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A Mixed Integer Programming optimization model for scheduling blood donors in disaster & emergency response: a case study of Nairobi region

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A Mixed Integer Programming Optimization Model for Scheduling Blood Donors in Disaster & Emergency Response: A Case Study of Nairobi Region

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Declaration and Approval

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the proposal contains no material previously published or written by another person except where due reference is made in the proposal itself.

Samuel Maina Githogori

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Approval

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Abstract

In recent years, Kenya has experienced tragedies ranging from natural disasters such as floods, terrorist activities such as the Westgate and Garissa University attacks, man-made tragedies such as road accidents and collapsed building, as well as tragedies resulting from reckless human behavior, such as fuel siphoning, and building next to power lines. When such kinds of disasters and tragedies occur, they have historically caused serious injuries that sometimes cause death. Also, during such events, medical emergencies arise, blood is one of the most critical components required by medial responder, and health facilities in order to perform transfusions that are necessary to save the lives of individuals. In the past, nationwide blood appeals have been conducted by authorities such as the Kenya Red Cross Society, media houses, politicians, and ordinary citizens, and Kenyans of Goodwill respond in large number at blood donation centers to donate blood. The challenge arising is that the system of appealing for blood is informal, unstructured and fragmented. It is difficult to track the effectiveness of ad-hoc methods of appealing for blood, and hard for potential blood donors to determine their eligibility in case they need to assist. The study proposed a mixed integer programming (MIP) model to optimize decision variables, which would determine the most optimal donation schedule and location for a given donor, based on whether they are eligible to donate, or not. The model sought to reduce the cost of responds, which is a function of the probability that a request for blood appeal will be posted, and the number of trips, distance, and cost it takes donor to respond. The model incorporated constraints such as donor availability within a given time block, and donor willingness to respond in a given region. The model's outcome suggested that increased donor flexibility leads to a decrease in cost per donation session, and an increase in available regions increases donor flexibility, hence lower cost per donation intervention session on the donor.

Keywords: *Blood donor, disaster, emergency, mixed integer programming, optimization.*

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Acronyms

CDC – Center for Disease Control and Prevention

IRIN - Integrated Regional Information Networks

KNBTS – Kenya National Blood Transfusion Service

MCI – Mass Casualty Incident

MIP – Mixed Integer Programming

NDMU – National Disaster Management Unit

OCHA - United Nations Office for the Coordination of Humanitarian Affairs

SOP – Standard Operating Procedures

WHO – World Health Organization

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Chapter One

Introduction

1.1 Background

Deaths resulting from injuries and violence constitute a major global public health concern, which has been neglected for many years. At least 14,000 people lose their lives daily due to injury (World Health Organization, 2014; Center for Disease Control and Prevention (CDC), 2019). This translates to at least 5 million deaths annually, from the same cause. Injury-caused deaths should be prioritized in the global health agenda as they account for 9% of all deaths in the world, a Figure that is 1.7 times higher than fatalities caused by tuberculosis, HIV/AIDS, and malaria combined (W.H.O, 2014; CDC, 2019) Injury is a board concept whose major causes include violence against others or oneself, burns, drowning, falls, poisonings, burns, and road traffic accidents (W.H.O, 2014). Deaths occurring from accidents tend to have a long-term psychological impact on the families and communities of those affected. Tragedies caused by injury deaths have been found to cause an irreversibly change in affected persons.

Kenya is one of the low-income countries most affected by injuries and violence, many of which lead to thousands of deaths, and an even higher number of injured persons. Road accidents, alone, cause 3,000-12,000 deaths annually in Kenya (W.H.O, 2018). Other major causes of injuries and deaths in Kenya include civil violence, between individuals, and between communities, natural disasters such as floods, terrorist activities such as those experienced in shopping malls, and learning institutions, human negligence in the case of building collapses, and isolated medical emergencies (PreventionWeb, 2014). In 2013, the Westgate Mall in Nairobi was attacked by terrorist from the Al-Shabaab terror group, leading to over 60 deaths and hundreds of fatal injuries (McConnel, 2013). Following the attack, there was a nationwide appeal for blood, which say thousands of Kenya avail themselves at different donation centers in Nairobi. During Kenya's post-election skirmishes of 2007/2008, over 1000 people died and thousands more sustained serious injuries requiring immediate medical attention (Schwartz & Colbran, 2014). These are some of the instances that justify the assertion that Kenya is an accident-prone nation, and when such events occur, people sustain injuries necessitating

One of the vital components that is at the core of most disaster and emergency responses in Kenya is the need for blood, and its availability in response to the tragedies. Historically, when emergencies of high magnitude arise, they are accompanied by significant blood loss by victims of the tragedies. As noted by Waweru (2017), in a news article for Capital FM, in times of disasters such as war, bomb blasts, and road accidents, blood transfusions are vital first interventions that enable medical teams to stabilize the patient in preparation for additional treatment. Sometimes transfusions may also be required during amputations, which may be necessary to save the lives of tragedy victims. Hospitals and other medical facilities become overwhelmed by the number of injury victims requiring immediate medical attention in order save their lives.

Many factors contribute to Kenya's relatively high risk of experiencing disasters and emergencies that would result to injuries and deaths. According to a report by the Integrated Regional Information Networks (IRIN), a former project of the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), there are many disasters, especially man-made ones, waiting to happen in Kenya (2011). For instance, construction undertaken under electric power lines or near petroleum pipelines put thousands of people living in proximity at risk. This issue was raised by Kenya's former Internal Security Minister, Orwa Ojode, regarding the construction of residential housing new the Jomo Kenyatta International airport, and other major airstrips such as Wilson (The New Humanitarian, 2011). Other looming disasters include floods, fires, especially those occurring in congested slum areas, siphoning petroleum from oil tankers, and road accidents (The New Humanitarian, 2011). These instances demonstrate that Kenya's risk exposure to disasters is significantly high.

Kenya is making significant strides in disaster preparedness through measures such as increasing ambulance services per county and health facilities, increasing medical supplies and emergency meals, and other intervention mechanism, but still lags in ensuring blood availability. During emergencies and disasters, humanitarian organizations such as the Kenya Red Cross, authorities such as the Kenya National Blood Transfusion Service, media houses, politicians, affected health facilities, and individuals embark on nationwide appeals for blood donations (European Commission, 2013; Ooko, 2018). However, such efforts have persistently failed to address the immediate and long-term need for blood to satisfy its demand during disasters and emergencies. Similarly, there is no mechanisms to determine their effectiveness in reaching eligible and potential donors. While a collective effort from multiple parties may be seen to maximize the potential to reach a large pool of donors, it is imperative to improve on timing, accuracy of appeal notification delivery, and targeting of the ideal blood donors.

1.2 Problem Statement

During major disasters and emergencies involving many injuries and causalities in Kenya, there lacks an effective system that instantly identifies the need for blood donations and sends out appeals to eligible donors. There is a need to ensure constant blood supply in Kenya's blood bank and responding facilities to cater for people in need (Amref, 2018). They also maintain large databases of their patients, including blood data which would indicate their blood types (Njuguna, 2012). Therefore, hospitals and related health facilities have the potential to respond more effectively to emergencies by sending out blood appeals to the ideal candidates and maximizing their chances of saving lives during emergencies (Dhingra, 2011). Millions of eligible blood donors are unaware of their status and potential to save lives during emergencies, disasters, and tragedies. Most people are also willing to donate blood, but are not sure where to proceed. Therefore, it is necessary to eliminate mitigate these challenges by developing a solution, which suggests and optimal donation schedule that accommodates the donor preferences and any constraints that may inhibit their willingness to donate blood during emergencies or on a regular basis.

1.3 Aim

This study aimed at develop mixed integer programming optimization solution that for scheduling blood donors during disaster and emergency response. The model proposed model would be used as a backbone for developing a schedule recommendation system that allows users (blood donors) to specific their schedule preferences, and then the system computes an optimal donation schedule that reduces costs of response. The model's goal was to determine individuals with the highest possibility of receiving and responding to the appeal, and then prompt them to respond to emergencies and disasters through blood donations. The model analyzes context information such as location of responding medical facilities, location of the donor, traffic conditions (such as trip duration to response facility) and the eligibility of the blood donor to donate blood, in order to determine the most suitable candidates for receiving initial notifications for blood appeal, and automatically adjusts its recommendations based on changes in the contextual factors specified.

1.4 Specific Objectives

i. To analyze the contextual data used to determine the decision-making process during emergency response in Kenya.

ii. To review existing decision models applied to contextual data for decision-making in mass blood appeals.

iii. To develop a mixed integer programming (MIP) model that optimizes contextual decision variables in decision-making during disasters and emergency response.

iv. To test validate the model the model developed for efficiency and optimality in schedule donors for blood donation during disasters and emergencies.

1.5 Research Questions

i. What is the context data used to inform the decision-making process during emergency response in Kenya?

ii. What are the existing decision models applied to contextual data for decision-making in mass blood appeals?

iii. How can a mixed integer programming (MIP) model that optimizes contextual decision variables in decision-making during disasters and emergency response?

iv. How can the MIP model be tested, and validated for efficiency and optimality in delivering scheduling of blood donor responders during emergencies?

1.6 Justification

Currently, Kenya lacks a standardized system for scheduling blood donors to respond to blood appeals during disasters and emergencies such as road accidents, building collapses, terror attack, violence and many other causes of injuries and deaths. Blood appeals and their responses have traditionally sent via mass broadcasts (The Standard, 2019). They have been unstructured and fragmented with no functional mechanism for targeting people who are eligible to donate blood and have the potential to save lives (Kenana, 2019). The proposed model can help bridge gap between donors and their capacity to respond to disasters and emergencies blood donations. The model can improve the process by maintaining an updated database of eligible blood donors, recommending donation schedules, identification of donation centers, and optimizing donor responses, and enable near real-time monitoring of accidents and disasters that may necessitate appeals for blood.

The solution is relevant as it seeks to optimize the factors that determine if a donor can respond to the appeal for blood donations, or not. It identifies constraints that may inhibit potential donors from responding to appeals, such as cost and availability. Similarly, the model is applicable even in emergencies that are not mass casualty events, that is, those that involve many deaths or injuries. It also creates more awareness of accidents and tragedies among communities of eligible blood donors, effectively creating a sense of constant and sustained awareness of their potential to help through blood donations. In addition, the model is scalable and can accommodate new response locations and still operate optimally. The solution could also be improved to schedule mass blood donations, monitor blood reserves to pre-empt shortages, and incorporate an incentive-based system for rewarding individuals who are consistent in their responses to appeals, and demonstrate constant commitment to donate blood.

1.7 Scope

The study was designed for use by all eligible blood donors who have access to a smart phone. Eligibility was determined based on the criteria provided by the Kenya National Blood Transfusion Service. For non-smartphone users, the model can be scaled down to determine an optimal donation schedule by estimating the location of an individual based on the records on file. Since disasters and emergencies can occur at any time and in any location in Kenya, the model was designed to scale with the ability of covering multiple response facilities in multiple regions, provided the regions it serves have adequate internet coverage for location precision, and for smartphone users to have the capacity to respond to appeals based on their preferred schedule.

1.8 Limitations

The study applies only to eligible blood donors who have access to mobile devices, preferably smart phones. The MIP model is not a blood matching service. Therefore, it may be inefficient in serving people who are in urgent need of blood, but are not currently receiving treatment in the responding facilities. Similarly, since the solution targets potential blood donors as the application's primary users, it discriminates against all other individuals who have the potential to assist with blood appeals during disasters and emergencies. The model's implementation also relies on smartphone devices as its primary mode of implementation is through an application. Functional internet or mobile network connectivity on the user's and administrator's application is key to the efficient execution of the model. Also, since it aims for real-time implementation, the MIP model may require users to be online when the disaster response in initiated. Therefore, potential users who reside in areas with poor or no internet, or GSM mobile network coverage, may be limited in using the model's solution even if they qualify as eligible donors.

Chapter Two

Literature Review

2.1 Introduction

This section provides a review of literature on optimization algorithms used for disaster management, including preparedness and response, based on decision variable occurring within the disaster context. It begins with a theoretical review focusing on the planned behavior perspective for explaining motivation to donate blood. The review proceeds to evaluate the different kinds of optimization and their application in aiding decision-making during disaster response and relief. It evaluates stochastic models, evolutionary algorithms, and mixed integer programming models. It proceeds to identify key gaps in existing research, and in Kenya's disaster response approach and proposes how the current study can eliminate the blood donor problem during disasters such as mass casualty events in Kenya, through an MIP scheduling algorithm for blood donors. This section concludes by proposing a conceptual model which illustrates how the key variables interact with the optimization model to produce the desired output, which is an optimal schedule for each donor.

2.2 Theoretical Review

Blood transfusion and organ donations are some of the vital procedures that can save life, or enhance its quality. The commonality between the two procedures is that they both rely on a community of well-wishers, who are primarily driven by goodwill, to donate blood and organs. According to the Australian Red Cross, the supply of blood and organs is always at a constant low (Australian Red Cross Blood Service, 2011). This trend exists even though people tend to have a positive attitude towards such humanitarian acts. In fact, studies have shown that people who donate blood are also likely to donate their organs upon death (Conesa, Zambudio, & Ramirez, 2004; Horton & Horton, 2001). Another study found that when people participate in one donation behavior such as blood donation, they are likely to participate in another, in future (Bekkers, 2010). Studies have applied social-cognitive models in attempts to understand the motivating factors' behind individual choices to donate blood or organs. The studies also aim at understanding the similarities or differences in people's motivation to donate, to inform the creation of cost-effective focused strategies that can encouraging donating behaviors within a given society (Boulware et al., 2002). Hence, it is important to understand the dynamics of donor motivation to inform intervention strategies during disasters and emergencies.

The commonality between blood and organ donation is that both practices, especially in the western world, involve organs whose supply is limited, and donation activities are not accompanied by external rewards such as financial incentives. In most cases, the donors and recipients are unknown to each other (Hyde, Knowles, & White, 2013). Some of the characteristics of blood donations is that they are conducted whilst the donor is alive, and blood is a resource, which the body can regenerate. It is also possible to donate blood multiple times (Sanner, 1998; Kluge, 2000; Piliavin, Shanteau, & Harris, 1990). There are many theories that have sought to explain why people's motivation to donate blood and organs may be different or similar. Some suggest that people may be motivated by altruism and the desire to help others (Morgan & Miller, 2002; Sojka & Sojka, 2008, Hyde & White; 2010). People may also be motivated by the fact that their actions will save or lives. It is also possible that individuals who donate blood and organs want to build a donor identity. However, the formation and importance of such an identity varies depending in the frequency of donation, and has a high potential for reinforcement if blood donation is continued (Masser et al., 2008). Thus, it is possible that when people are encouraged to donate blood more frequently, they can continue the trend by themselves if they desire to build a donor identity.

