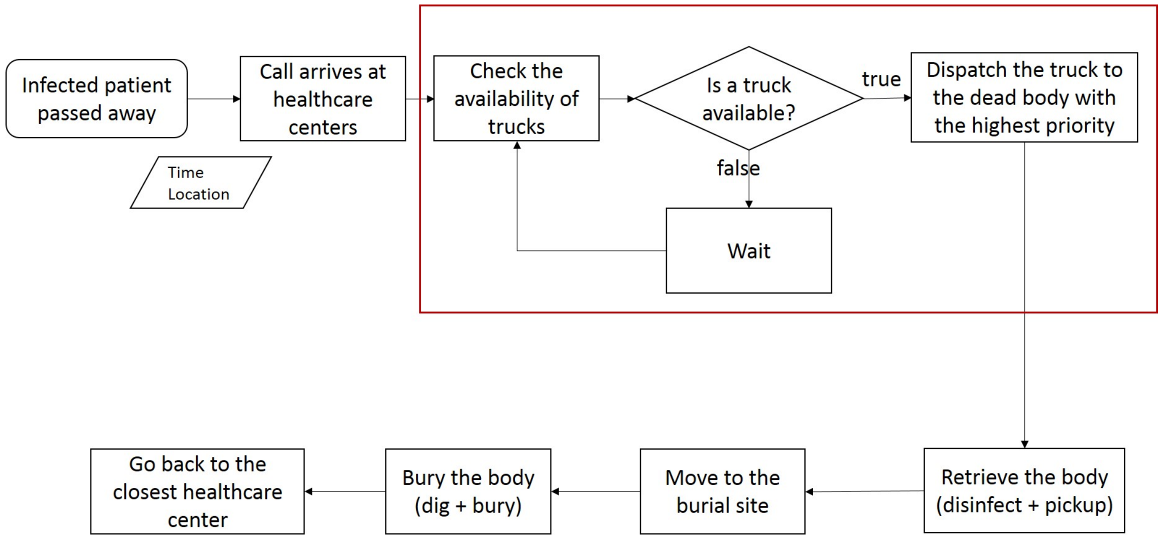
	Without intervention	Global intervention - Mar 25 2014	Global intervention Sep 24 2014	Local intervention
v = 27	Scenario_{11}	Scenario_{21}	Scenario_{31}	Scenario_{41}
v = 40	Scenario_{12}	Scenario_{22}	Scenario_{32}	Scenario_{42}
v = 53	Scenario_{13}	Scenario_{23}	Scenario_{33}	Scenario_{43}

- Scenario_{ij}
- i: different interventions, i={1, 2, 3, 4} = {without intervention, global - Mar 25, global - Sep 24, local}
- j: different number of trucks, j={1, 2, 3} = {27, 40, 53} trucks
- v: the number of trucks

5.3 Simulation Logic

Simulations logic is developed based on the burial processes of the 2014 Ebola epidemic. The basic operational processes are same even though the specific conditions differ from each scenario model.

Once Ebola patient deceases, the notification call arrives at the healthcare offices. Then the officer records the time of the body occurrence with its location. If a truck is available,



- Our methodologies will solve the red box

Figure 5.1. Simulation logic

an officer allocates it to the request following the determined policy. Otherwise, officer puts the request in waiting list, referred to as the Request Truck Queue, until a vehicle becomes available, then he assigns the available vehicle to the highest priority remains' location, which is resulted from the policy.

The truck departs to the affected place then as soon as it arrives, the burial team starts disinfect their bodies as well as the surrounding environment where the body is located. Then team members safely pack the body into the body bag, carry it to the waiting truck, and finally complete the retrieving process.

The truck heads to the burial site, which is available and the closest region among possible burial sites. Upon the truck arrives at the designated site, the body is buried completely. Then the truck and the burial team head back to the closest healthcare office. Even though the frame of the simulation is same across the different scenarios, the way of dispatching available trucks to the affected remains are different according to the policies.The simulation logic is visualized in Figure 5.1.

6. RESULTS

We have developed continuous simulation models for the casualty transportation problem with ARENA. The starting time of simulations is March 25, 2014 when the 2014 Ebola outbreak occurred. Each scenario is simulated for a hundred replications. The maximum number of created entities (Ebola remains) is 4808 obtained from the Centers for Disease Control and Prevention report (CDC, 2015).

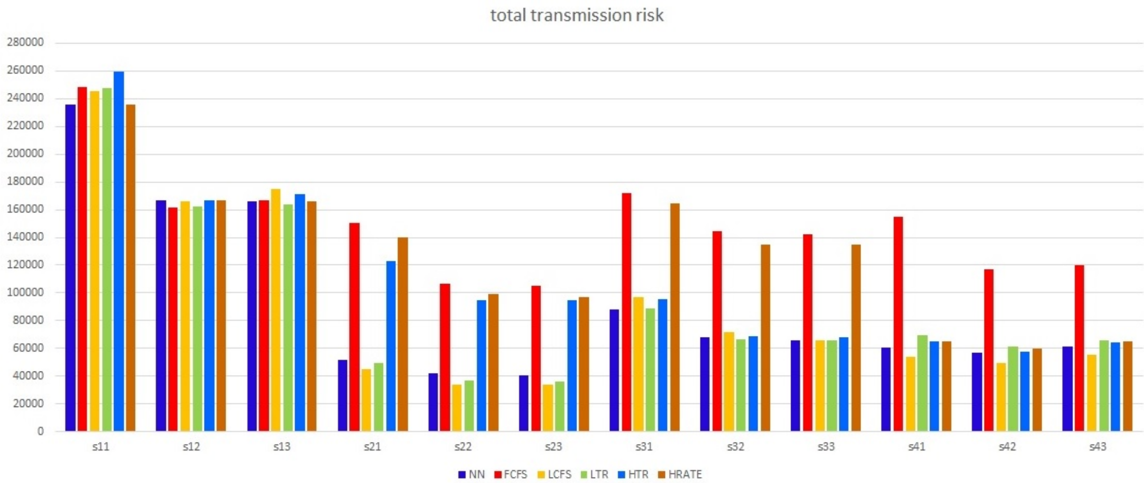
6.1 Experiments Results

After running different simulation models, we achieved the total transmission risk value under six policies for twelve scenarios (Table 6.1). Also, we have visualized the experiments results in Figure 6.1 and Figure 6.2. The simulation parameters are same across twelve scenarios.