2.3 Theory of Planned behavior

One of the theories that has been proposed to explain the motivations and decisions of people to donate blood is the theory of planned behavior (TPB). The theory holds, "a person's intentions (readiness to act) as the most proximal determinant of his or her behavior" (Hyde et al., 2013). Factor that inform a person's intentions include a person's attitude towards donation behavior (attitude can be positive or negative), subjective norm (how they perceive social pressure social approval for their donation actions), and perceived behavioral control (PBC). The latter involved the perceived ease of complexity of performing the behavior, which is also a direct predictor of the behavior (Ajzen, 1991; Ajzen, 2002).

With respect to blood donations, people are expected to have greater intentions to donate when they have more positive attitudes towards the exercise, perceive people within their social circles are supporting their decisions to donate, and when they believe that blood donation is a simple thing to do (Hyde & White, 2009; Masser et al., 2008). The original TPB model has been extended to include additional variables to enhance the model's capacity for predicting intentions and/or behaviors of blood and organ donors. The variables include a person's feeling towards the responsibility of donating (moral norms), and self-identity, which is the person's individual view of self as the kind that would donate blood or organs (Armitage & Conner, 2001; Godin, et al., 2005).

2.4 State of Blood Donations in Kenya

Following the recent terror attacks, and especially the most recent one in January, there has been renewed focus on the alarming state of blood donations in the country, especially during disaster and emergency. Beyond disasters, thousands of Kenyans in hospitals across the country require blood for transfusion every day, for different treatment purposes such as surgery. The current director of the Kenya National Blood Transfusion Services (KNBTS) notes that in the three days that the public responded to the mass blood appeal for the dusitD2 attack victims, about 822 pints were collected, an exceptionally high number (Kenana, 2019). She further notes that such occurrences where donations are in large numbers typically occur immediately following a mass blood appeal broadcast. An interesting statistic that was discovered in the study regarding the nature of blood donations and utilization in Kenya is that about seven Kenyans need blood every ten minutes, as shown in Figure 2.4.1. Essentially, the demand for blood in Kenya outweighs supply at any given time. When combined with the constant likelihood of a mass casualty event occurring, then the situation is one that warrants an intervention to ensure constant blood supply, or at the very least, guarantee blood availability when it is needed.

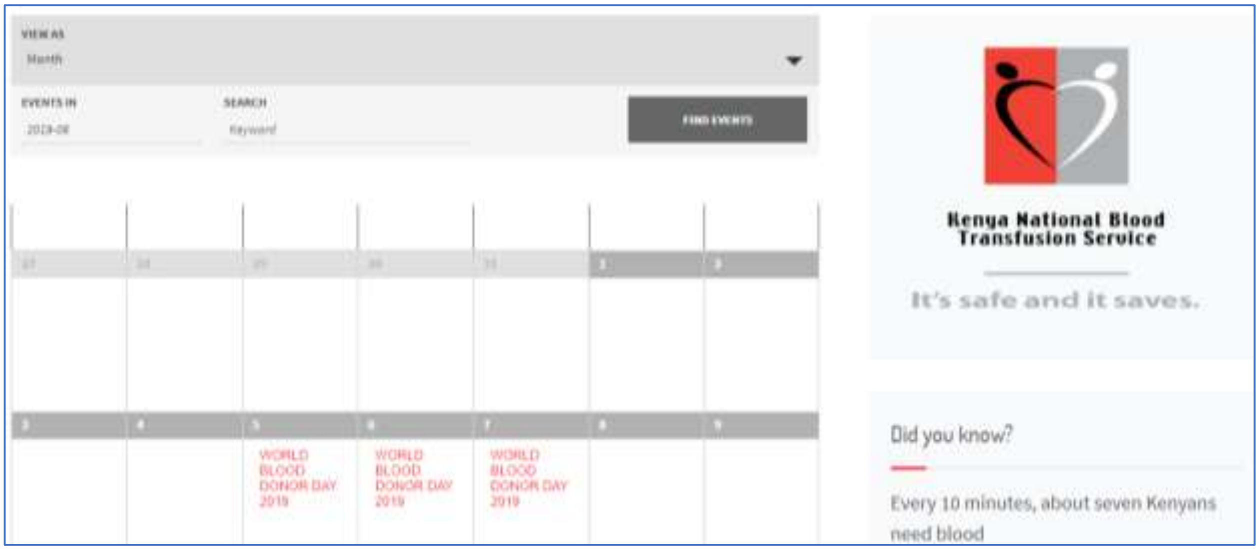

Figure 2.4.1 KNBTS Statistic on Blood Demand (KNBTS, 2019)

One of the challenges that inhibits consistence in ensuring adequate blood supply is that a vast majority of Kenyans are not aware of the essence of blood as a critical element of survival, and most importantly, the constant need to have it in ample supply because it can be required indefinitely. At any given time, a potential donor can become the intended receipient of blood since events such as accidents can occur at any time and impact anyone who is affetced. Beyond incidents such as MCIs, the demand for blood is heightened by many health conditions being treated in hospitals independent of disasters or MCI. For instance, a recent artcile in the Daily Nation noted that blood shortages tend to affect women and children mostly. Conditions such as postpatern haemorrhages account for about 35 percent of maternal deaths (Kenana, 2019). treatment for diseases such as cancer, kidney and liver diseases, aneamia, and even stabilzing and treatment of road accident survivors all require blood. These are situations where the millions of eligbile blood donors in Kenya have an opportunity to intervene, especailly during emergency when blood demand is heightened.

The challenge of inadequate bllod supplies is multidimesnional and cuts across different sectors. The reality of Kenya's blood reserves sitautaion is that they are almost empty and the orgnaization that are klegally nmandated to conduct collection exercses to replenish the exhausted stocks are underfunded and understaffed, according to findings from a 2019 expose by the Saturday Standard. The annual collection rate of blood donations by the KNBTS constanly falls short of the intended target. According to The Standard (2019), the KNBTS has collected 164,275 units of blood, against the annual target of 300,000 units. Its is unclear whether the units collected are within a one year period. Assuming that the findings were pointing to an annual collection rate, then it would represent about 55 percent of the targettted collection, which is considered adeaute to meet the blood demand for Kenya's medical sector. A brief audit of the KNBTS website revealed that in a span of three months (Februrary, April, May), there are not sheduled blood collection events in the country, which supports findings of the Standard expose. The next schedule is in June as the events timetable indcates in the website captute A screenshot of the colelction events callendar of KNBTS is shown in Figure 2.4.2 for the month of May 2019.

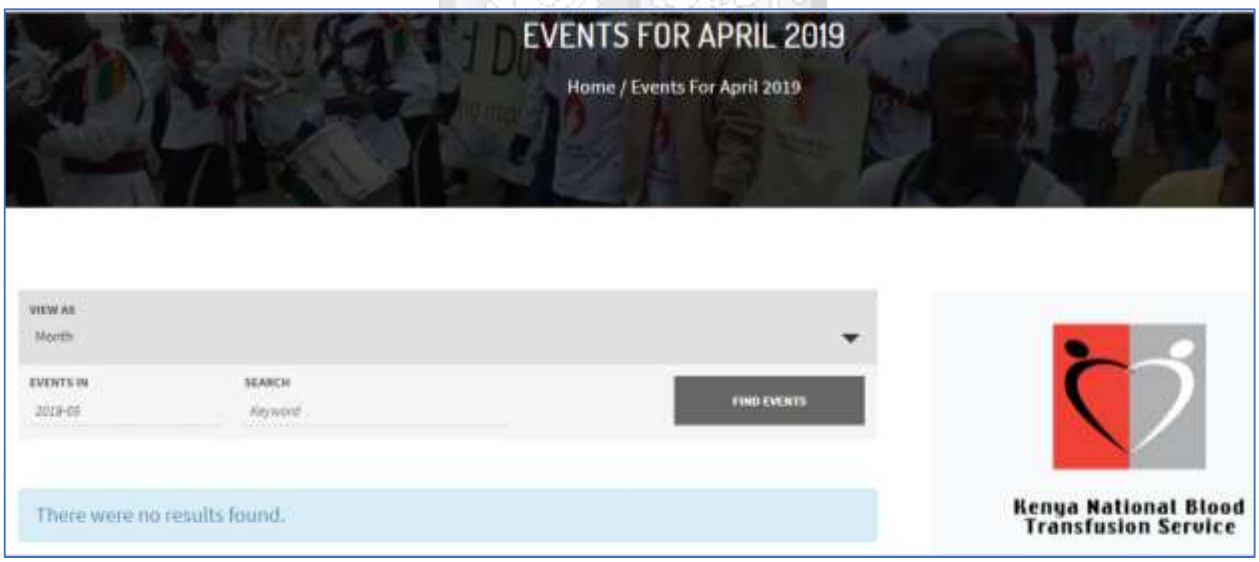

Figure 2.4.2: No Collection Event Scheduled for May 2019 (KNBTS, 2019)

Beyond the institutional issues noted, another inhibitor to adequate blood supplies, as revealed in the Kenyan context, is the lack of public awareness of blood donation centers in the country. Kenana (2019) notes that Kenyans lack awareness on where to donate blood. In many instances, they only donate blood when there is a mass appeal because it is normally accompanied by locations where they can show up to donate. This occurrence is despite the fact that according to the criteria for blood donations in Kenya, as defined by the KNBTS, people within the stipulated age group (16-65) are eligible to donate blood at least three (females) to four (males) a year, provided all other conditions are met, as shown in the Table 2.4.1, which summarizes the blood donation criteria used in Kenya (Kenya National Blood Transfusion Services, 2013). It is worth noting that blood also has a short shelf-life of about 35-42 days (Kenana, 2019). Hence it cannot be stored for long. Thus, fully resolving the issue of blood supply while ensuring efficient utilization, and no wastage, the culture of blood donation should be promoted among, and adopted by Kenyans. The culture can be promoted by the blood collection and disaster response agency collaboration in adopting technology-driven solutions such as scheduling models that can optimize the variables that determine if Kenyans respond to donation appeals or not.

Table 2.4.1 KNBTS Blood Donation Criteria

Blood Donation Criteria (KNBTS)	
Variable	**Value**
• **Hemoglobin**	12g/dcl
• **Blood Pressure**	Normal
• **Weight**	At least 50 Kilograms
• **Age**	16 - 65 Years
Donor Ineligibility	
• **Under Medication** • **Recently Vaccinated** • **Recently Tattooed/Pierced** • **Chronic illness** • **Women in menstrual period** • **Breastfeeding women** • **Below 50 Kgs**	
Donation Frequency	
• **Men**	**Every 3 months**
• **Women**	**Every 4 months**

Another criterion applied in the transfusion stage involves ascertaining that the donor and recipient are a match, and that the patient in need of the blood can benefit from the donor's humanitarian deed. While the donor has no control over this process, the fact that he/she has contributed to ensuring there is an adequate and available supply of blood maximizes the chances that a match will be achieved from the many blood samples available. Matches are determined by blood groups, as shown in Figure 2.4.3, as summarized by the Australian Red Cross Blood Service (2019). However, the process is conducted in the latter stages of the intervention process, which are not within the scope of this study.

Donor's Blood Type

Patient's Blood Type	O-	O+	B-	B+	A-	A+	AB-	AB+
AB+	✓	✓	✓	✓	✓	✓	✓	✓
AB-	✓		✓		✓		✓	
A+	✓	✓			✓	✓		
A-	✓				✓			
B+	✓	✓	✓	✓				
B-	✓		✓					
O+	✓	✓						
O-	✓							

Figure 2.4.3: Donor-Recipient Blood Matching (Australian Red Cross Blood Service, 2011)

2.5 Nature of Disasters and Emergencies in Kenya

The important role of Kenyan citizen, and the public in general, in assisting during emergencies is a demonstration that blood donation is a critical component of Kenya's disaster response strategy, even though such intervention measures are not addressed Kenya's disaster management guidelines or protocols (National Disaster Management Unit, 2016). There are three major mass casualty incidents that have happened in Kenya in the last 5 years, all linked to terrorism activities. In 2013, the Westgate shopping mall in Nairobi Kenya was raided by terrorist during the day, on September 21st (Gettleman & Kulish, 2013). After law enforcement agencies eliminated the threat, at least 67 people had been confirmed dead, and over 175 people sustained non-fatal injuries. In total, the incident resulted in over 240 casualties (Howden, 4). From these incidents, it is important to consider the disaster response process from the authorities mandated with the responsibility, including the stage of response where blood donor was requested to donate blood to hospitalized victims of the incident.

In a separate, but related incident two years later, in April 2015, the same group of terrorists from the Al Shabab terror organization attacked a learning institution in Garissa, the Garissa University college, unlike in the Westgate terror attack, the incident began in early morning hours, and continued well into the day. In total, it took less than 24 hours to eliminate the terror threat. In contrasts, it took the law enforcement officers over 24 hours to contain the Westgate terror threat. In the Garissa attack, at least 147 lives were lost, majority of whom were students studying at the institution (Mutiga, 2015). Some enforcement agents who were early responders to the incident also died in the process of executing their duties. During the Garissa attack, at least 147 people died, while another 70 were confirmed to be injured (Human Rights Watch, 2015). However, the actual number of deaths and injuries was expected to rise later after the incident was resolved (Human Rights Watch, 2015). The injured were taken to local hospital (accident response facilities) within the proximity of the institution, while critically injured persons were airlifted to Nairobi by the disaster management authorities.

Recently, in January 2019, Kenya suffered another major setback in its national security efforts and achievements when members of the same terror groups struck again by launching an attack in a Nairobi hotel, the dusitD2. The attack began in the afternoon of Tuesday, January 15. Several hours after the attack began, it was contained by Kenya's law enforcement agents from multiple agencies. At least 15 people were confirmed dead (Burke, 2019). Another 28 people who were injured in the attacks were rushed to nearby hospitals (responding facilities) for further treatment (BBC News, 2019). The attack was of a smaller scale compared to the other two even though it took several hours to eliminate the threat, implying some injured persons could have been trapped at the scene of the incident for as long as the threat containment process was underway.