Table 6.1.
Total Transmission Risk

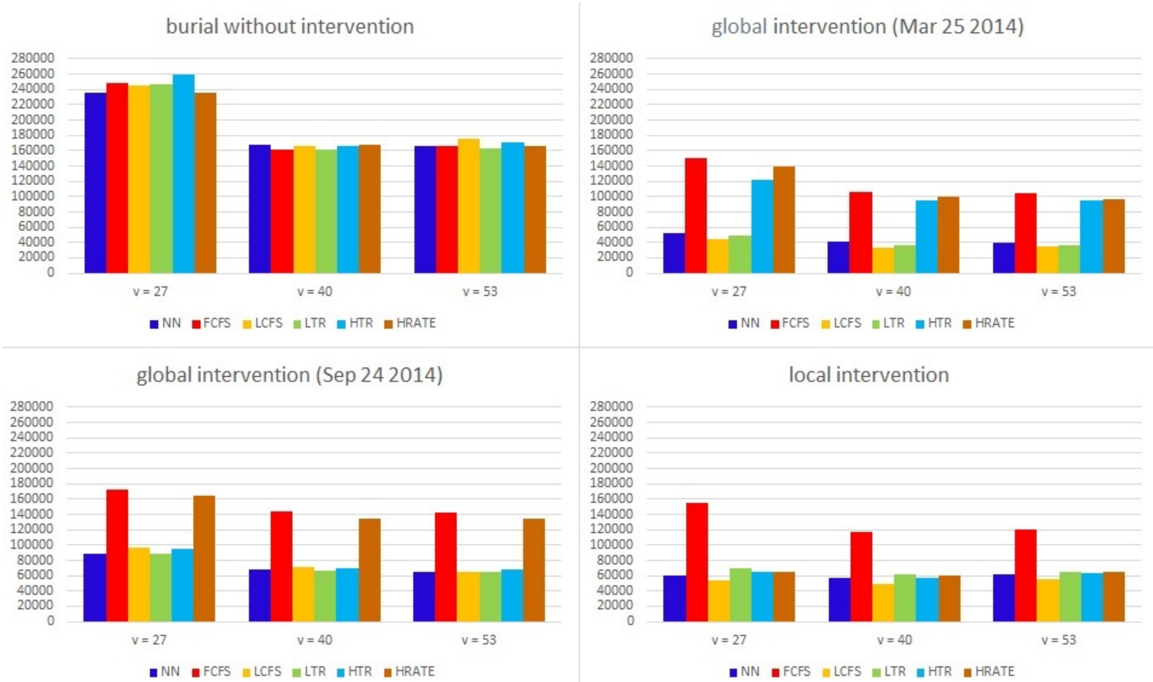
	Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
Scenario 1 Burial without intervention						
(1) v = 27	235,926	248,768	245,153	247,319	259,349	235,926
(2) v = 40	166,895	161,186	166,354	161,951	166,554	166,895
(3) v = 53	166,060	166,509	174,890	163,499	171,084	166,059
Scenario 2 Burial with global intervention - March 25 2014						
(1) v = 27	51,539	150,298	45,018	49,605	122,621	139,967
(2) v = 40	41,999	106,253	33,985	37,092	94,540	98,976
(3) v = 53	40,368	105,169	34,187	36,141	95,024	97,095
Scenario 3 Burial with global intervention - September 24 2014						
(1) v = 27	88,223	172,184	96,882	88,479	95,342	164,768
(2) v = 40	68,121	144,284	71,365	66,557	69,059	134,634
(3) v = 53	65,430	142,212	65,711	65,527	67,766	134,848
Scenario 4 Burial with local intervention						
(1) v = 27	60,458	155,198	54,034	69,553	65,077	64,697
(2) v = 40	56,790	116,802	49,067	61,087	57,244	59,725
(3) v = 53	61,045	119,986	55,269	65,657	64,025	64,908

- v: the number of trucks
- Policy 1: NN, Policy 2: FCFS, Policy 3: LCFS, Policy 4: LTR, Policy 5: HTR, Policy 6: HRATE



-sij: scenario ij
-colored bar: each policy

Figure 6.1. Experiment results - total transmission risk (all scenarios)



-Total transmission risk within each scenario
-colored bar: each policy
-v: the number of trucks

Figure 6.2. Experiment results - total transmission risk (each scenario)

6.2 Scenarios Analysis

Before analyzing the suggested policies' performance, we analyze the output within each scenario to compare the effect of intervention.

6.2.1 Scenarios 1 - burial without intervention

As seen in the Table 6.1, as the number of trucks increases, the total transmission risk decreases because healthcare organizations can respond fast with more trucks. Within the scenario 11, 12, and 13, say 1's, the total transmission risk is around 274% greater on average than the results from the other scenarios. Particularly, the total transmission risk under the policy 1, 3, and 4 significantly differs from the value under same policies in other scenarios (the risk under policy 1, 3, and 4 in the scenario s11, 12, and 13 is 332%, 379%, and 337% greater than the values from other scenarios respectively).

To be specific, the average value of the total transmission risk function under the scenario 1's is 250%, 189%, and 263% greater than on average under the scenario 2's, 3's and 4's respectively. It means that without any intervention, burial activity would not be able to reduce the total transmission risk further even with the adequate policy.

The high transmission risk within the scenario 11, 12, and 13 is predictable because there is no intervention strategy that can reduce the total transmission risk. In these scenarios, since the transmission rate of a remains is constant at value 0.78 before burial team retrieves and buries the body, the total transmission risk function depends on the truck's traveling time and burial processing time.

Also, when looking closer at the scenario 13, the total transmission risk is higher than that from the scenario 12. The main factor is the deficiency of burial team.

6.2.2 Scenarios 2 - burial with global intervention - March 25 2014

Next, within the Scenario 21, 22, and 23 (the global intervention starts right after Ebola outbreak occurs), the total transmission risk is discovered as low compared to other scenarios even though the risk under policy 5 and 6 within the scenario 2's can not be said lower than that in other scenarios. Since the global intervention begins concurrently when the disease outbreaks, we can expect that the transmission would be much lower than before when it swept the area. This result assures that the faster the intervention strategy is conducted, the lesser the transmission risk is.

Compared with the Scenario 31, 32, and 33, say 3's, in which the global intervention starts 183 days after the outbreak occurs, the total transmission risk within the Scenario 2 is reduced by 32% on average than the risk under the Scenario 3's.

Also, the risk under policy 1, 2, 3, and 4 within the scenario 2's is lowered by 25% on average compared to the local intervention strategy (scenario 41, 42 and 43).

However, the total transmission risk resulted from policy 5 and 6 within the scenario 2's is 72% greater than that within the scenario 4's. We will analyze the experiment results from policies' perspective in Section 6.3 but the former interpretation leads us to the fact that both policy 5 and 6 are not adequate under the scenario 2's but under the scenario 4's.