The three events were selected for review because they have key characteristics common across them, which also inform the disaster response process in Kenya, as far as blood appeals and donations are concerned. For instance, all three events involved terror attacks by the Al-Shabaab militant group (Agence France-Presse, 2019). The three events were unpredictable in the sense that even though possible intelligence may have existed regarding their imminent occurrence, it was not enough, or acted upon early enough for disaster response authorities in Kenya to prepare for the attacks and their possible outcomes. The attacks, which can be considered unpredictable, also had the potential to cause more harm had response from law enforcement agencies been interrupted of delayed. Most importantly, and in relation to the current study, these events involved different degrees and response levels from disaster management and response authorities in Kenya such as the NDMU, and the Kenya Red Cross, who were responsible for coordinating relief operations including evacuation of the dead and injured persons from the incident scenes (NDMU, 2014). Finally, the events also resulted in a considerable number of injured persons, and a corresponding mass blood appeal by disaster response authorities, to aid the injured persons as a mechanism for intervention in the incidents.

There are many more incidents of a similar nature that have occurred in the country within the last half decade year period, that have also resulted in mass casualties, or a significant number of deaths, as summarized in Table 2.5.1. In many of these instances, a mass blood appeals normally accompanies such incidences, sometimes after they are concluded, or during the response process. For instance, in the Westgate attack, mass blood donations followed especially 24 hours after the incident occurred. According to a report by the Daily Nation, about 1500 people had reported to Kenyatta hospital to donate blood for victims of the incident, within one day of its occurrence (Nation Reporter, 2013). People continued to donate blood well after the incident had been concluded. One of the donors at the Kenyatta National Hospital was quoted as saying, “I am here to help, and if possible, I will come back if they ask for more. I really want to help the victims of this terrible attack” (Nation Reporter, 2013). Other donors showed up with family members to aid in blood donation. In the incident, some of the other donation centers set up to receive blood donations were either within the responding facility (hospitals), or their vicinity.

Table 2.5.1: Summary of Mass Casualty Incidents in Kenya Since 1975 (NDMU, 2014)

Date	Disaster	Region	Casualties	Response	Remarks
1975	Terrorism - bomb blast	Nairobi - OTC bus	27	Government investigation	Political instability
1981	Terrorism – bomb blast	Nairobi - Norfolk hotel	5	International investigation	Linked to M/East crisis

1993	Ngai-Ndethya Train crash	Mtito-Andei	140 dead, 6000 rescued passengers	Kenya railways, GoK	Train crushed into bridge and plunged into river
1994	Ferry accident	Mombasa	270 Dead	Navy and Ports Authority rescue operation	Overloading and faulty engine blamed
1997-1998	Floods – El Nino	Countrywide L. Victoria basin most affected	1.5 million people affected. Damage to infrastructure, property and crops	GoK, UN, NGOs, El Nino Emergency Project	Outbreak of water-borne diseases
1998	Terrorist attack – bomb blast	Nairobi – US embassy	214 dead, 5,600 injured	Kenya Army rescue operations	Restriction on border entry points
2000	Terrorist attack – bomb blast	Kericho	101 dead		Speeding bus collided with another bus
2002	Bombing	Kikambala	13 dead, 80 injured	Kenya Police, IDF, KDF	Paradise Hotel bombed
2004	Landslides	Nyeri District	5 dead	Local communities	
2004	Food Poisoning (Aflatoxin)	Makueni, Machakos, Kitui	82 dead, hundreds hospitalized	Medical supplies, food inspection	Landslides in Kenya not fully studied
2005	Alcohol Poisoning	Machakos	50 dead, scores blinded	Medication, crackdown on illicit brew	Indication of poverty level
2006	Nyamakima Building collapse	Nairobi	11 dead, 70 injured	Soldiers, firefighters, Israel Army, Kenya Red Cross	Unfinished five-storey building collapsed
2007-2008	Post-election violence	Countrywide	1,133 dead, thousands injured	GoK, Kenya Police, NGOs, Kenya Red	Nation-wide violence triggered by 2007 election results disagreements.

				Cross, Hospitals	
2009	Nakumatt Fire, NRB	Nairobi	29 dead, hundreds injured	GoK, NCC, Fire Brigade, NYS, Military, Kenya Red Cross	Fire in a supermarket in Nairobi CBD
2009	Sachangwan oil spill	Molo	113 dead, 200 injured	GoK, hospitals, Kenya Red Cross	Oil spill from an overturned truck burst into flames
2011	Sinai fire incident	Nairobi	121 dead, 67 injured	GoK, Police, Kenya Red Cross, Hospitals.	Kenya Pipeline fire
2013	West gate terrorist attack	Nairobi	67 dead, 205 injured	Military, Police, EMS, Kenya Red Cross, Hospitals	Terror Attack in a mall
2013	Ntulele Road Accident	Narok	42 dad, 33 injured	Police, Kenya Red Cross, Hospitals.	City to City bus veered off the road and plunged into a valley
2014	Likoni church terror attack	Coast	6 dead, 15 injured	Police, Kenya Red Cross, Hospitals.	Terror Attack
2014	Gikomba Terror attack	Nairobi	10 dead, 103 injured	Police, EMS, Kenya Red Cross, Hospitals	Terror Attack
2014	Mpeketoni attack	Coast	65 dead, 4 injured	KDF, Police, EMS, GoK, Kenya Red Cross, Hospitals	Terror Attack
2015	Garissa University – Terror attack	Garissa County	148 dead, 79 injured	KDF, Kenya Police, EMS, Kenya Red Cross, Hospitals	Terror attack by Al-Shabaab on Garissa University

2019	dusitD2 Hotel	Nairobi County	21 dead, tens injured	GSU, Kenya Police, Kenya Red Cross, Hospitals	Terror attack by Al-Shabaab at dusitD2 Hotel complex

In such incidences, the willingness of Kenyans to donate blood as means of responding to, and intervening in the disaster is undoubtedly evident and unquestionable. Even when incidence occur in one location, it is possible for Kenyan's to offer blood donations from other distant regions. In the case of the Westgate attack, residents from Kisumu, a region that is at least 300 kilometers away from the scene of the incident responded to the mass blood appeal (Kang'ethe, 2013). Another important finding from a preliminary study of mass casualty incidents such as terror attacks is that it is common practice that emergency facilities of the closest proximity to the incident scenes are the main recipients of the injured persons. Universally, it is standard practice for disaster responders to rely on facilities that are closest to the incident scenes, unless they are also compromised, for instance, in the case of disasters resulting from natural calamities such as floods or earthquakes. Therefore, in the case of the Westgate attack, the responding emergency facilities were hospitals within proximity to the incident site, including MP Shah Hospital, and Kenyatta National Hospital, among others. In the recent dusitD2 terror attack, hospital receiving the injured victims included the Aga Khan hospital, M.P. Shah hospital, Avenue Hospital, and the Kenyatta national hospital (Omondi, 2019). All these hospitals were within a 5-kilometer radius of the incident.

Given these scenarios, and the dynamics of the response mechanisms from the disaster management authorities, and the Kenyan public, it is evident that blood donation, even though not covered within the disaster response protocols of the country, as vital to the relief process. The Table 2.5.2 summarizes the three major events, the number of persons injured, the responding facilities, and the number of donors reporting to the facility. Although the donor numbers are not officially confirmed, they provide an idea of the nature of public response to mass blood appeal for blood during such incidents. It is also worth considering the nature of mass broadcasts as a mechanism for communicating important information regarding blood appeals. Mass broadcast channels are conventionally utilized in Kenya for mass blood appeals include television (TV), radio, and social media. These avenues are the most preferred because they ensure maximum reach in the audiences they target. For instance, in the recent dusitD2 attack, the Kenya Red Cross posted a request for blood appeal through Twitter (Omondi, 2019). Politician, celebrities, media personalities, and heads of disaster management and response authorities are the most common origins and promoters of mass blood appeals, perhaps in a bid to emphasis the urgency, or enhance the validity and legitimacy of the requests made on mass broadcast platforms.

Table 2.5.2: Recent Terror Events in Kenya, and Resulting Injuries

Incident	Location	Injured Persons	Responding Facilities	Estimated Number of Donors
Westgate terror attack	Nairobi	175	Kenyatta N. Hospital, M.P. Shah, others	Over 3000
Garissa Terror Attack	Garissa	70	Garissa Level 5 Hospital, others	Over 500
dusitD2 Terror Attack	Nairobi	28	Kenyatta N. Hospital, M.P. Shah, Avenue, Aga Khan	At least 800

2.6 Disaster Management in Kenya

In Kenya, Disaster management is a responsibility of the National Disaster Management Unit. The authority was established by a presidential directive (Ref. No. CAB/NSC/14/2/32) in 2013. NDMU is the overall authority overseeing disaster management operations, including disaster preparedness planning, and disaster response activities. To assist in running in the effective running of its operations, NDMU has the following components within it:

a) Command Structures
b) Operating Budget
c) Standard Operating Procedures (NDMU, 2016).

For on-site management of disaster, the NDMU has established a command structure that is headed by the Incident Commander, who is the overall authority or coordinating disaster response and relief during (NDMU, 2014). Figure 2.6.1 shows the command structures as specified in the National Emergency Response Plan & Standard Operating Procedures (SOPs) of the NDMU. As seen in the illustration the incident commander has direct oversight of the Medical Commander, who coordinates the evacuation of incident victims to response facilities. The facilities could be hospitals or morgues, depending on the nature of the fatalities.

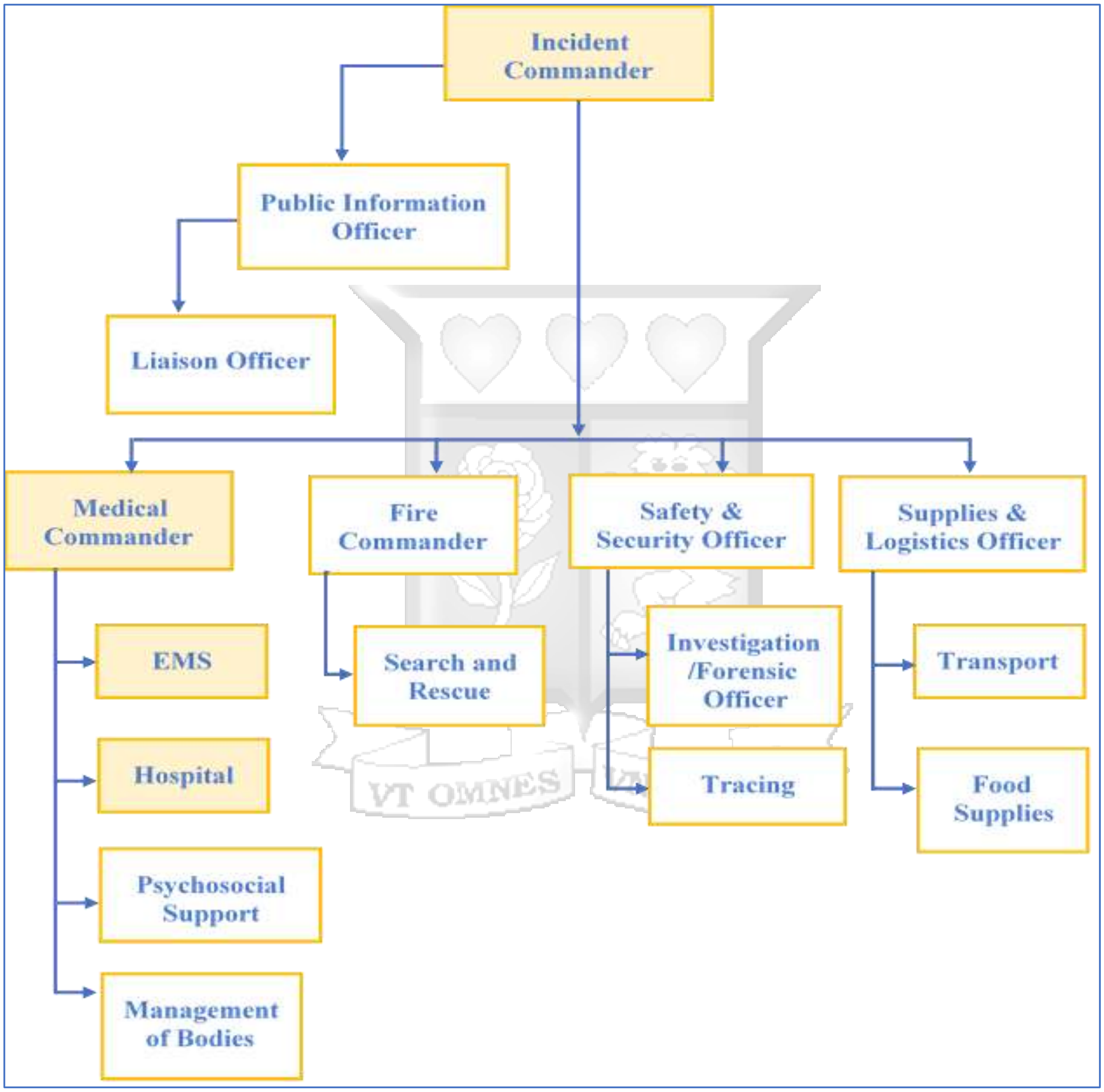

Figure 2.6.1: NDMU Command Structure (NDMU, 2014)

With regards to blood donation as a response and intervention mechanism during disasters and emergencies, the authority in charge of authenticating a legitimate demand for blood supply is the medical commander in coordination with the incident commander. However, the actual demand information is provided by the responding facilities, which are contained within the command structure, as “Hospitals” (NDMU, 2014). After validation of blood demand, the mass broadcast is issued to the public to appeal for blood, even though that protocol is not covered within the NDMU SOPs.

2.7 Stakeholders in a Mass Casualty Incident (MCI)

2.7.1 Coordination and Command Structure in an MCI

In an MCI, there various functions of the involved in disaster response. Key among them include:

1) MCI Activation

When a mass casualty event (MCI) occurs in the country, the director of the National Disaster Operation Centre (NDOC) is responsible for declaring, activating, and mobilization of the response necessary for the event. In case the Director is unavailable or incapacitated., the Director of the NMDU assumes those responsibilities (NDMU, 2014). Upon the declaration and activation of the MCI, all the stakeholders linked to the event deploy with the goal of saving lives, as per the protocol.

2) Hospital Response: Alert and Notification

For a hospital to respond to an incident, there are two primary approaches: it can receive an advance warning, which recognizes that an untoward incident is likely to happen; or a post-incident warning, which is likely to disrupt normal hospital operations. Advance warning information can originate from multiple sources, including police intelligence communicated through a clearly-defined communication plant, EMS, or a local EMA notification, which confirms that a special event or on involving a mass gathering is ongoing (NDMU, 2014). An advance warning could also be a weather forecast that may hint on conditions which are unfavorable or threatening.