6.2.3 Scenarios 3 - burial with global intervention - September 24 2014

In the scenario 3's, the total transmission risk is about 24% and 25% greater than average results from the scenario 2's and 4's respectively, although the risk under the scenario 3's is reduced by 53% compared to the scenario 1's.

Within the scenario 3's, the transmission risk reaches high values before the global intervention begins due to the fact that the strategy is put into the affected regions about 200 days after Ebola virus attacked the region. Thus, the transmission risk within the scenario 3's is observed as high, which is resulted from the late intervention strategy. Also, it takes time to reduce the transmission rate despite the fact that the global intervention just begins. This fact shows when Liberian government distributed the protective kits around September 24, it seemed too late to control the outbreak, consequent leading to more infectious cases and deaths. Therefore, it assures that fast response is critical under Ebola situation as shown in the scenario 2's.

In addition, the late intervention strategy would be less favorable than the local intervention. In the scenario 4's, the total transmission risk is about 80% of the risk from the scenario 3's. This fact supports that if there is not enough relief supplies such as hygienic kits, it would be recommended that local intervention such as education for the community members should be operated.

6.2.4 Scenarios 4 - burial with local intervention

Lastly, based on the experiment results from the scenario 41, 42, and 43, the local intervention can reduce the transmission risk more than the global intervention if the global strategy is conducted late. This fact is supported by the fact that the total transmission risk is lowered by 25% in the scenario 4's when compared to the results from the scenario 3's.

When looking closer at the experiment results under each policy, the total transmission risk under policy 1, 2, 3, and 4 in the scenario 4's is about 33%, 8%, 29%, and 38% greater than risk from policy 1, 2, 3, and 4 within the scenario 2's respectively. This observation can be interpreted as the evidence that the fast global intervention would surpass the local intervention strategy with competent policies.

However, the total transmission risk is reduced by 41% on average under policy 5 and 6 within the scenario 4's compared to the results under same policies in the scenario 2's. It means that even though global intervention is conducted in the very beginning of Ebola outbreak, inappropriate policies for burial activity would hinder the effect of the global intervention.

Considering all these aspects, the local intervention is proven to one of the signicant action to reduce the total transmission risk. Also, if there is no global intervention due to the limitation of supplies, it is highly recommended to start the local intervention strategy. Furthermore, local intervention will beat the global intervention if the global strategy starts later. Finally, policies for the burial determine the influence of the global intervention, even though the global intervention begins early.

6.3 Policies Analysis

The experiment results shows that the nearest neighbor, last come first served, and the lowest transmission risk policy tend to reduce the total transmission risk across the scenarios, although in some scenarios those polices can not be considered as the best.

All analysis is based on the experiments results (Table 6.1) with using the average total transmission risk value as well as analyzing the statistical variances among the suggested six policies. Likewise, with the results from simulation, we performed Analysis of Variance (ANOVA) and pairwise comparison among policies under each scenario. Except scenario 12, all policies can not be considered the same based on ANOVA results (Table 6.2).

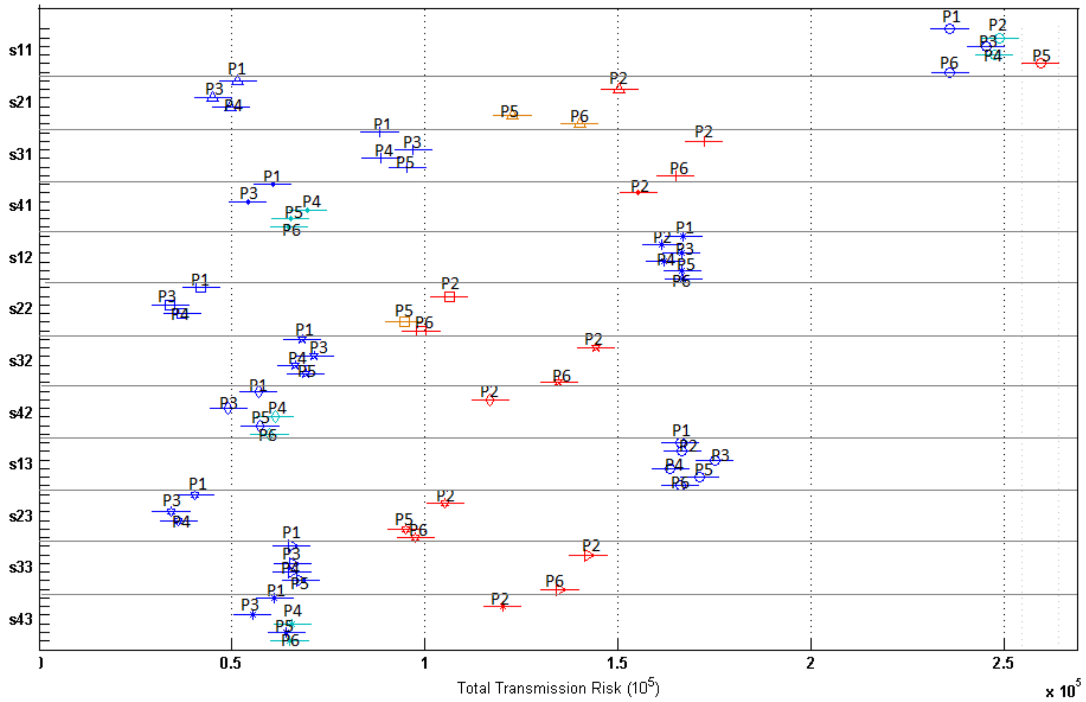
Table 6.2.

ANOVA Results

	F-value	p-value
Scenario 11	10.39	0.00
Scenario 12	0.93	0.46
Scenario 13	2.30	0.04
Scenario 21	3159.30	0.00
Scenario 22	857.16	0.00
Scenario 23	959.73	0.00
Scenario 31	1036.20	0.00
Scenario 32	936.61	0.00
Scenario 33	865.38	0.00
Scenario 41	3659.70	0.00
Scenario 42	1008.70	0.00
Scenario 43	1349.40	0.00

- H_0: all six policies have the same effect on the total transmission risk
- Confidence interval: 95%