Hospitals can receive three key types of notifications: An *Advisory* is issued when a system response is not necessary, but there is potential for a response; An *Alert* is issued when the probability for a response is high of imminent, and this kind of notification ought to trigger an elevated degree of response preparedness; An *Activation* occurs when a response for the MCI for the hospital is required (NDMU, 2014). The notifications are typically received by the local Public

Health Department, of the emergency management office. In typical cases of MCI, hospitals are unlikely to receive warning of an incident. They mostly rely on situational assessments as indicators or confirmation that something has happened, from sources such as TV, radio, EMS radio, significant utility loss (such as a blackout) or victims who arrive early and share details of the event (NDMU, 2014). Information accuracy and clarity tends to increase as situational awareness progresses.

The immediate information required by hospitals to aid in response preparedness includes, but is not limited to:

a) Incident type (include specific hazard if known)

b) Incident location

c) Types and number of injuries

d) Special interventions taken (e.g. decontamination or bus transportation)

e) Estimated time of arrival (ETA) of first-arriving EMS responders (e.g. ambulances) (NDMU, 2014).

2.7.2 Operational Levels (Bronze, Silver & Gold)

There are three key operational levels that successful scene management needs to adhere to: They include:

a) **Bronze –** field (A joint command post is set up).
b) **Silver –** A remote command center near the scene (e.g. a regional station).
c) **Gold –** At policy/strategic level (NDMU, 2014).

1) Bronze Level Operations

At this level MCI management happens at the scene of the incident while under the guidance of the Incident Commander. It contains the following command positions:

a) Medical Commander
b) Fire Officer
c) Investigator/Forensic Officer
d) Supplies and Logistics Officer

e) Public Information Officer
f) Liaison Officer
g) Safety and Security Officer (NDMU, 2014).

2) Silver Level Operations

This management level requires the establishment of a remote command post, which is not close to the MCI scene, but is capable of offering support to the response activities through enhanced resource mobilization and harmonization. Key roles at Silver Level include:

a) Planning and Operations
b) Administration and Finance
c) Technical experts (Engineers, Medical, Security, etc.)
d) Information Management

3) Gold Level Operations

These operations occur at policy/strategic level. These commands include:

a) Cabinet meetings
b) The relevant Parliamentary committees (NDMU, 2014).
c) Inter-sectoral committees (NDMU, NDOC, etc.)
d) Inter-agency committees (IFRC, UN, KRCS, ICRC, etc.)

The proposed model operates at the Bronze level of operations, which normally involves events occurring at the scene of the incident, including the evacuation of injured persons.

2.8 Empirical Review

The following section reviews common optimization algorithms, and the contexts in which they are applied, including their application in disaster response and relief. The classic transportation problem is first discussed, as a benchmark for understanding the problem of demand and supply, and how it can be model to minimize cost as a form of optimization.

2.8.1 The Classic Transportation Problem

One the pioneering concepts in the field of optimization in operations research is the classic transportation problem. In resolving this problem, the goal is to minimize the cost of transporting a single commodity from a given (known source) to a known destination. This problem, which originated from the field of industrial logistics is a classic case in the computing paradigm of linear programming (Dantzig, 2016; Song, 2017). In the problem, a proposed optimization model accepts the following inputs:

a) Total number of units generated (produced) at the source.
b) The total number of units that are needed at each of the destinations in the network
c) The cost of transporting one unit from each of the sources, to each of the destinations (Song, 2017; Taylor, 2007).

The model's main goal is the minimization of the total transportation cost for the units from their sources to the destinations they are required. In order to solve the problem, the following steps are applied:

a) Formulating the initial solution, which is feasible.
b) Checking for optimality of the solution (which achieves lowest costs), and;
c) Iteratively improving current solution (Song, 2017).

The classic network problem is a network problem. Networks are directed graphs, which can be represented in the form of $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{A})$ as shown in Figure 2.8.1.

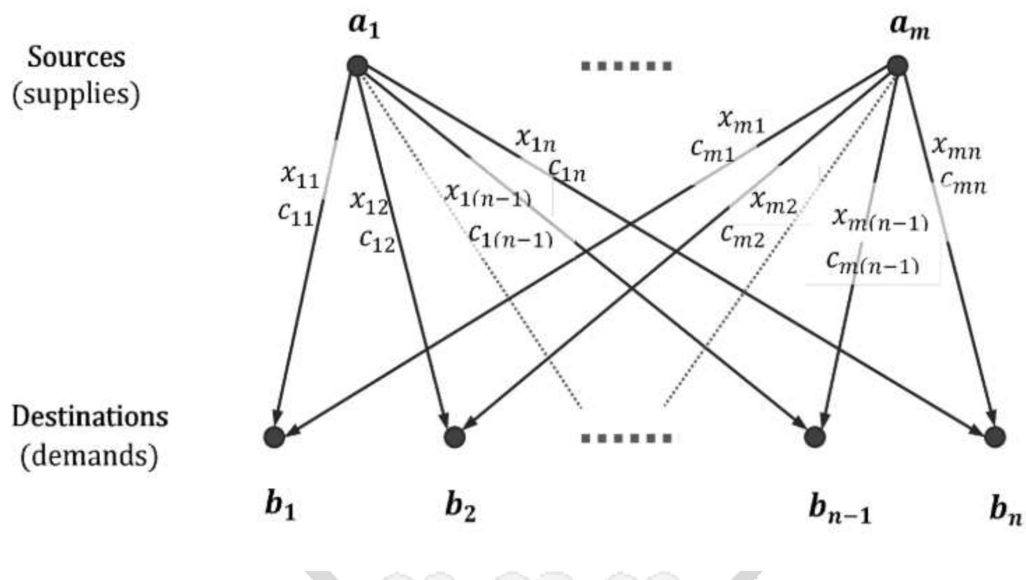

Figure 2.8.1: The classic transportation problem

2.8.2 Network Optimization

Numerous studies have been conducted on disaster response, and its dynamic aspects. For example, studies have sought to create optimization models that will support evacuation of injured victims, while others have sought to address the complex challenge of resource mobilization and distribution because in many emergencies, the demand for disaster relief resources tend to outweigh their supply. A study by Fereiduni and Shahanaghi (2016) proposed a network optimization model which aimed at assisting in allocation and location decisions during multiple disaster periods. The robust optimization model proposed by the study beings by proposing a single model, which assist decision-makers to make optimal decisions regarding the location of disaster response, the evacuation procedures, and the allocation of disaster relief resources, simultaneously. The other aspect of the study is creating a model which accommodates the uncertainties and dynamics that characterizes disasters, and how their impact the response process. In addition, the Fereiduni and Shahanaghi (2016) use the Monte Carlo simulation to simulate random scenarios and numbers, which model possible disruption that may occur within the distribution network during disaster response.

The study's proposed approach is a robust optimization, which attempts to model the entire disaster relief supply chain in a real-world scenario. The model considers that an ideal humanitarian network contains for functional stages:

a) Stage 1: Identifying and confirming relief bases
b) Stage 2: Establishment of relief tents relative to the disaster location
c) Stage 3: The set of affected regions
d) Stage 4: Hospitals that receive injured victim, and supply blood to relief tents for transfusions.

The network considers the location of relief bases is typically determined by their proximity to the affected region, and the maximum storage capacity of commodities that the centers can accommodate, including relief vehicles.

2.8.3 Stochastic Optimization Modelling

Another approach taken by research in optimization for disaster response is modelling for disaster relief planning under uncertainty. The basic idea of two-stage stochastic programming is that (optimal) decisions should be based on data available at the time the decisions are made and cannot depend on future observations. The two-stage formulation is widely used in stochastic programming. The general formulation of a two-stage stochastic programming problem is given by:

$$\min_{x \in X}\{g(x) = f(x) + E_{\xi}[Q(x,\xi)]\}$$

Equation 2.8.1: First-stage minimization function

where $\boldsymbol{Q}(\boldsymbol{x},\boldsymbol{\varepsilon}\ )$ = the optimal value of the second-stage problem.

$$\min_{y}\{q(y,\xi)\,|\,T(\xi)x + W(\xi)y = h(\xi)\}.$$

The classical two-stage linear stochastic programming problems is formulated in the following way:

Equation 2.8.2 Second stage minimization function

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & g(x) = c^T x + E_\xi[Q(x, \xi)] \\ \text{subject to} \quad & Ax = b \\ & x \geq 0 \end{aligned}$$

Where $\boldsymbol{Q}(\boldsymbol{x}, \boldsymbol{\varepsilon}\ )$ = the optimal value of the second-stage problem.

$$\begin{aligned} \min_{y \in \mathbb{R}^m} \quad & q(\xi)^T y \\ \text{subject to} \quad & T(\xi)x + W(\xi)y = h(\xi) \\ & y \geq 0 \end{aligned}$$

Uncertainty modelling has been addressed through approaches such as stochastic programming for distribution of relief commodities through prediction of probable scenarios. A study by Barbarosog˘lu and Arda (2004) applied stochastic programming in a two-stage model for disaster response during earthquakes. Stochastic models have also proven useful in scheduling of routes for relief vehicles after disaster occurs. Research has also demonstrated the application of stochastic optimization in the preparation phase of disaster management to aid in determination of medical supplies storage locations. Another study by Mete and Zabinsky (2010) also applied two-stage stochastic programming to model optimization during the disaster preparedness and response phases of disaster management. In the first stage, the stochastic model's goal is determination optimal aid positioning, while the second stage informed decision for distribution of resources. Stochastics models have also been applied in modelling for multiple objectives and nodes on a network. For example, a study by Najafi et al. (2013) created a multi-objective, multi-period, multi-commodity, and multi-node stochastic model for managing.

2.8.4 Mixed Integer Programming

Mixed integer programming is a recent and rapidly emerging optimization paradigm for disaster relief. Linear programming maximizes (or minimizes) a linear objective function subject to one or more constraints. Mixed integer programming adds one additional condition that at least one of the variables can only take on integer values. The technique finds broad use in operations research. The mathematical representation of the mixed integer programming (MIP) problem is Maximize (or minimize):

$$\boldsymbol{z} = \boldsymbol{C}\boldsymbol{X}$$

Subject to:

$\boldsymbol{A}\boldsymbol{X} \leq \boldsymbol{b}, \boldsymbol{X} \geq \boldsymbol{0}$, some x_i are restricted to integer values

where:

$$\boldsymbol{X} = (x_1, x_2, \dots, x_n)'$$
$$\boldsymbol{C} = (c_1, c_2, \dots, c_n)$$
$$\boldsymbol{b} = (b_1, b_2, \dots, b_m)'$$
$$\boldsymbol{A} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$$

Equation 2.8.3: Decision Variables, Constraints, and Constraint Bounds

MIP models are preferred especially when modelling the transportation of causalities into response facilities such as hospitals. The goal, in such a case, would be the minimization of transportation cost, and the unsatisfied demand for transport resources. In MIP models, weights can be used to differentiate between goods, and casualties, according to a study by Özdamar (2011). The study proposed a mathematical model combined with a route management procedure, which is the model, output post-processor. The study was a multi-objective and multi-criteria one. The first phase of the problem involved coordination of resource delivery, such as medicine, vaccine, blood, I.V. fluids, among others, to the areas affected by disasters, using helicopters (Özdamar, 2011). The second phase of the problem was evacuation of the injured persons, from the affected areas, using helicopters.

2.8.5 Research Gaps

Many of the studies conducted on optimization models for variables that aid in decision-making for disaster responses have applied a wholesome approach, with many seeking to address the entire disaster relief supply chain. As seen in the study by Fereiduni and Shahanaghi (2016), the robust optimization model accounted for all phases of the humanitarian network, including relief tents, hospitals, disaster locations, and relief resources. The primary gap identified in the model, with respect to the current study, is that it accommodates blood supply as a fixed resource, whose quantity and location is already known, and whose origin and destination are already predetermined. In contrast, the proposed mixed integer programming model handles blood as a scare resource, whose availability is unknown and not guaranteed until a disaster occurs. Similarly, the location of the relief centers in the proposed mode is pre-determined as many injuries that require transfusion are normally handled at hospital level, and not on site as in the Fereiduni and Shahanaghi model (2016). The proposed MIP model accounts for the fact that the blood resource is contained within human responders, whose role becomes relevant in the final phase of disaster response, after evacuation of injured victims. The MIP model should account for a response variable, which models the decision of blood donors (human responders) to respond to the appeal for blood or not.

2.9 Conceptual Framework

This section discusses the proposed conceptual framework for the MIP optimization model.

2.9.1 Decision Variables

The following Figure 2.9.1 shows the variables to be used in the optimization model. They are mainly concerned with the response facility and the donor because the donation process happens between the two parties.

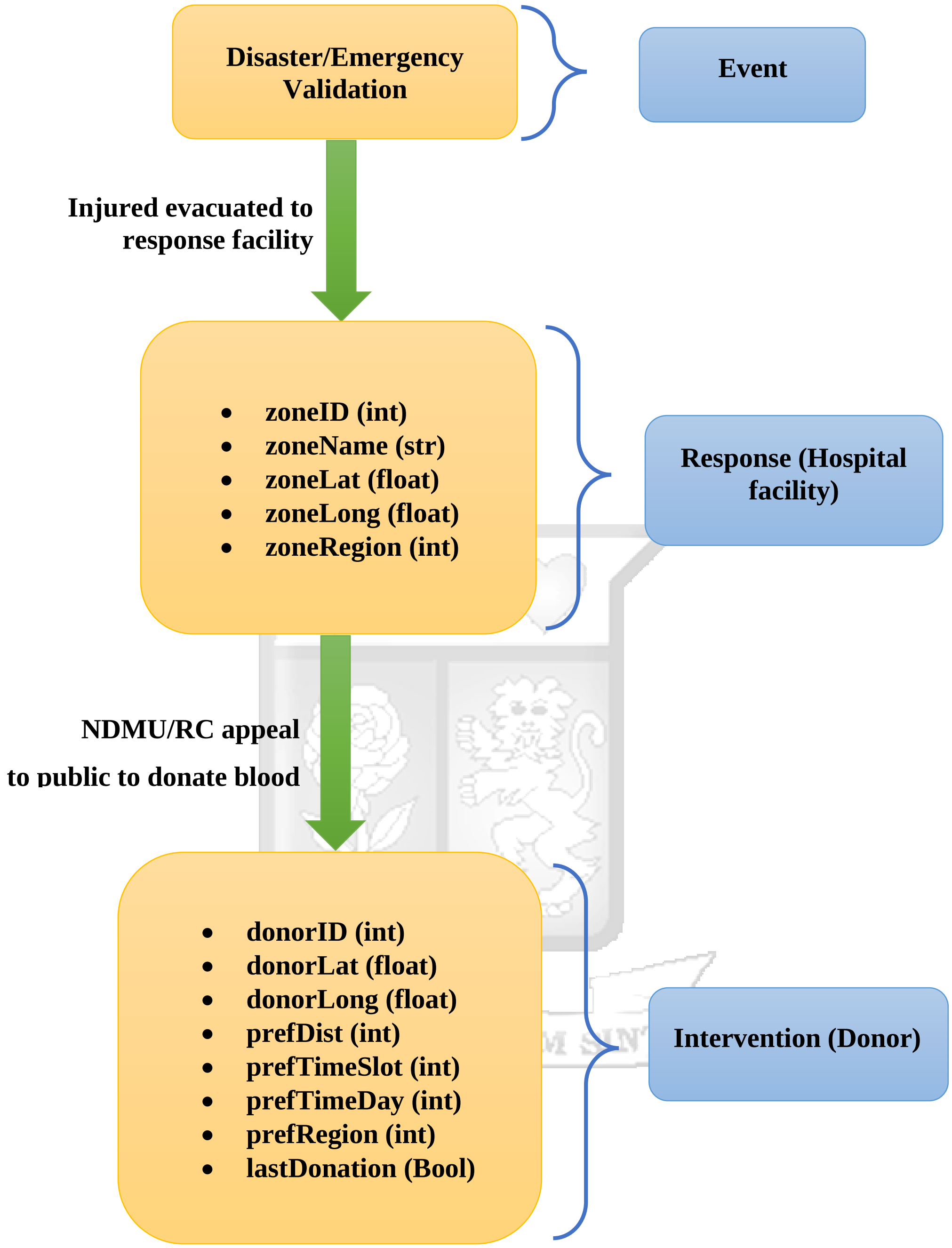

Figure 2.9.1: Model variables

Each parameter accepts multiple variables, it was not possible to represent them in the diagram, hence their exclusion. However, each parameter accommodates the respective variables outlines in Figure 2.6 above. The model accepts three main parameters, each of which contains constraints occurring within them. The MIP model generates an objective function. The model's expected outputs include calculating the minimal disaster response time, the optimal response facility, the optimal donor, and then determines the relevant notifications to be sent to then optimal intervention (donor), as shown in Figure 2.9.2

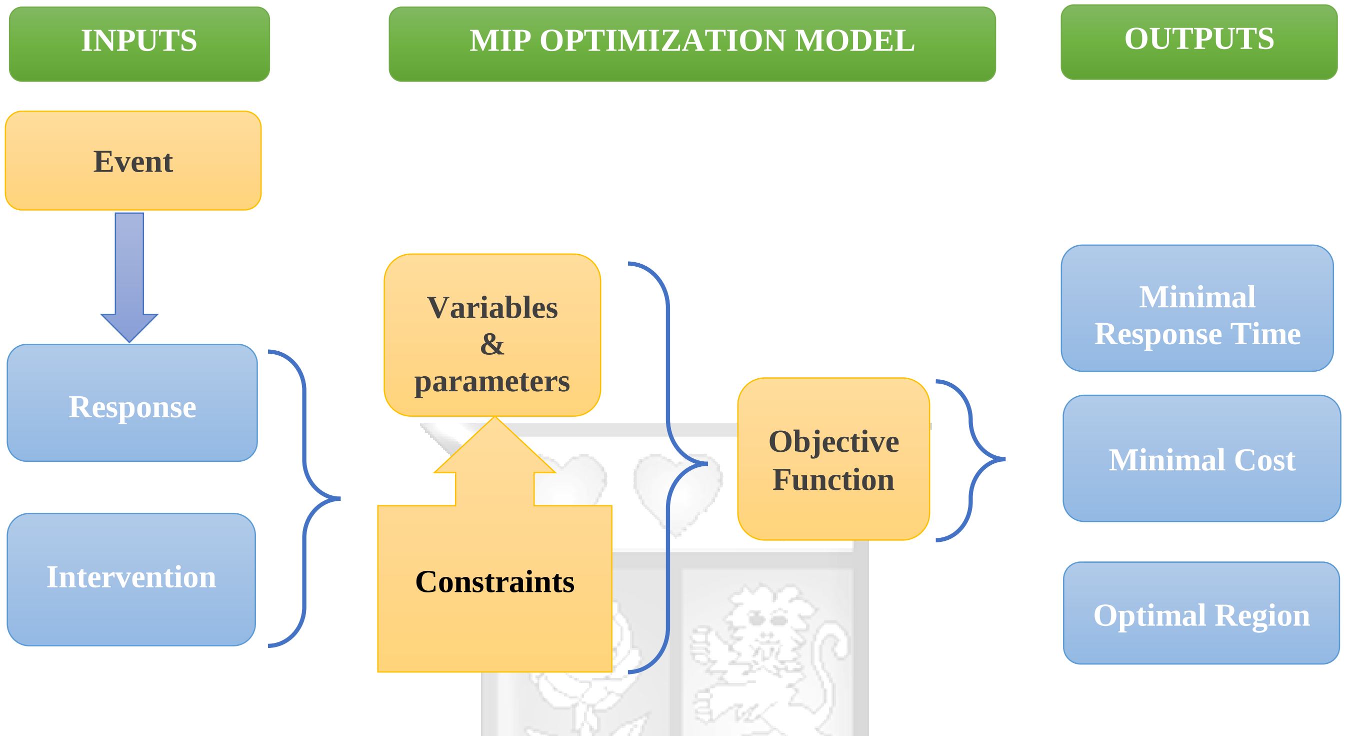

Figure 2.9.2: Model conceptual framework

Chapter Three

Research Methodology

3.1 Introduction

The following section provides an overview of the procedures and key methods applied to actualize the study. The research methodology was informed by the study's objectives and corresponding research questions outlined in Chapter 1. This chapter covers key methodological components such as the research design, research methods, data collection methods, and the implementation approach. The methodology was designed around the problem of lack of an optimal schedule for blood donations is Kenya when disaster strikes. By optimizing decision variables using MIP, it is possible to create an optimal schedule for eligible donors based on key preferences and possible constraints, thus maximizing their potential for responding to blood appeals.

3.2 Research Design

The study combined both qualitative and quantitative research designs. The application will be obtaining qualitative data from different stakeholders in Kenya's disaster response apparatus. The study adopts and experimental design, which Creswell (2013) describes as the application of scientific methods to establish the relationship between cause and effect of variable groups in a study. The goal of experimental designs is to control for all other variables apart from the independent one. Hence, the experimental design analyzes the independent variable's impact on the dependent variable. The experiment in the study was to determine how the optimization of decision variable would impact a donor's potential for responding to an appeal when presented with an optimal donation schedule.

3.3 Study Location

For the purpose of simulating the data that is required for the study, the optimal location for basing this research is the Nairobi Metropolitan area, which accommodates the major response centers that are activated during disasters and emergencies. They include the major hospitals such as Kenyatta National Hospital, MP Shah Hospital, Aga Khan University Hospital, Parklands Avenue Hospital, and the matter hospital.

3.4 Target Population

The model targeted blood donors who are normally requested to aid in donating blood to injured persons being treated at the activated response facilities, during disasters and emergencies. On the other hand, the data used in the model was simulation data that models a real-world scenario.

3.5 Population Sampling Procedure

For data collection, the key main sources sampled were two main groups: blood donors, and, disaster response authorities in Kenya, including representatives from the Kenya Red Cross Society, as NDMU-appointed authorities. Purposive sampling was applied in sampling disaster management authorities because they are few and their roles are specialized, implying they cannot be substituted. Random sampling was applied to the blood donor population.

3.5.1 Sample Size Calculation

The study applied the Cochran formula for calculating an ideal sample size when a desired level of precision, desired level of confidence, and the estimated proportion of the attribute present within a given population. The formula is especially ideal for both large and small populations. The formula is defined:

$$\boldsymbol{n_0 = \frac{Z^2pq}{e^2}}$$

Where:

a) e is the desired level of precision (i.e. the margin of error),
b) p is the (estimated) proportion of the population which has the attribute in question,
c) q is 1 – p.

The sampling calculation made the following assumptions:

1. Over half of the donors in the population are eligible to donate, hence **p = 0.5**
2. Desired confidence level = **95%**
3. Desired precision = **+/- 5%**

4. 95% confidence level = Z value of 1.96, provided normal tables.

Hence:

$$\left((1.96)^2(0.5)(0.5)\right)(0.05)^2 = 385$$

Given the number of registered donors within the red cross application is 1793, the Cochran formula can be enhanced since the population targeted is small. The modified formula is represented:

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}}$$

$$n = 385 \div (1 + (385 - 1)/1793)$$

$$= 317$$

The blood donors are categorized into blood groups, and members are encouraged to join depending on their respective blood groups, as shown in Table 3.5.1

Table 3.5.1: Number of Members per Blood Group on Red Cross App

Blood Group	Members
0-	155
0+	662
B+	284
B-	42
AB+	118
AB-	33
A+	349
A-	150
TOTAL	**1, 793**

3.6 Data Collection

3.6.1 Online Survey

Online surveys were part of the instruments of data collection applied. The surveys proved useful when collecting quantitative data, such as location data, frequency of donation, and awareness of eligibility criteria. The survey sought to obtain general information about the target population, including their location of residence, workplace location, age group, gender, and blood group. This information was required to create eligibility criteria for target users, including determination of constraints for blood appeal response.

3.6.2 Structured and Unstructured Interviews

Interviews were conducted with selected disaster response authorities in Kenya, specifically from the Kenya Red Cross society's Disaster Command Center. The main purpose of the interview was to determine the decision-making process in the stage of disaster response, which involves appealing to blood donors to assist in the process. Unstructured interviews were conducted with disaster response authorities and the general public to identify some of the disaster response challenges associated with the blood appeal process, and possible solutions to them.

3.6.3 Secondary Sources

Due to the fragmented and unstructured nature of blood donations in Kenya during disasters and emergencies, there lacks enough quantitative data on response rates, demand levels, and number of injured persons per blood group. Hence, data on such subjects was obtained from media outlets that report on disasters and emergencies when they occur. They include news articles featuring stakeholders of Kenya's disaster response authorities, and the Kenya National Blood Transfusion service, who can provide valid information regarding issues tied to disaster response in the county.

3.7 Data Analysis

The data obtained was analyzed using standard statistical operations to determine measure such as mean, and frequencies. It was used to determine the most ideal variables for optimization using the MIP model. The model can be used as the backbone of an appeal notification application for donors.

3.8 MIP Model Design

The MIP models assumes a procedural approach, which include the following stages:

3.8.1 Clustering of Response Locations

This stage of the model involved identification of the main response region and then determining the central locations for the demand clusters. These response sites are the major hospitals in Nairobi, for the sake of the study, as shown in Table 3.8.1. They were obtained by selecting the response facilities that account for the largest number of injured persons who are evacuated to the facilities during disasters such as MCIs. They include:

Table 3.8.1: Responding facilities and their coordinates

Hospital	Latitude	Longitude
Kenyatta National Hospital	-1.300788	36.807215
Matter Hospital	-1.306520	36.834317
MP Shah Hospital	-1.262216	36.812015
Aga Khan Hospital	-1.261395	36.824391
Avenue Hospital	-1.264482	36.817501

The locations were represented in form of longitudes and latitudes are these data types are necessary to calculate other key variables required for the MIP model.

3.8.2 Calculating Radius of Response Locations

The second step of the model creation involved determining the radius of each location, which determines the maximum distance from the response facility that the potential donor should be operating within for them to have the maximum potential for response. Radius was calculated by obtaining the minimum Euclidian distance of each facility to the other four facilities samples are response sites in the study. In order to maximize response, the donors needed to be operating within the radius of the facility.

3.8.3 Determining Model Variables and Parameters

The MIP model's primary variable is $\boldsymbol{Y}\_\{\boldsymbol{ab}\}$ which takes the parameters of the response facility's location, and the time block assigned for the response from the donor. The model's variable accommodates certain parameters that would be considered during variable optimization. Some of the sample parameters used by the model include:

i. $\boldsymbol{C}\_\{\boldsymbol{ab}\}$ **:** The expected total cost of navigating region b during within time a.
ii. $\boldsymbol{X}\_\{\boldsymbol{a}\}$ **:** A Boolean variable indicating whether the donor is willing to responds to request within time a.

There are some more parameters that will be discussed in detail in the system implementation stage.

3.8.4 Determining Model Constraints

The key constraints that affect the variables were then defined for the model. Since donor flexibility is key to maximizing their potential for response, then the model should target individuals with the least constraints to their flexibility. The following is a sample of the constraints applied to the model:

i. In constraint 1 $\boldsymbol{X}\{\boldsymbol{a}\} = \mathbf{1}$ indicates that the donor is willing to respond at time block $\boldsymbol{a}$, and **0** otherwise.
ii. In constraint 2, $\boldsymbol{W}\{\boldsymbol{b}\} = \mathbf{1}$ indicates that the donor is willing to operate within region $\boldsymbol{b}$**,** and **0** otherwise.

There are several other constraints applied to the model, which were discussed further in the system implementation stage. Table 3.8.2 shows a summary of the constraints applied to the model:

Table 3.8.2: Model constraints and explanations

Constraints	Explanations
$y_{a,b} \leq X_a, \forall a, b$	Constraint on time availability
$y_{a,b} \leq W_b, \forall a, b$	Constraint on region preference
$\sum_{a,b} x_{a,b} \leq T_{max}, \forall a, b$	Constraint on maximum time
$\sum_{b} x_{a,b} \leq 1, \forall a, b$	Constraint for responding in region only
$y_{a,b} \in, 0, 1, X_a \in 0, 1, W_b \in 0, 1$	Model's Boolean variables
$a \in A, b \in B$	A = set time block, B= set region

3.8.5 The MIP Methods

The MIP method was then constructed based on demand data obtained from the response facilities, and the time it takes to complete a trip from the donor location to the facility. The goal of the MIP method is to obtain an optimal schedule that donors can utilize when responding to calls for blood donation during disaster response. Therefore, the model's resultant MIP was determined to be:

$$\boldsymbol{min : Cost = \sum_{a,b} C_{a,b} \, . x_{a,b}}$$

Subject to:

$$y_{a,b} \leq X_a, \forall a, b$$

$$y_{a,b} \leq W_b, \forall a, b$$

$$\sum_{a,b} x_{a,b} \leq T_{max}, \forall a, b$$

$$\sum_{b} x_{a,b} \leq 1, \forall a, b$$

$$y_{a,b} \in \{ 0, 1\}, X_a \in \{0,1\}, W_b \in \{0,1\}, \boldsymbol{a} \in A, b \in B$$

3.8.6 Creating the Objective Function

The MIP's objective function was then obtained, and its goal was to minimize the cost of the donor over the course of his/her response session to the disaster/emergency's appeal for blood donations. Therefore, the objective function applied was:

$$\boldsymbol{C_{ab} = p(new\ appeal) \times minimum\ number\ of\ trips\ per\ session}$$

Further computations on the objective function will be covered in depth in the systems implementation stage of the study.