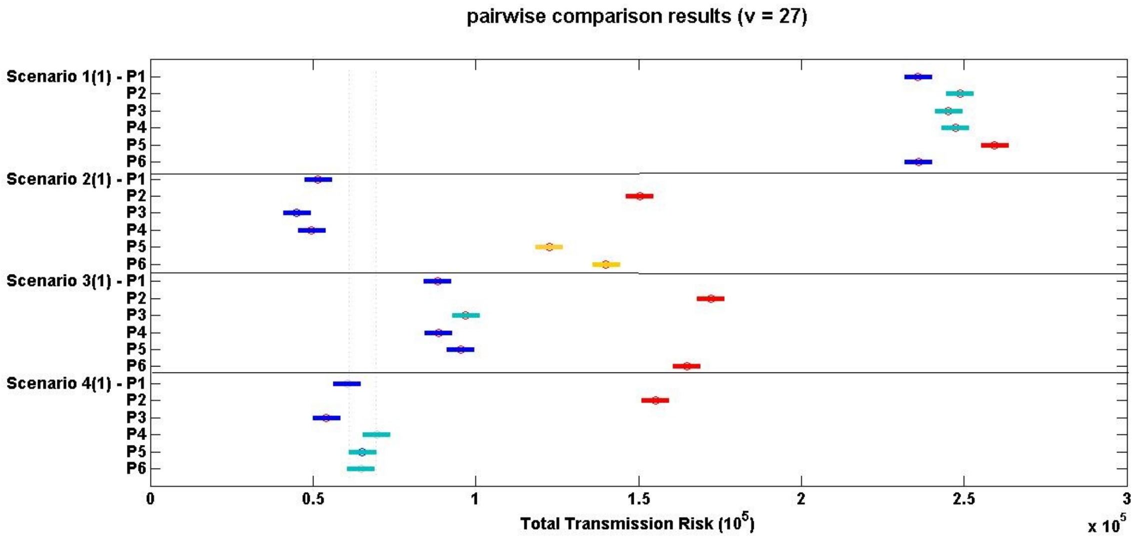
To analyze how six policies differ from each other, we performed the pairwise comparison (Figure 6.3, Figure 6.4, Figure 6.5, Figure 6.6) then classified them into 1) Best, 2) Good, 3) Poor, and 4) Worst group (Table 6.3, Table 6.4). The best and good groups are colored by blue and light blue respectively. The poor and the worst are colored by yellow and red respectively. The length of bar in the pairwise comparison represents the variance of the total transmission risk.



- The Figure 6.3 indicates how the six policies differ from each other in each scenario
- blue: best, light blue: good, yellow: poor, red: worst
- P1, P2, ... ,P6 represent Policy 1, Policy 2, ..., Policy 6
- y-axis: sij (scenario ij)
- x-axis: total transmission risk

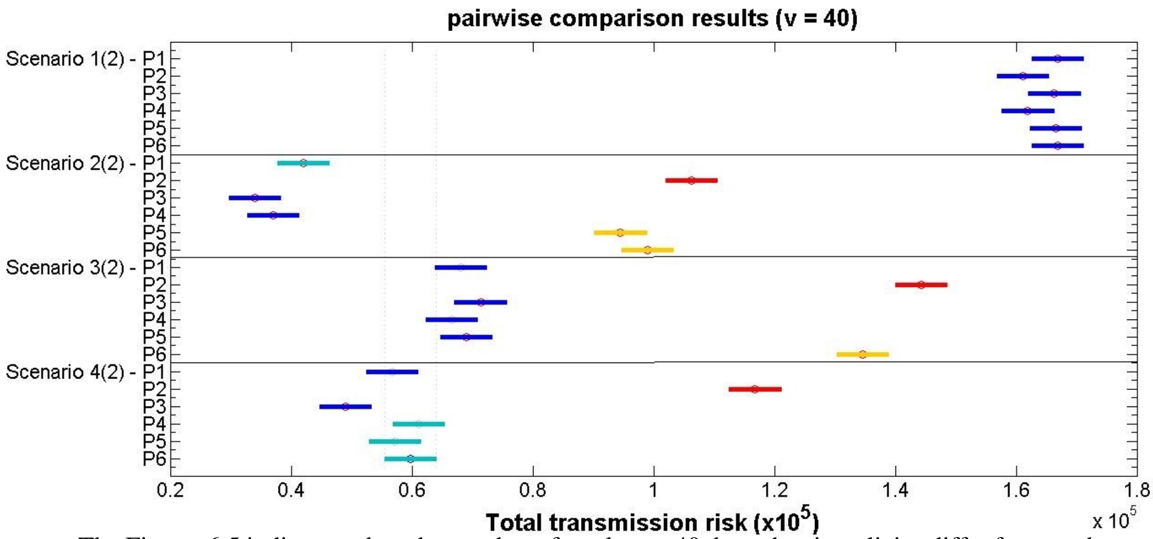
Figure 6.3. The pairwise comparison results

We summarize the pairwise comparison results in Table 6.3 and Table 6.4.



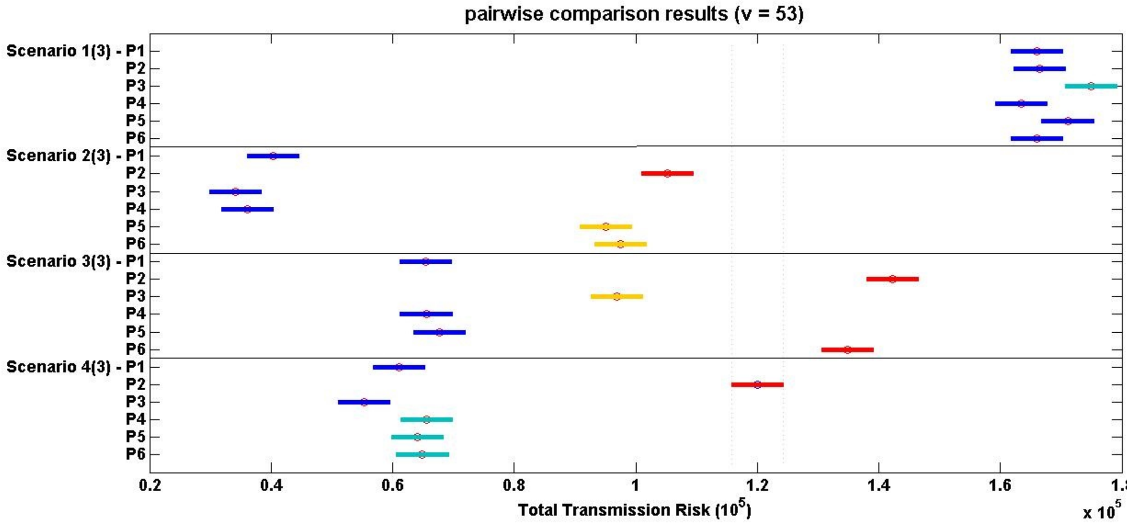
- The Figure 6.4 indicates when the number of trucks are 27, how the six policies differ from each other within each scenario
- blue: best, light blue: good, yellow: poor, red: worst
- y-axis: P1, P2, ... ,P6 represent Policy 1, Policy 2, ..., Policy 6
- x-axis: total transmission risk
- v: the number of trucks

Figure 6.4. The pairwise comparison results (v=27)