3.8.7 Python Implementation

The model was then implemented programmatically in MATLAB, a programming tool and environment tailored for mathematical computation, including optimization problems.

3.8.8 Model Performance

The model was run at least 100 times for each input instance. Computation times and objective values were obtained and recorded.

3.8.9 Determining Optimality

Optimality of cost was calculated against changing time blocks within a given response session.

3.9 System Development Methodology

Due to the limited time constraint on the model's development and testing, the Rapid Application Development (RAD) paradigm was applied in the study model implementation stage. RAD is a methodology that attempts to compress the development process such that a high-quality system can be obtained using the least investment costs. One of the advantages of RAD is that it can be a suitable methodology when the nature of the problem and its objectives are well-defined. RAD is also useful when the user group is also defined clearly, and when the project is time-sensitive. The RAD methodology contains four key phases as shown: requirements phase, user design, construction of the system, and cutover. The construction and user design phases can be repeated until user requirements are met. The phases are explained in detail in Figure 3.9.1.

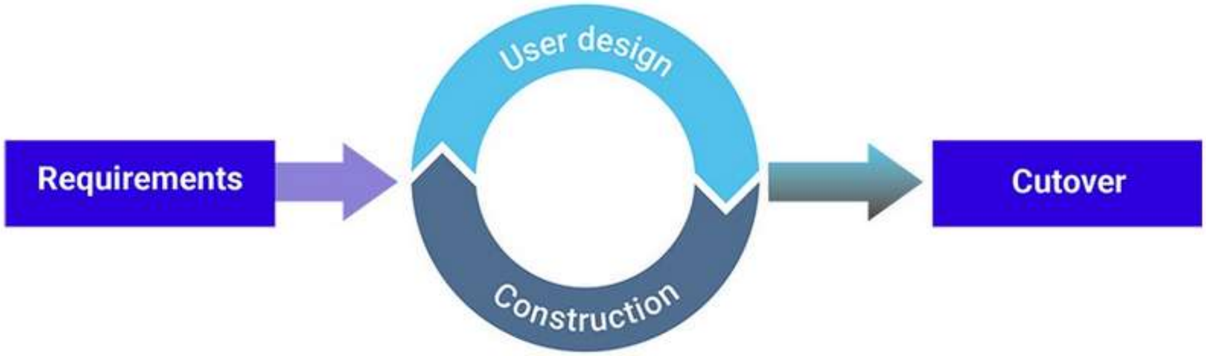

Figure 3.9.1: RAD Methodology

3.9.1 Requirements Planning Stage

This stage mainly involved collecting of all the relevant data, both quantitative and qualitative, which will be required in the MIP optimization model. The data was obtained from the public (potential donors), disaster response authorities in Kenya, and secondary sources such as the media. The data would be used to derive decision variable to be modeled by the system.

3.9.2 User Design Stage

This stage involved designing the architecture of the proposed model, and how users can interact with it. The design stage relied on Unified Modelling Language (UML diagrams) to describe process and data flows, as well as model execution flow. In the design stages, diagrams such as use cases, sequence diagrams, and class diagrams are designed. The main tool used for this stage was the Visual Paradigm Software.

3.9.3 Rapid Construction Stage

This stage involved actual model implementation through specification of objective functions, variable, their parameters, and their constraints. The modeling environment used was a combination of MATLAB and Python, in different implementation stages of the model.

3.9.4 Cutover Stage

This stage involved testing of the computed model using different types of simulated data to obtain outputs and measure for optimality.

3.10 Ethical Considerations

The study recognizes the need to adhere to the ethical and legal requirements of scientific studies in the country and in the context of software development. One of the emerging ethical issue is obtaining user data, sharing user data, and maintaining privacy and confidentiality. Since some of the data required to test and validate the solution is personal data, such as age, areas of residence, and blood group, the study accompanied its surveys and requests for information with privacy policies that explain how user data is utilized and whether or not the data will be shared. The study also incorporated a consent forms in its survey to enable users authorize collection and utilization of data by the application and the service it provides.

Chapter Four

System Design and Architecture

4.1 Introduction

The following chapter provides a comprehensive description and analysis of the proposed mode's design and architecture. The system is based on the optimization model obtained through the mixed integer programming (MIP) paradigm, and implemented through the IBM Simplex optimization algorithm. The system design and architecture are represented using Unified Modeling Language (UML) diagrams.

4.2 System Requirements Analysis

The system requirements analysis aims at determining the expectations of the users who will interact with the system being built. Therefore, the process largely involved determination of the tasks that are important in identifying the needs of different system stakeholders. Therefore, an effective requirement analysis is one that analyzes, documents, manages and validates the system requirements. The sections will define the functional and non-functional requirements for the proposed MIP-based optimization model. It provides and in-depth analysis of the requirements achieved by the model with respect to the study's primary objectives.

4.2.1 System Software Functional Requirements

Functional requirements are concerned with modelling the behaviors of the system from a business/operational perspective. These functions should primarily reflect user roles and tasks, or the systems goals and activities. The proposed MIP optimization model's functional requirements include: *Business rules, transactions and their adjustment, reporting requirements, legal requirements, and external interfaces*. The requirements are listed in Table 4.2.1.

Table 4.2.1: Functional Requirements

Functional Requirements
Business Rules
i. The system based of the MIP optimization model should support one category of users: donors ii. The proposed model should accept data input in form or response location and donor data. iii. The model should support a notification service to the main users **iv.** The MIP model should be implemented through an end-user application for the main user.
Transactions and Adjustments
i. The model should allow user input of requested data. ii. The model should allow modification of user input.
Reporting Requirements
i. The optimization model should incorporate a module, which allows for scheduled or on-demand reporting on transactions happing within unit time.
Legal Requirements
i. The system based on the optimization model should be able to prompt different categories of users to read, accept or reject its terms of service and privacy policy on data collection and usage.
External Interfaces
i. The model should support one main user interface: donor interface **ii.** A possible second interface can be derived from the model to support administrator transactions.

4.2.2 System Non-Functional Requirements

Non-functional requirements specify the “quality attributes” of the system. They offer a criterion with which to judge the overall operating of the system, and not specific functionalities as addressed in the functional requirements. The attributes covered in the system include security, performance, usability, and compatibility, among others. The essence of creating non-functional requirements is to enhance user experience, prevent system errors, ensure uptime, reliable results, and optimal utilization of resources. The MIP-based system includes the following non-functional requirements, as shown in Table 4.2.2.

Table 4.2.2: Non-Functional Requirements

Attributes	Requirement
Usability	The system should have the least learning and operation time, and allow fast integration into mobile or web applications.
Accuracy	The model should provide accurate approximations of optimal donation schedules and costs of response to blood appeals
Reliability	The system should maintain the highest mean time between failures (MTBF) as possible to maintain its reliability especially during disasters and emergencies.
Response Time	The system should have instant or near-instant response time.
Legal	The system has clear provisions for protecting information privacy, data usage, and intellectual property rights.

4.3 System Architecture

The system architecture captures the proposed model’s design including the minimum user requirements that are achieved through the model or the resultant system it supports. The proposed architectural analysis addresses how different components of the model supports its functionality.

Since the proposed solution is an optimization models, its components are primary data, users, and the algorithm that manipulates the data. Additional components that can be built on top of the model include the web server that supports running of the model in real-time, and an application server that supports the end-user interface, which can be built on top of the model upon its validation.

4.3.1 Partial Domain Model

The partial domain model is a system diagram, which represents most of the vital concept of the proposed optimization model. The domain model integrates components that include the primary objects that interact with the system. In the proposed model, the end user includes the blood donor, and the data they input include schedule preferences, and availability. Secondary location and traffic data are also included in the proposed model. The schematic also captures high level attributes. Figure 4.3.1 shows the partial domain model for the proposed solution.

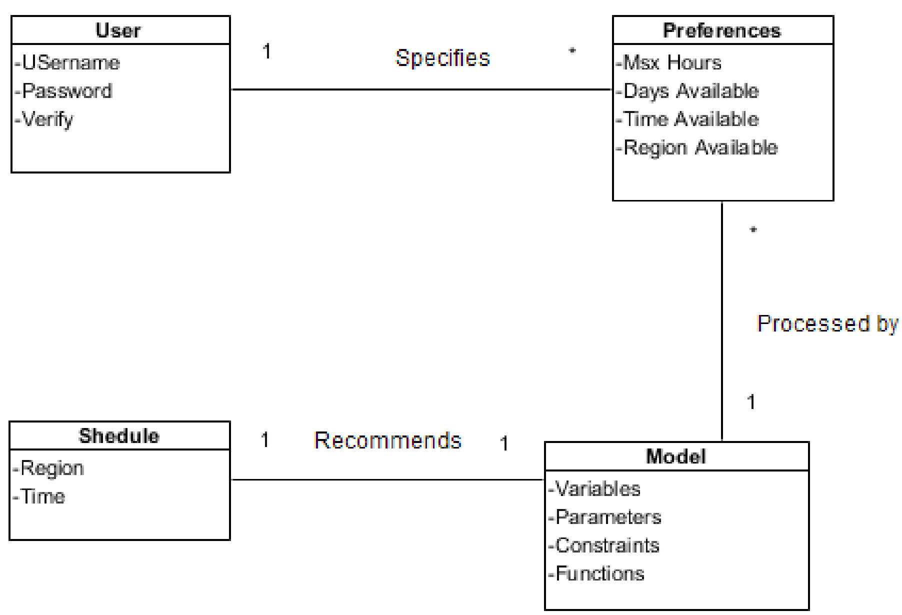

Figure 4.3.1: Model Partial Domain

4.3.2 Use Case Diagram

Use cases are UML diagrams that represents users and how they interact with the model. The primary actor is the blood donor, who is supposed to input his/her donation schedule preferences in the model system. The user will interact by providing the information via an interface, and the model responds by providing output in form of an optimal schedule recommendation. The use case diagram is shown in Figure 4.3.2.

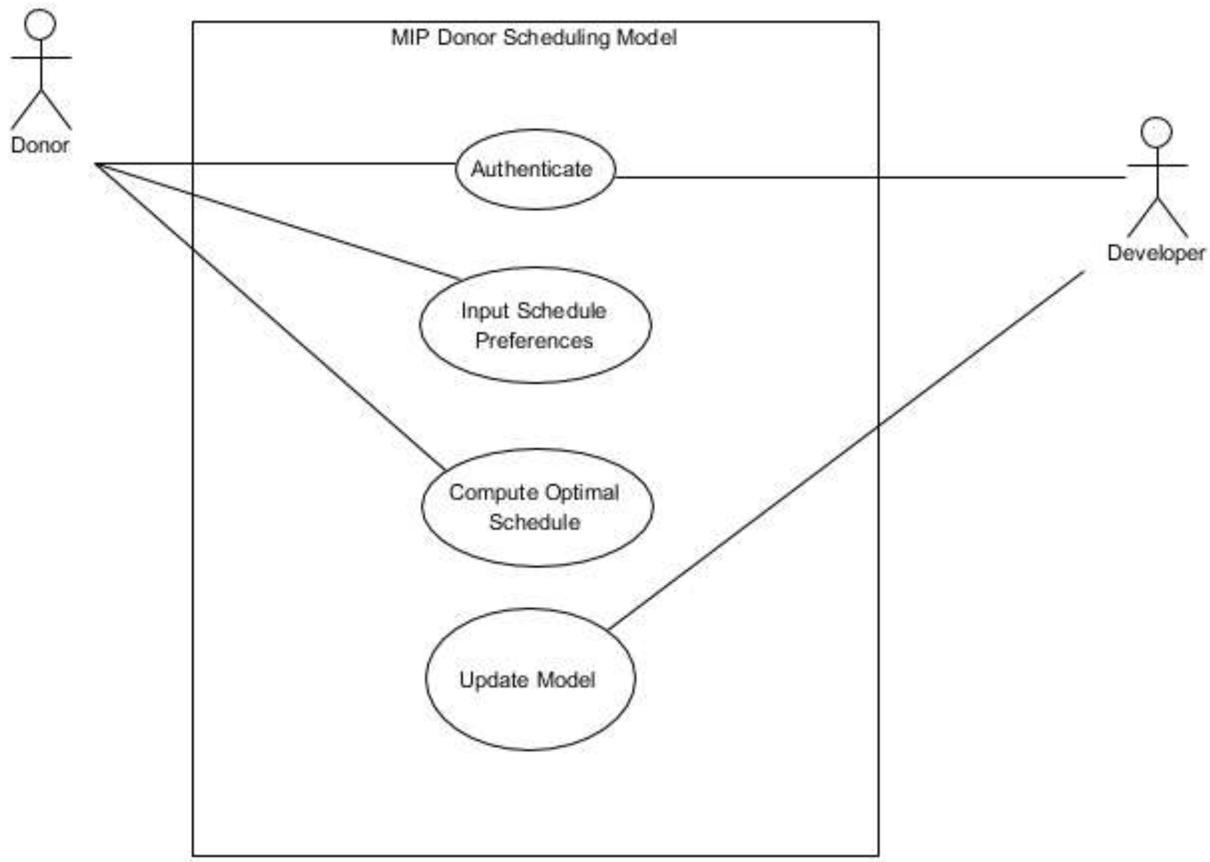

Figure 4.3.2: Use Case Diagram

4.3.3 Use Case Flows

This section expounds on Figure 4.2 by specifying primary actors, success scenarios, pre, and postconditions of the model.