- The Figure 6.5 indicates when the number of trucks are 40, how the six policies differ from each other within each scenario
- blue: best, light blue: good, yellow: poor, red: worst
- y-axis: P1, P2, ... ,P6 represent Policy 1, Policy 2, ..., Policy 6
- x-axis: total transmission risk
- v: the number of trucks

Figure 6.5. The pairwise comparison results (v=40)



- The Figure 6.6 indicates when the number of trucks are 53, how the six policies differ from each other within each scenario
- blue: best, light blue: good, yellow: poor, red: worst
- y-axis: P1, P2, ... ,P6 represent Policy 1, Policy 2, ..., Policy 6
- x-axis: total transmission risk
- v: the number of trucks

Figure 6.6. The pairwise comparison results (v=53)

Table 6.3.
Grouping the Pairwise Comparison Results

	11	12	13	21	22	23	31	32	33	41	42	43
Policy 1	B	B	B	B	G	B	B	B	B	B	B	B
Policy 2	G	B	B	W	W	W	W	W	W	W	W	W
Policy 3	G	B	G	B	B	B	G	B	P	B	B	B
Policy 4	G	B	B	B	B	B	B	B	B	G	G	G
Policy 5	W	B	B	P	P	P	B	B	B	G	G	G
Policy 6	B	B	B	P	P	P	W	P	W	G	G	G

- 11, 12, 13, ,,, , 42, 43 denote the scenario
- Best (B), Good (G), Poor (P), Worst (W)

Table 6.4.
Results of Grouping

	Best	Good	Poor	Worst
Policy 1	11	1	0	0
Policy 2	2	2	1	9
Policy 3	8	3	1	0
Policy 4	8	4	0	0
Policy 5	5	3	3	1
Policy 6	3	3	4	2

6.3.1 Policy 1 - nearest neighbor

As we expected, the response time is further reduced by following the nearest neighbor policy than the rest of policies, which is consequent on the lowest total transmission risk in almost every scenarios. Actually policy 1 turns out as the best rule among the suggested policies. This is because the transmission risk comprises the response time and the transmission rate and the response time mainly depends on the distance in the suggested problem. That is to say, the distance is the most dominant factor for the response time. Accordingly, if the distance between an infected body and a vehicle is smaller, the response time can be lowered. Hence, the response time is lowered under the policy 1 consequent on the low total transmission risk.

Within the scenario 1's, the nearest neighbor policy has the exact same risk value with the highest transmission rate policy due to the fact that the transmission rate is constant before the burial processes are operated because there is no intervention strategy in the scenario 1's. Thus, we can consider the nearest neighbor and the highest transmission rate combined with the closest distance as the same.

6.3.2 Policy 2 - first come first served

The first come first served policy is noted as the remarkably worst policy in the scenarios 2, 3, and 4 despite the fact that the FCFS rule has the second lowest total transmission risk in the scenario 12.

The reason why the first come first served policy fails under Ebola environment is that the FCFS does not consider distance between the remains and the truck, which would increase the response time.

When examining both the simulation logic and the total transmission risk function, an available vehicle is dispatched to the remains, that has the highest transmission risk among the waiting remains at the Request Truck Queue under the first come first served rule. Although FCFS policy looks similar to the highest transmission risk policy (policy 5), FCFS policy cannot reduce the total transmission risk mainly because FCFS policy does not include the concept of distance which policy 5 considers.

The other reason that makes the FCFS to be undesirable is the logarithmic form of the total transmission risk function. Since the increasing rate of the risk function decreases logarithmically at rate 0.0125 or 0.025 per hour depending on the given situation, if the system is operated under the first come first served policy, the remains' transmission risk would reach at almost the convergent point of the function. Therefore the first come first served policy is not the best approach for the casualty transportation problem.

Notwithstanding that policy 2 has the best results within the scenario 1, the other policies also have good results within that scenario. In the scenario 1, as mentioned in section 6.3.1, since the transmission rate of a demand is constant at value 0.78 before retrieving the demand. As a consequence, the objective function value wholly depends on the response time, which results in there are no big differences among the policies, although the average values of the total transmission risk under each policy are not the same.

6.3.3 Policy 3 - last come first served

The last come first served policy that is the reverse form of the first come first served is observed as one of the competent rule among the suggested policies. Indeed, the policy 3 is resulted as the third best rule along with the scenarios excluding the scenario 33. However, in consideration of the fact that the scenario 33 reflects the real world well, the poor result in this setting can be a critical issue to the practical world. Notwithstanding, it has the lowest total transmission risk in the scenario 21, 22, 23, 41, 42, and 43.

Compared to the first come and first served policy, albeit the last come first served policy also does not consider the distance, it yields much lower transmission risk than the FCFS policy for the sake of, again, the shape of transmission risk function. Considering the form of the transmission risk function, it increases more steeply at the beginning and later it increases slowly due to the reduction rate of the transmission rate function. Under the LCFS policy, the system remove the remains that has the lowest total transmission risk among waiting deceased victims at Request Truck Queue before the total transmission risk converges to the higher value. That is if the remains' waiting time for a truck is reduced, the future transmission risk can be lowered as well. Again this aspect stems from the logarithmic property of the total transmission risk function and exponentially decreasing form of the transmission rate function. Therefore, LCFS rule outperforms the FCFS.

6.3.4 Policy 4 - lowest transmission risk

The lowest transmission risk policy is discovered as the second best one among the proposed policies. This policy has the lowest total transmission risk within the scenario 13 and scenario 32 and the second lowest in the scenario 12, 21, 22, 23, 31, and scenario 32. It does not have either poor or worst result across the scenarios. Therefore the lowest transmission risk policy is one of the best policies for the casualty transportation problem.

This policy uses the expected transmission risk at time when the burial team arrives at the remains' place. The expected risk is achieved by containing the notion of distance between the waiting request and the available vehicle. As we explored that the nearest neighbor policy can reduce the risk strikingly, the LTR policy also has low total transmission risk across the scenarios because it includes the distance component like the NN.

As the convergence of the total transmission risk function, the lowest transmission risk finds the demand that has the minimum expected risk value among the waiting demands and serve it before the risk increases to the convergent point. Reflecting this aspect, the policy 4 can be interpreted as the combination of the policy 1 and policy 3. Hence, the policy 4 takes advantage of both policies, which results in the second best policy.

6.3.5 Policy 5 - highest transmission risk

As the opposed to the lowest transmission risk, the highest transmission risk policy cannot be said whether it is favorable or unfavorable. This policy indeed depends on the given scenarios. Albeit it is shown as an undesirable rule within the scenarios 11, 21, 22, 23, it works well in the rest of scenarios.