Use case: Compute/Derive Optima Schedule

Primary Actor: Blood donor

Preconditions: The model computes ideal donation schedule based on donor's schedule preferences

Postconditions: Donor inputs schedule preferences

Basic Flow:

i. The user is prompted to input the schedule preferences
ii. User inputs preferences such as maximum hours, days available, time available, and region available.
iii. The model accepts the input.
iv. The generates parameters and constraints from the inputs
v. Model creates objective function.
vi. Model computes function's outcome.
vii. Model recommends optimal donation schedule.

Extensions

If 2 fails;

i. Check the inputs types to determine if required data types match
ii. Try data input again

The model requires regular updates of data set because some types of data used are subject to change such as the locations and location clusters, and traffic data. Hence the developer will constantly review the model and update where necessary to maintain optimality.

Use case: Update model

Primary Actor: Developer

Preconditions: Model can produce recommendations for donor schedules

Postconditions: New data sets must be updated

Basic Flow:

I. Developer review model's datasets
II. In case additions of modifications are necessary, developer updates model
III. In case of regions, Euclidian distance and cluster are recomputed
IV. Regions are updated
V. Other function-associated data such as traffic is updated.
VI. New model is updated.

Extensions

a) If one fails, halt model update
b) If 3 fails, check 5

c) If 5 fails, cease model update.

4.3.4 Context Diagram

A context diagram's purpose is to visually represent the data flow of the model at high level, between the core processes and the inputs and outputs involved. Figure 4.3.3 shows the MIP model's context diagram.

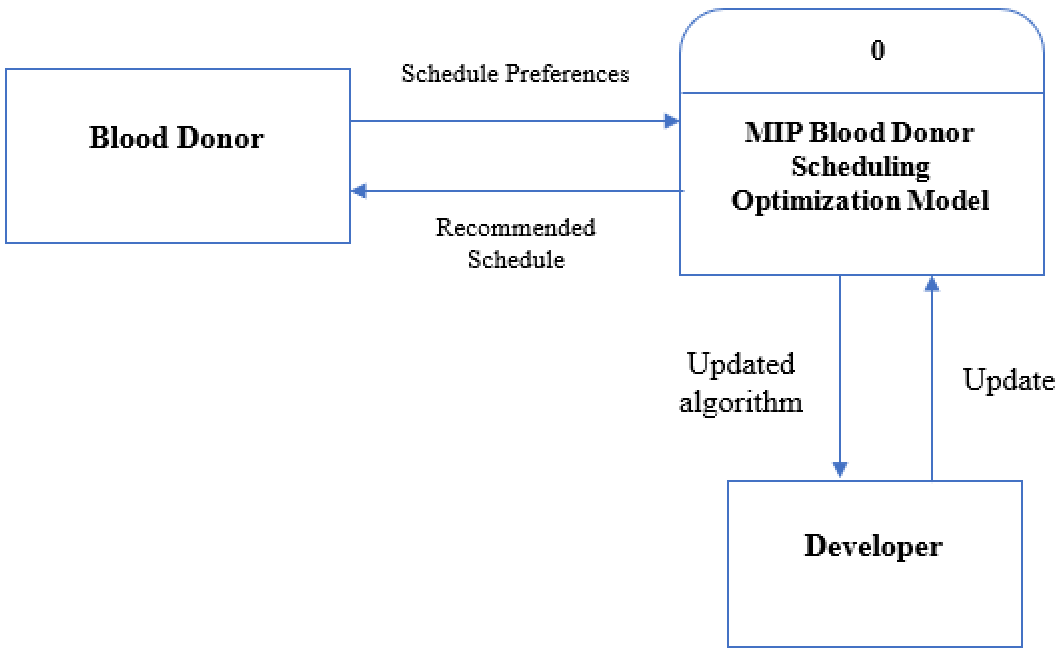

Figure 4.3.3: Context Diagram

4.3.5 Class Diagram

Class diagrams are, also referred to as Design class diagrams (DCSs) represent the classes of objects that make up the model. Classes are the logical containers within which the execution objects and their corresponding instructions are stored. Classes are implementable through different programming languages, primarily object-oriented ones. Classes are characterized by unique names, attributes and the methods that manipulate the attributes. Objects captured within the sequence diagrams have corresponding classes since in OOP, they are the instances of a class. Figure 4.3.4 shows the model's class diagram.

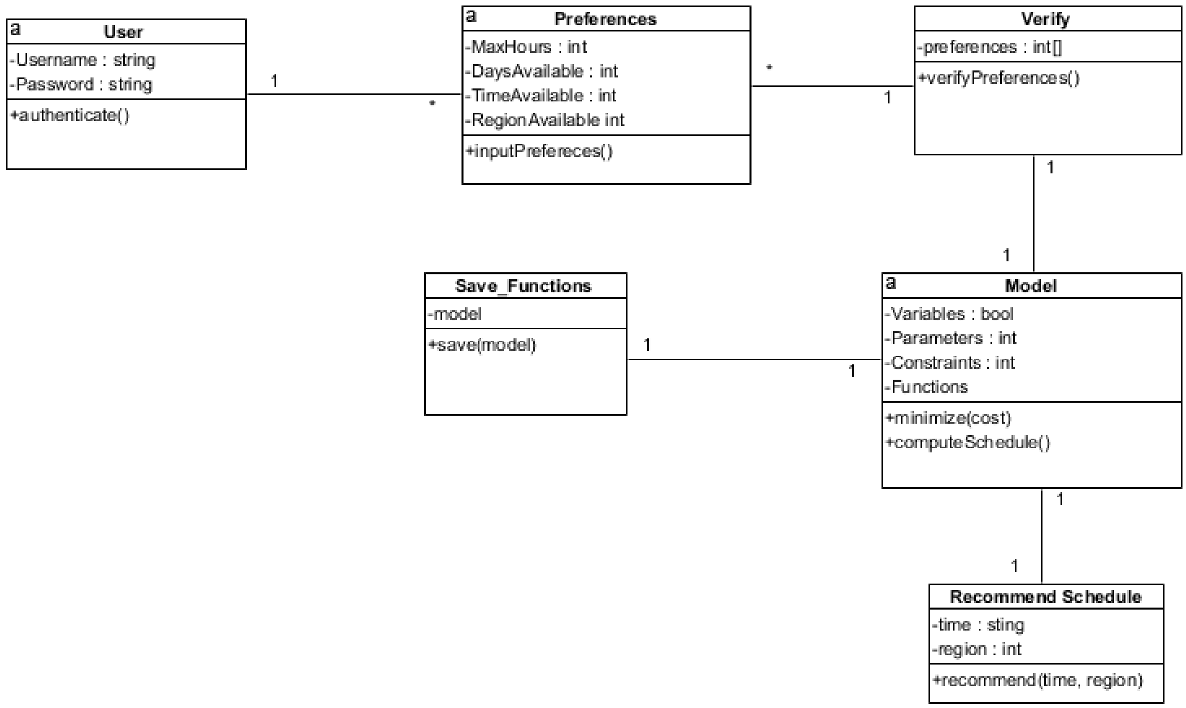

Figure 4.3.4: Model Class Diagram

Chapter Five

System Implementation and Testing

5.1 Introduction

This chapter details the technical implementation of the proposed MIP model for maximizing donor response. The model is broken down into logical execution steps that are derived from the decision criteria used by the NDMU to respond to MCE and other forms of disasters in the country. Emphasis on the NDMU criteria ensures that the model fits the protocol approved by law, hence adhering to the legal requirements and maximizing the effectiveness of the model.

5.2 Development Environment

The objective principle and objective functions will be modelled in the MATLAB programming environment, which is a standard software for modelling mathematical functions, and especially useful in computations involving vectors and matrices.

5.3 The MIP Optimization Model

5.3.1 Location Identification and Clustering

During disaster response operation, as per the NDMU protocol, successful confirmation of a disaster by the **incident commander** leads to an activation of hospital facilities, **by the medical commander**, that can respond to the disaster by receiving injured persons. At the hospital level, the authority in charge acknowledges the activation and initiates a protocol for receiving injured persons. However, in the Kenyan context, not all hospitals responding to a disaster are well-equipped to handle blood transfusions. Thus, the first step involves identifying only those hospitals capable of providing emergency or trauma care, including provision of blood transfusion, as represented in Table 5.3.1. In Nairobi, they include Kenyatta National Hospital, Matter Hospital, Aga Khan Hospital, MP Shah Hospital, and Avenue Hospital.

These facilities have been receiving the highest number of causalities/injuries during emergencies and disasters occurring within Nairobi. Therefore, they are considered the priority response facilities by the NDMU, and the medical commander.

Table 5.3.1: Responding Facilities and Coordinates

Hospital	Latitude	Longitude
Kenyatta National Hospital	-1.300788	36.807215
Matter Hospital	-1.306520	36.834317
MP Shah Hospital	-1.262216	36.812015
Aga Khan Hospital	-1.261395	36.824391
Avenue Hospital	-1.264482	36.817501

5.3.2 Radius Computation

Computing the radius of each response facility is important, because the radius specifies the maximum distance from each facility that the population of donors should be operating, in order to maximize the potential for their response. Since transfusions need to occur within a limited window of time, after which the injured patients, risks death or permanent injury, the radius helps define minimize the time within which a donor can respond.

To compute the radius, the model considered the minimum Euclidian distance of each facility to the other four facilities. Thus, each response facility will have a unique radius relative to the other four. The goal of applying Euclidian distance is to ensure the radius captures the regions within which the randomly distributed donors will be at the highest proximity to one or more of the response facilities (Hospitals). The following is the equation, as shown in Figure 5.3.1, for calculation of the Euclidian distance, which is later executed using MATLAB.

```
dMatrix = ones(5);
lc1= Centroids(1,:);
lc2 = Centroids(2,:);
lc3 = Centroids(3,:);
lc4 = Centroids(4,:);
lc5 = Centroids(5,:);

%Calculate Euclidian distance
d12 = sum((lc1-lc2).^2).^0.5;
d13 = sum((lc1-lc3).^2).^0.5;
d14 = sum((lc1-lc4).^2).^0.5;
d15 = sum((lc1-lc5).^2).^0.5;
dMatrix(1,1:5) = [1 d12 d13 d14 d15];

d21 = sum((lc2-lc1).^2).^0.5;
d23 = sum((lc2-lc3).^2).^0.5;
d24 = sum((lc2-lc4).^2).^0.5;
d25 = sum((lc2-lc5).^2).^0.5;
dMatrix(2,1:5) = [d21 1 d23 d24 d25];

d31 = sum((lc3-lc1).^2).^0.5;
d32 = sum((lc3-lc2).^2).^0.5;
d34 = sum((lc3-lc4).^2).^0.5;
d35 = sum((lc3-lc5).^2).^0.5;
dMatrix(3,1:5) = [d31 d32 1 d34 d35];

d41 = sum((lc4-lc1).^2).^0.5;
d42 = sum((lc4-lc2).^2).^0.5;
d43 = sum((lc4-lc3).^2).^0.5;
d45 = sum((lc4-lc5).^2).^0.5;
dMatrix(4,1:5) = [d41 d42 d43 1 d45];

d51 = sum((lc5-lc1).^2).^0.5;
d52 = sum((lc5-lc2).^2).^0.5;
d53 = sum((lc5-lc3).^2).^0.5;
d54 = sum((lc5-lc4).^2).^0.5;
dMatrix(5,1:5) = [d51 d52 d53 d54 1];
```

```
d1 = min(dMatrix(1,:));
d2 = min(dMatrix(2,:));
d3 = min(dMatrix(3,:));
d4 = min(dMatrix(4,:));
d5 = min(dMatrix(5,:));
```

Figure 5.3.1: Radius Computations

5.3.3 Model Decision Variables and Parameters

The model's key variable is informed by the response location, and the time block assigned to that response. The time block essentially dictates the most optimal time for which the donor response will have the greatest impact. The decision variable is represented as follows:

$$\boldsymbol{Y}\_\{\boldsymbol{ab}\}$$

where

a: corresponding time

b: corresponding region

The model the applies the following parameters to the decision variables:

i. $\boldsymbol{C}\_\{\boldsymbol{ab}\}$ **:** The expected total cost of navigating region *b* during within time *a*.

ii. $\boldsymbol{X\_\{a\}}$ **:** A Boolean variable indicating whether the donor is willing to responds to request within time *a*.

iii. $\boldsymbol{W\_\{b\}}$: A Boolean variable which indicates whether the donor is available to respond within region *b*.

iv. $\boldsymbol{T\_\{max\}}$: The maximum number of hours the donor is willing to dedicate to the intervention period (when responding to donation request).

5.3.4 Model Constraints

Blood donors, who are expected to be randomly distributed within the high demand areas, may have a high potential for response because they are flexible. When a disaster or emergency occurs, the goal is to have the model target individuals who have the least constraints to their flexibility, hence the utilization of time and location, as well as cost and availability. For the MIP to model flexibility accurately, the following constraints are applied:

i. In constraint 1 $\boldsymbol{X\{a\} = 1}$ indicates that the donor is willing to respond at time block $\boldsymbol{a}$, and **0** otherwise.

ii. In constraint 2, $\boldsymbol{W\{b\} = 1}$ indicates that the donor is willing to operate within region ***b*,** and **0** otherwise.

iii. In constraint 3, **Tmax** is a function that ensure the response session per individual will not exceed the maximum number of hours that a donor is willing to commit per session.

iv. Constraint 4 ensures that **for each time block**, *a*, **only one region**, *b*, will be recommended.

v. In constraint 5, the decision variable $\boldsymbol{Y\{ab\}}$, and the parameters $\boldsymbol{X\_\{a\}}$ and $\boldsymbol{W\_\{b\}}$ are binary (0 or 1).

Table 5.3.2 summarizes the model constraints by their definitions and their corresponding explanation.

Table 5.3.2: Model Constraints and Explanations

Constraints	Explanations
$y_{a,b} \leq X_a, \forall a, b$	Constraint on time availability
$y_{a,b} \leq W_b, \forall a, b$	Constraint on region preference
$\sum_{a,b} x_{a,b} \leq T_{max}, \forall a, b$	Constraint on maximum time
$\sum_{b} x_{a,b} \leq 1, \forall a, b$	Constraint for responding in region only
$y_{a,b} \in, 0, 1, X_a \in 0, 1, W_b \in 0, 1$	Model's Boolean variables
$a \in A, b \in B$	A = set time block, B= set region

5.3.5 Method

A mixed integer programming (MIP) mode can be constructed based on the **demand data** from the disaster response facilities, and the **duration of time** it takes to make a trip to the facilities. The model's goal is to find the most optimal response schedule for donors during disasters, and even ordinary emergencies that are not mass casualty incidents. MIP is preferred because it is flexible in that it allows for some variables to be integers (or not), upon obtaining a solution.