Taking a closer look at the policy 5, it would take the demand which is located furthest from a vehicle. Suppose that the body 1 occurred at t_1 before the body 2 occurs at t_2. One of the vehicles becomes available. Let's assume that the distance between the vehicle and the body 1 and the body 2 is 60mi and 100mi respectively. After evaluating the expected total transmission risk, the body 2 possesses the higher risk thus the vehicle is dispatched to it. In this situation, the policy 5 comprises the LCFS and the furthest distance strategy.

In the reverse situation, it includes the FCFS and the furthest distance strategy. Hence, considering the experiment results under the FCFS and LCFS policy, the highest transmission risk policy really depends on the scenarios and conditions at each time.

6.3.6 Policy 6 - highest transmission rate combined with nearest neighbor

Despite the fact that the highest transmission rate combined with nearest neighbor and NN policy can be considered same in the scenario 11, 12, and 13, the policy 6 is shown as the second worst rule. Other than the scenarios 11, 12, 13, 41, 42, and 43, the policy 6 is examined as the poor strategy because it considers only instantaneous rate. Even though it includes the nearest neighbor principle, the rate does not give an intuition about the future total transmission risk.

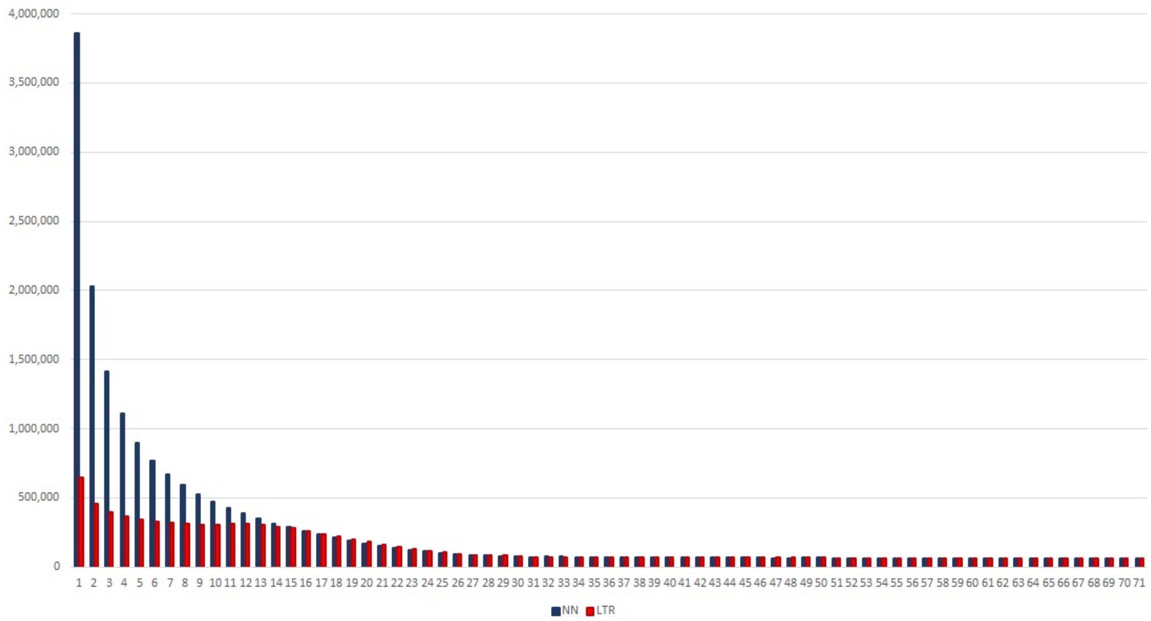
To sum up, we recommend favorable policies in the order of the policy 1 (NN), policy 4 (LTR), policy 3 (LCFS), policy 5 (HTR), policy 6 (HRATE), and policy 2 (FCFS).

6.4 Vehicles Analysis

Based on the pairwise comparisons, we explored the effect of the number of vehicles on the total transmission risk under best two policies. Since real world is depicted in the scenario 3's, which is the global intervention begins on September 24 2014, we analyzed the sensitivity within the scenario 3. Thereby we will suggest the guideline for Ebola eet management by proposing the minimum number of trucks required to be maintained under outbreak.

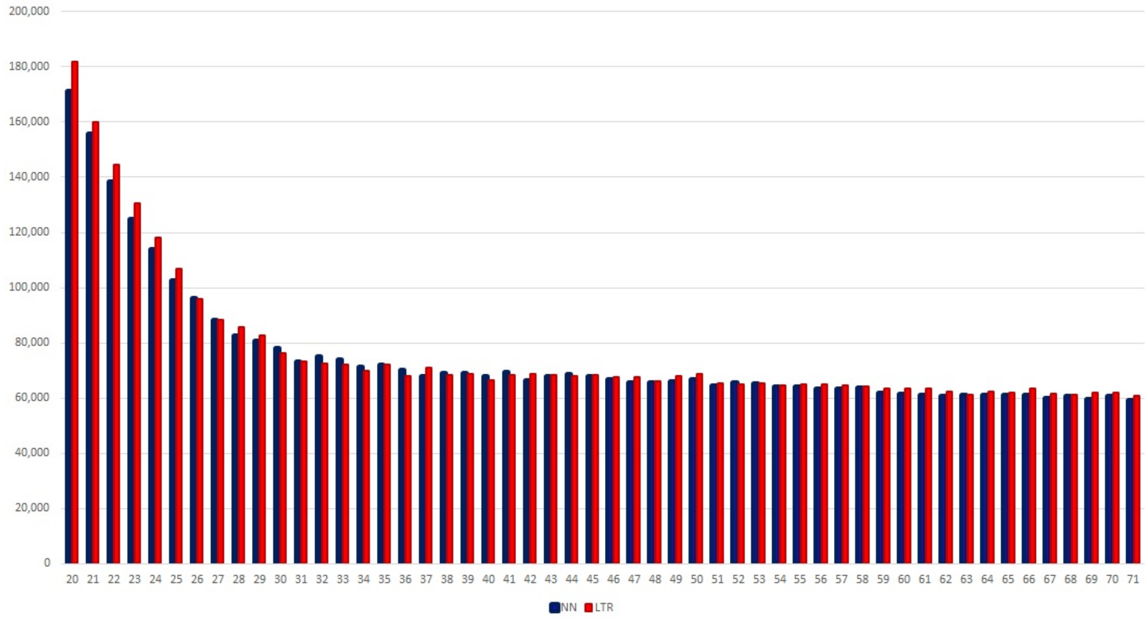
By changing the number of trucks, we plotted the total transmission risk value under the nearest neighbor policy and lowest transmission risk policy when the global intervention put in the system on September 24 2014, which is the scenario 3 (Figure 6.7). To show the graph accurately, the number of trucks is from twenty in Figure 6.8.