In the problem modelled above, the donor has a limit to the time he/she allocates to the donation request due to many constraints, some definite and others indefinite. Therefore, the goal of the model is to maximize the probability that the donor will respond, by minimizing the cost of responding to the request. Therefore, the resultant, MIP is:

$$min : Cost = \sum_{a,b} C_{a,b} \, . x_{a,b}$$

Subject to:

$y_{a,b} \leq X_a, \forall a, b$

$y_{a,b} \leq W_b, \forall a, b$

$\sum_{a,b} x_{a,b} \leq T_{max}, \forall a, b$

$\sum_{b} x_{a,b} \leq 1, \forall a, b$

$y_{a,b} \in \{0, 1\}, X_a \in \{0,1\}, W_b \in \{0,1\}, \boldsymbol{a} \in A, b \in B$

5.3.6 Formulating Objective Function

The goal of the model's objective function is to minimize the cost on the donor's side over the course of his/her response schedule per session. The same can be used on normal blood donation cycles because the goal is the same, and so are the parameters. To achieve this, the model minimizes the expected cost for each region, **b**, within time block **a**. Therefore, the expected cost**,** $\boldsymbol{Y}\_\{\boldsymbol{ab}\}$ can be calculated using the equation:

$$\boldsymbol{C_{ab} = p(new\ appeal) \times minimum\ number\ of\ trips\ per\ session}$$

Since the regions selected by the study are based entirely on high demand for blood during disasters and emergency, the model assumes the probability for a blood appeal falls within a uniform distribution of 0.5 and 1. Therefore, the probability for new appeal, $\boldsymbol{p(new\ appeal)}$ can be calculated using the following formula:

$$\boldsymbol{P_{New\ Appeal\ Response} = P_{min} + \frac{P_{max} - P_{min}}{D_{max} - D_{min}} - D_{max} * (D_i - D_{min})}$$

Where:

- $\boldsymbol{P}\_\{\boldsymbol{min}\}$ and $\boldsymbol{P}\_\{\boldsymbol{max}\}$ represent the lower bounds of the uniform distribution (0.5 and 1) used to determine the probability of a new appeal occurring.
- $\boldsymbol{D}\_\{\boldsymbol{min}\}$ and $\boldsymbol{D}\_\{\boldsymbol{max}\}$ represent the minimum and maximum response counts for a given region and the allocated time block.

It is also important to factor in the number of trips a donor can make to the response center as they will affect cost of intervention. Therefore, since the allocated time block per response session is 2 hours, to calculate the maximum number of trips the donor can make in region *b* during time block *a*, the following formula is applied:

$$\boldsymbol{Minimum\ number\ of\ trips} = \frac{\boldsymbol{7200s}}{\boldsymbol{Maximum\ trip\ duration}}$$

5.3.7 Implementation in MATLAB

The above model was implemented in MATLAB through a central program. MATLAP models the MIP solution described above using the *intlinptog* function.

a) Launching the MIP Model

Figure 5.3.2 shows the source code for launching MIP model

```
%% Set Parameters
max_hrs_session = 4; % Maximum number of hours a donor can participate
in a donation session
tslot_available = ones(7,24); % Represent the timeslot when the donor
is available
% Adjust the available time
%tslot_available(3,:) = 0;
%tslot_available(5,:) = 0;
%tslot_available(6:7,:) = 0;
%tslot_available(:,1:14) = 0;


region_available = ones(5,1); % Indicate which of the 5 regions donors
is available to move to.
avg_cost_trip = 150; % Average cost of executing a trip to the
response center.
p_max = 1; % Maximum Probability that the donor will get an appeal
request
```

```
p_min = 0.5; % Minimum Probability that the donor won't get an appeal
request

%% Launch the MIP Solver
[x,obj_ip,time_ip] =
Solve_IP(max_hrs_session,tslot_available,region_available,avg_cost_tri
p,p_max,p_min);
```

Figure 5.3.2: Launching MIP Solver

5.3.8 Solving the MIP

Solving the MIP begins with defining a function that represents the entire donor problem, which is what the MIP will solve, as shown in Figure 5.3.3.

```
%% This function solve the IP Model of Donor Scheduling Problem
function [x,obj_ip,time_ip] =
Solve_IP(max_hrs_session,tslot_available,region_available,avg_cost_tri
p,p_max,p_min)
```

Figure 5.3.3: Solving the MIP

5.3.9 Data Snippets

Different types of data were utilized by the model, and they are captured within the files imported externally to the programming environment of the datasets used is variability data. The data shows the region, their longitudes and latitude, as shown in Figure 5.3.4 and 5.3.5. This data is important in informing the time and availability preferences for blood donors at different periods during the week.

donorID	donorName	donorGender	donorCell	bloodGroup	donorLat	donorLong	prefDay
101	Samuel	M	254725629836	A-	-1.248828	36.818995	Monday
102	Mary	F	254725629836	B+	-1.262331	36.817914	Tuesday
103	John	M	254725629836	B+	-1.395074	36.97086	Saturday
104	Esther	F	254725629836	O-	-1.260009	36.817639	Monday
105	Jack	M	254725629836	O+	-1.267971	36.811192	Saturday
106	Mike	M	254725629836	A-	-1.269623	36.811353	Saturday
107	Florence	F	254725629836	A+	-1.253739	36.813694	Saturday
108	James	M	254725629836	O+	-1.273738	36.828754	Saturday
109	Eric	M	254725629836	O+	-1.395335	36.748172	Saturday
110	Solomon	M	254725629836	O+	-1.395335	36.748172	Saturday
111	Steve	M	254725629836	O+	-1.273738	36.828754	Sunday
112	Dan	M	254725629836	O+	-1.273738	36.828754	Monday
113	Emily	F	254725629836	O+	-1.273738	36.828754	Sunday
114	Stacy	F	254725629836	A+	-1.273738	36.828754	Monday
115	Mercy	F	254725629836	A+	-1.319923	36.781893	Sunday
116	Sam	M	254725629836	A+	-1.3199	36.801596	Saturday
117	Jane	F	254725629836	O-	-1.3199	36.801596	Sunday
118	Tony	M	254725629836	O-	-1.3199	36.801596	Saturday
119	Emma	F	254725629836	B+	-1.3199	36.801596	Saturday
120	Paul	M	254725629836	B+	-1.395335	36.748172	Saturday

Figure 5.3.4: Sample Donor Data

zoneId	zoneName	zoneLat	zoneLong	zoneRegion
z1	Kenyatta National Hospital	-1.300968	36.806979	47
z2	Agha Khan Hopsital	-1.261395	36.824659	47
z3	MP Shah Hopsital	-1.263375	36.812004	47

Figure 5.3.5: Sample Zone Data

Chapter Six

Discussion

6.1 Introduction

This chapter discusses the model's outcome relative to the study's objectives outlined in the initial chapters. The primary objective was to create a model that would optimize decision variables that assist blood donors to schedule donations during disaster response events, following the occurrence of MCIs or related incidents. The model can then be a backbone to support an end-user application run by the donor to enable them to select the most ideal schedule to respond to an appeal for blood donations by the disaster response agencies such as the Kenya Red Cross. The model was based on Mixed Integer Programming paradigm, because it is a useful approach to optimization, when the outcome of the model is of integer or non-integer types. It can accommodate both types of outcomes. In designing of the model, some of the user inputs included preferred response houses, day of week available, region available, and the time available to respond.

6.2 Study Outcomes

The study established that flexibility of blood donors is influenced by many factors including the cost to the response facility, the time taken to execute the entire response process including donations, and the availability of the time within the region and time block provided for response. The study was able to compute the major demand locations for blood donations within a given zone, for instance Nairobi, including their corresponding geolocation coordinates. The model was able to determine the highest and lowest costs for the donors depending on day of week, time slot selected, and preferred region, and the model concluded by provided an optimal schedule that minimizes total cost of responding to a donation appeal.

Successful execution of the model allows users to input the specific parameters that are necessary to develop an optimal schedule for a blood donor to respond within a weekly schedule, assuming the response regions and facilities are requesting donations on a regular basis, and during major disasters such as MCIs.

Table 6.2.1 shows an example of user input into the model. The data is simulated, and attempts to model real-word scenario.

Table 6.2.1: Sample User Input

Donors	Parameters & Values			
	Max Hours/Session	**Day (s) Available**	**Time Available**	**Zone Available**
Donor 1	3	Mon, Tue, Thur	12PM - 2PM	1,2
Donor 2	4	Fri, Sat, Mon	5PM – 8PM	3,4
Donor 3	3	Sun, Tue, Wed	12PM – 3PM	3,5
Donor 4	4	Mon	3PM – 8PM	1
Donor 5	5	Wed	6PM – 8PM	2

The model outputs an optimal schedule recommendation based on the inputs provided by the donor. Table 6.2.2 shows the model's sample output in form on an optimal schedule, which has the lowest cost of responding to an appeal request.

Table 6.2.2: Sample Model Output

Donors	Recommendation	
	Optimal Time	**Zone Available**
Donor 1	12PM - 1PM	2
Donor 2	5PM – 7PM	4
Donor 3	12PM – 4PM	3

Performance of the model was measured in computation time. For the model to be effective in the real world, it needs to be able to scale, computationally, as the number of inputs, and variables increase. Performance and optimality were computed as the ideal measures. The goal of these measures is computing the impact of increasing **Tmax**, the regions, and their time blocks, on the cost incurred by the donor per session, and the computation times of the model.

6.3 Model Performance

The model ran 100 simulations for each instance of data input and in each simulation, the computation time, and corresponding objective values were obtained. To avoid biased instances, regions and their corresponding time blocks were selected randomly. The computation graph revealed an increase in the model's computation time as the time blocks increased, and a decrease in computation time when the maximum operating hours per session decreased.

6.4 Optimality

The model's optimality measure indicated when the available time blocks for donor response are increased, the donor's schedule becomes more flexible. Therefore, the model establishes a positive correlation between increasing donor flexibility, and the reduced cost of responding to a blood appeal request.

Chapter Seven

Conclusions and Recommendation

7.1 Conclusion

The study succeeds in analyzing the blood donor problem, as part of the overall disaster response challenge in Kenya. When disasters such as terror attacks, mass casualty road accidents, and natural calamities strike, disaster response agencies issue a mass broadcast for donors to respond by volunteering to donate blood. While this solution has been effective to some degree in past disaster responses, it is not optimal. Hence, a need was established to solve the donor problem by modelling just the part they play in the response process, which is the final stage of intervention. Research has shown that Kenyans are of goodwill and will respond to mass blood donation appeals in large numbers.

This is evident from the recent cases of disasters in Kenya, such as the 2013 Westgate terror attacks. The challenge herein is that it is difficult to coordinate movement of donors to the response facilities they are needed urgently. Similarly, donors, who operate out of goodwill, since blood donations is not a commercial venture in Kenya, may experience constraints that may limit their flexibility and hence, their ability to donate blood. Such constraints include costs, distance from response facilities, and unavailability during the time when they are needed, which is when the disaster or emergency occurs. The study succeeded in achieving its objectives in the following ways:

a. For the first objective, contextual data applied in determining the decision-making process was determined to be emergency, response facility data. The study determined that donor information is a crucial component in the disaster response process during blood appeal.
b. For the second objective, through extensive literature review in chapter 2, the study established the existence of a disaster response protocol defined and executed by the NDMU and other mandated authorities. There are, however, no digital systems that coordinate the scheduling and notification of blood donors during mass and regular blood appeals.

c. The third objective was achieved by creating a model, which would suggest an optimal donation schedule for eligible donors. The model used Mixed-Integer Programming optimization paradigm.
d. The fourth objective was obtained by running the model and testing for optimality and performance. The model was able to return optimal solutions for each donor instance, but it complexity increased with increase in optimization iterations.

The model, which is based on mixed integer programming, an optimization algorithm was proposed, designed, and tested, to derive an optimal donation schedule that donors can utilize when called upon to donate during emergencies and disasters. The model has proved useful because it is able to accommodate all the critical decision variables, their parameters and constraints, as would be the case in a real-world scenario for a blood donor. The model also utilizes real-world context data design the optimization algorithm. Optimization is a critical process in disaster response not just for optimizing decision variables and scenarios, but also for informing policy formulation regarding disasters and intervention mechanism.

7.2 Recommendations

Based on the outcomes of the study and implementation of the MIP model, the study outlined the following key recommendations:

a) An optimization model is necessary to help scheduling blood donor for donation as an intervention measure for disaster response. The scheduling algorithm can model key variables that aid in decision-making on the donor's side. An MIP optimization model is appropriate because it can accommodate user preferences and constraints that may impact their ability to donate.

b) The study also recommends the disaster response agencies to mobilize donors to register on their membership and donation platforms because the model relies heavily on the interaction with donors through mobile applications. Hence, for donors to realize the usefulness of the model, it is imperative they align themselves with agencies concerned with disaster response.

7.3 Directions for Future Work

a) The proposed model mainly relies on decision variables obtained from context data as it occurs during an emergency or disaster. It has limited predictive capabilities. Hence, future studies should focus on integrating a predictive element for disaster occurrence into the optimization model to boost efficiency further.

b) The model's implementation can only be achieved through smartphone implementation on the user's side. Hence, it is limited in its capacity for maximum coverage of potential donors since many may lack access to smartphones despite their eligibility. Hence, the model can be expanded further to incorporate USSD capabilities for non-smartphone users.

c) Although the MIP model has proven superior when handling optimization outcomes that are either integers of not, future studies can consider the possibility of utilizing hybrid optimization techniques to tests for their optimality when functioning separately or in combination.

d) Future studies can also focus of designing optimization models for the entire disaster response process, including the event and response optimization, so that when combined with MIP optimization at intervention level, the solution can be more efficient compared to currently, where it performs with ad hoc optimization at the upper levels of the disaster response hierarchy.

e) Future optimization algorithms can also consider incorporating even more variables, their parameters, and constraints, to ensure more optimal solutions that are capable of modeling real-world scenarios more accurately.

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Appendix One

Originality Report

Thesis Corrections_MIP Model

ORIGINALITY REPORT

7%	3%	2%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

A Mixed Integer Programming Optimization Model for Scheduling Blood Donors in Disaster & Emergency Response: A Case Study of Nairobi Region

Samuel Maina Githogori

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A Thesis Submitted to the Faculty of Information Technology in partial fulfillment of the requirements for the award of Master of Science in Information Technology degree.

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Master of Science in Information Technology