When looking at both policies' total transmission risk values, they converge to 60,000 approximately. The reason is because of the limitation number of the burial teams. Once



- *x-axis: the number of trucks*
- *y-axis: total transmission risk*
- *dark blue: nearest neighbor policy, red: lowest transmission risk policy*
- *environment: scenario 3 (global intervention - September 24 2014)*

Figure 6.7. The total transmission risk according to the number of trucks

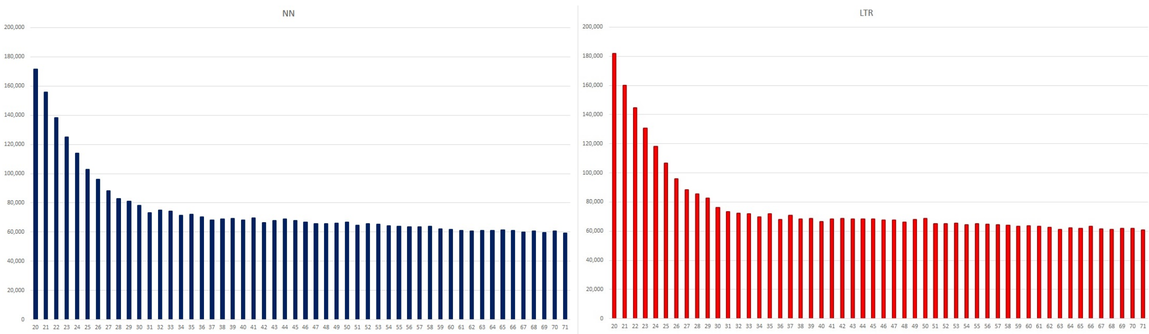


- *x-axis: the number of trucks (≥ 20)*
- *y-axis: total transmission risk*
- *dark blue: nearest neighbor policy, red: lowest transmission risk policy*
- *environment: scenario 3 (global intervention - September 24 2014)*

Figure 6.8. The total transmission risk according to the number of trucks (≥ 20)

we fix the maximum number of burial team at specific value, even though the number of trucks increases over that value, the system is affected a little.

Before operating about eighteen trucks, under the NN policy, the total transmission risk is almost twice to six times greater than the LTR policy. From near the number of trucks is eighteen, however, the NN policy can lower the transmission risk more than the LTR policy. This observation advocate that if there are very limited number of trucks under Ebola situation, LTR policy would be superior to the NN policy. Nonetheless, if healthcare organizations have more vehicles than that limited number of trucks, the NN policy is recommendable.



- The total transmission risk under each policy
- Left: under the nearest neighbor policy
- Right: under the lowest transmission risk policy

Figure 6.9. The total transmission risk under the NN and the LTR (≥ 20)

Under the NN policy, the total transmission risk decreases exponentially as the number of trucks increases. If the number of trucks is sixty approximately, the differential of the risk function becomes close to zero but still positive (Figure 6.9). That is to say, even though healthcare organizations get more trucks than sixty and try to lower the risk, the reducible total transmission risk value is small unless the organizations employ more burial workers.

On the other hand, under the LTR policy, the transmission risk also decreases exponentially but considering the initial risk value, which is about a third to a half of the initial risk value of the NN policy, the decreasing rate of the total transmission risk function is less than the NN policy. Then also with around sixty trucks, the total risk function starts decreasing slowly (Figure 6.9). This suggests the approximated lower bound of the number of trucks in the Ebola epidemic case.

Furthermore, the policy 1 is affected more by the number of eet than the policy 4 due to the characteristic of policy 1. Since the policy 1 considers only distance, as the number of vehicles increases the distance between the truck and the demand is more likely closer, which results in the higher exponential reduction rate than that of the policy 4. This observation supports that, LTR policy will have the lowest or lower total transmission risk among the suggest policies whenever the resource is not sufficient.

Based on the plotted graphs, we analyzed the sensitivity of total transmission risk caused by different number of trucks.With this analysis, the LTR policy is recommended when there are very limited number of trucks, that is less than about eighteen trucks in Ebola environment. If the number of available vehicles increases the NN policy is better than LTR policy. Then once the number of available trucks reaches around sixty, more trucks would be redundant in terms of reducing the total transmission risk function.

7. CONCLUSION

7.1 Summary

Logistics under the disaster and epidemic environment is referred as humanitarian logistics, which comprehends the preposition of the emergency stocks, to build infrastructure, to aid victims, and to provide relief supplies. Humanitarian logistics is the most signicant operation in emergency situation because it is directly connected to relief victims.

Especially, in the 2014 Ebola outbreak in West Africa humanitarian logistics was critical since the high transmission risk of Ebola remains can be curtailed by the rapid burial. We defined the casualty transportation problem to minimize the transmission risk of deceased victims under Ebola environment. The casualty transportation problem is the variant of dynamic pick-up and delivery problems. Since during execution of routing, a truck determines the next demand, pick up the demand, and transport it to the aimed burial site, the rapid burial problem can be considered as the application of dynamic pick-up and delivery problems.

The casualty transportation problem of the 2014 Ebola was deciding the next demand to be served. Also, there were too many infected deceased victims to be retrieved fast due to the resource deciency. In addition, adequate guideline for Ebola casualty transportation was insufficient and the decision making rule to route vehicles were unknown. Also, little literature has handled casualty transportation problems and the transmission model of affected corpses.

Considering this aspect, we define the casualty transportation problem. Also, we define the total transmission risk function under Ebola situation. The total transmission risk function ($B_d(t)$) that we developed is the updated version of the transmission rate function ($\beta_d(t)$), which is available in the literature. $B_d(t)$ encompasses the response time, transmission rate of each infectious remains, and the total number of remains. Minimizing $B_d(t)$

is the objective of our problem. Hence, minimization of the total transmission risk implies shorter response time and less risk caused by corpses. This functions is updated when the routing is executed thus our problem is dynamic.

To solve the casualty transportation problem, we established six policies to minimize total transmission risk. The policies are nearest neighbor, first come first served, last come first served, lowest transmission risk, highest transmission risk, and highest transmission rate combined with the nearest neighbor policy. With the total transmission function, we evaluated the six policies and found the best performing ones, which reduces the total transmission risk in different scenarios.

To examine the effectiveness of the suggested policies, we developed the simulation models which renders the 2014 Ebola outbreak in Liberia thoroughly. By defining twelve scenarios, we described the 2014 Ebola outbreak in Liberia. All the experiment settings were based on the empirical data from the actual articles and literature.

After running the models with different scenarios, we concluded that the nearest neighbor policy and the lowest transmission risk policy outperform rest of the policies. Next, the last come first served policy is also discovered as one of the competent rules among the suggested policies. To support this fact, we analyzed the experiment results by analyzing the variance and comparing those policies statistically.

Furthermore, to propose the minimum number of fleet we changed the number of trucks within the best policies then plotted the total transmission risk along with the different number of trucks. The graphs showed that if around sixty trucks are available within the nearest neighbor policy and the lowest transmission risk policy, the rapid burial process can be operated well thus burial teams can retrieve infectious remains fast and the total transmission risk is reduced.

7.2 Future Work

The future work might be to elaborate the total transmission risk function integrating the susceptible population around infected remains. The proposition for the minimum number of vehicle can be formulated mathematically, optimized and generalized to entire infectious disease environments and not only to Ebola condition. From this perspective, although the suggested simulation models are for the 2014 Ebola outbreak in Liberia, it can be improved and generalized for the entire infectious disease considering the number of susceptible population and the total transmission risk function of different infectious diseases.

APPENDIX

Appendix A: Ebola Case Counts

The data of confirmed Ebola cases and deaths in Liberia is recorded in the following pages. This data is obtained from Centers for Disease Control and Prevention (CDC, 2015).

WHO report date	Total Cases	Total Deaths
3/25/2014	0	0
3/26/2014	0	0
3/27/2014	8	6
3/31/2014	8	6
4/1/2014	8	2
4/2/2014	8	5
4/7/2014	18	7
4/10/2014	22	14
4/17/2014	27	13
4/21/2014	27	13
4/23/2014	34	11
4/30/2014	13	11
5/5/2014	13	11
5/14/2014	12	11
5/23/2014	12	9
5/27/2014	12	9
5/28/2014	12	9
6/2/2014	13	9
6/5/2014	13	9
6/10/2014	15	10
6/11/2014	15	10
6/18/2014	33	24
6/24/2014	51	34
7/2/2014	107	65
7/7/2014	115	75
7/8/2014	131	84
7/14/2014	142	88
7/16/2014	172	105
7/21/2014	196	116
7/24/2014	224	127
7/28/2014	249	129
7/31/2014	329	156
8/3/2014	391	227
8/4/2014	486	255
8/8/2014	554	294
8/12/2014	599	323
8/13/2014	670	355
8/15/2014	786	348
8/19/2014	834	466
8/21/2014	972	576
8/22/2014	1082	624
8/28/2014	1378	694
9/6/2014	1871	1089
9/8/2014	2046	1224
9/12/2014	2081	1137
9/16/2014	2407	1296
9/18/2014	2710	1459
9/22/2014	3022	1578
9/24/2014	3280	1677
9/26/2014	3458	1830
10/1/2014	3696	1998
10/3/2014	3834	2069
10/8/2014	3924	2210
10/10/2014	4076	2316
10/15/2014	4249	2458
10/17/2014	4262	2484
10/22/2014	4665	2705
10/25/2014	4665	2705
10/29/2014	6535	2413
10/31/2014	6535	2413

11/5/2014	6525	2697
11/7/2014	6619	2766
11/12/2014	6822	2836
11/14/2014	6878	2812
11/19/2014	7069	2964
11/21/2014	7082	2963
11/26/2014	7168	3016
11/28/2014	7635	3145
12/3/2014	7635	3145
12/10/2014	7719	3177
12/17/2014	7797	3290
12/24/2014	7862	3384
12/31/2014	8018	3423
1/7/2015	8157	3496
1/14/2015	8331	3538
1/21/2015	8478	3605
1/28/2015	8622	3686
2/4/2015	8745	3746
2/11/2015	8881	3826
2/18/2015	9007	3900
2/25/2015	9238	4037
3/4/2015	9249	4117
3/11/2015	9343	4162
3/18/2015	9526	4264
3/25/2015	9602	4301
3/26/2015	9602	4301
3/27/2015	9602	4301
3/30/2015	9602	4301
3/31/2015	9712	4332
4/1/2015	9712	4332
4/2/2015	9712	

4/7/2015	9862	4408
4/8/2015	9862	4408
4/9/2015	9862	4408
4/10/2015	9862	4408
4/13/2015	9862	4408
4/14/2015	9862	4408
4/15/2015	10042	4486
4/16/2015	10042	4486
4/17/2015	10042	4486
4/18/2015	10042	4486
4/19/2015	10212	4573
4/19/2015	10042	4486
4/21/2015	10212	4573
4/22/2015	10212	4573
4/24/2015	10212	4573
4/26/2015	10322	4608
4/28/2015	10322	4608
4/29/2015	10322	4608
5/2/2015	10322	4608
5/3/2015	10564	4716
5/3/2015	10507	4691
5/5/2015	10564	4716
5/6/2015	10564	4716
5/9/2015	10604	4769
5/10/2015	10604	4769
5/12/2015	10604	4769
5/13/2015	10604	4769
5/16/2015	10666	4806
5/19/2015	10666	4806
5/20/2015	10666	4806
5/24/2015	10666	4806

5/26/2015	10666	4806
5/27/2015	10666	4806
5/30/2015	10666	4806
5/31/2015	10666	4806
6/4/2015	10666	4806
6/5/2015	10666	4806
6/6/2015	10666	4806
6/7/2015	10666	4806
6/9/2015	10666	4806
6/10/2015	10666	4806
6/13/2015	10666	4806
6/14/2015	10666	4806
6/16/2015	10666	4806
6/17/2015	10666	4806
6/21/2015	10666	4806
6/23/2015	10666	4806
6/24/2015	10666	4806
6/29/2015	10666	4806
6/30/2015	10666	4806
6/30/2015	10666	4806
7/3/2015	10706	4811
7/4/2015	10670	4807
7/5/2015	10670	4807
7/8/2015	10670	4807
7/9/2015	10672	4807
7/10/2015	10672	4807
7/13/2015	10672	4807
7/14/2015	10673	4808
7/15/2015	10673	4808
7/16/2015	10672	4808
7/17/2015	10673	4808

7/20/2015	10673	4808
7/21/2015	10673	4808
7/22/2015	10672	4808
7/23/2015	10673	4808
7/24/2015	10673	4808
7/27/2015	10673	4808
7/28/2015	10673	4808
7/29/2015	10672	4808
7/30/2015	10672	4808
7/31/2015	10672	4808
8/3/2015	10672	4808
8/4/2015	10672	4808
8/5/2015	10672	4808
8/6/2015	10672	4808
8/7/2015	10672	4808
8/10/2015	10672	4808
8/11/2015	10672	4808
8/13/2015	10672	4808

(Centers for Disease Control and Prevention, http://www.cdc.gov/vhf/ebola/outbreaks/2014-west-africa/previous-case-counts.html)

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