

UNIVERSITY OF THE WITWATERSRAND,  
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**DRONE-BASED DELIVERY OF  
CLINICAL SPECIMENS IN A RURAL  
ENVIRONMENT: A FEASIBILITY  
STUDY**

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for the degree of Master of Science in Engineering by Research*

*in the*

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# Declaration of Authorship

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# *Abstract*

A framework is developed for the implementation of an autonomous drone-based delivery system. The concept stems from the need for more efficient methods of clinical transport in underdeveloped regions.

A case study of a region in Mpumalanga investigates the requirements of the delivery system and scale of the intended solution. The travelling salesman problem (TSP) is used to determine that a region with 19 request points can be serviced by a single drone with a 30 minute flight range and 2 - 4 kg payload capacity.

A notional region containing 20 clinics and one laboratory is used to simulate scenarios with dynamic request points using a reward-based inspection algorithm. Delivery routes are optimised based on global conditions.

An evaluation of the inspection algorithm resulted in the drones averaging 103.53 km in 139.21 minutes. A framework is thus developed which allows for a theoretical scenario analysis for future implementations.

The specimen turnaround time from clinic to laboratory is assessed using 120 scenarios of varying wind speed and request generation rates. In wind conditions similar to that observed in Mpumalanga (5 - 25 km/h), the drone averaged 93.94 minutes per request. At a request rate of two requests per hour the drone delivered an average of 180 samples generated in the first nine hours of simulation. At a request rate of one request every 6 hours the drone averaged 29 samples.

Future work could include an in depth study of seasonal request rates and weather pattern data in order to influence the path of the drone for a further optimised approach as well as the development of more advanced optimisation algorithms.

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# Chapter 1

## METHODS OF CARE

### 1.1 INTRODUCTION

The rise in drone deployment has increased exponentially in the last decade as a result of the introduction of multi-copters. As the use of drones has numerous benefits, one being low risk to human life, drones can be used for situations such as storm data collection [1], forest fire surveillance and battlefield reconnaissance [2]. Local uses include surveillance of national parks to ward off poachers and gather information on wildlife ecology [3, 4]. This dissertation proposes the use of drones for the delivery and transportation of clinical specimens, Point of Care (POC) devices and urgent medication in rural environments.

In South Africa, 45.5 % of people live below the poverty line according to the 2011 census [5]. This classification suggests that these people have limited access to housing, transport and basic necessities. Due to a lack of investment in the region, the level of education with regard to medical attention is poor. The regions also show a shortage of educators who would otherwise provide preventative skills to the local population which could help minimise the spread of illnesses such as HIV as well as facilitate the treatment of the infection [6]. These underdeveloped regions could benefit greatly from any supplementary methods that assist with patient care.

In addition, in rural and suburban environments it is not always possible to transport specimens within the necessary time frame for the patient to be treated. Therefore a question arises as to whether or not the use of drones for the delivery of medical or clinical samples can improve on turnaround times. This will ultimately determine if drone delivery is capable of being used in real life conditions in South Africa.

In order to quantify the capabilities of a drone delivery system within the context of a rural environment, a case study of a suitable region must be performed, whereby a model



of a drone delivery scenario can be established. This will allow for the development of a framework for a feasibility analysis through an optimisation simulation. The framework will grant the ability for future assessments of the proposed solution.

On a case by case basis however, monetary costs are not always the priority, but often the delivery time and the ability to meet the clinical requirements of the patient is just as important. For this reason an in depth study must be completed in order to determine the optimum care approach to any given situation. This approach must factor in the method of delivery and infrastructure of the given region.

This dissertation covers the various methods of clinical specimen and POC delivery, such as airborne or drone-based delivery as well as courier or vehicular services. In addition, the issue of limited laboratory access is addressed for the prospect of increasing the accessibility in underdeveloped regions using the proposed delivery method. The intention of the research is not to solve the problem of medical transport but rather to build a framework whereby the possibility of drone delivery can be assessed.

A limited feasibility study is conducted in order to determine if the delivery concepts discussed in this dissertation can be implemented in real life scenarios should the framework prove effective.

## **1.2 PROBLEM STATEMENT**

The problem presented in this dissertation is the limited access to laboratories and clinics in underdeveloped regions in South Africa. This dissertation proposes the use of drones to replace the current method of specimen and POC device delivery for specimen testing. This proposal discusses using drones to deliver packages to and from laboratories and clinics in order to increase accessibility and improve on turnaround times. The proposal claims to improve on efficiency while reducing overall cost to the patient and stakeholders. This method has never been used before in a commercial environment and it is therefore difficult to assess the full capabilities and limitations of such a system. For this reason, a study must be undertaken in order to develop a framework that is required for the simulation and further implementation of a system which will aid in assessing a real world outcome, should the system be feasible.

### 1.3 PURPOSE OF RESEARCH

Clinical specimen delivery is important as the outcome can be a matter of life or death. Clinical specimens from laboratory tests can determine the treatment required for an ill patient and the sooner the results are determined the sooner treatment can begin.

The handling and delivery of clinical specimens and POC devices is generally performed by a trained individual who has knowledge of safety and handling procedures. Motorcycles or passenger vehicles are commonly used as the mode of transport and the vehicle in use is marked with the necessary pictogram to represent the contents of the cargo. The delivery method is much like a hand-to-hand courier where the parcel is never left unattended and is signed off by the recipient.

The specimens in transit may be but are not limited to, excreta, secreta, tissue samples and fluids, blood and pharmaceutical medication such as antiretrovirals or point of care devices [7]. These specimens may be harmful if they come into contact with the handler or the environment. The transport of a vial of blood of a patient suspected of contracting a contagious disease such as Ebola could cause dire effects if not treated with the correct procedures. This is why it is necessary that the packaging containing these samples is secure and sheltered from the elements. If the parcel were to detach before arrival the packaging is required to contain any spills in order to be disposed of with minimal effect.

The use of drones to transport these samples and POC devices may aid in response time between the laboratories and doctors. Another advantage of this proposed method is the ability to transport medical samples for a patient in critical condition in inaccessible locations. Whereas previously a motor vehicle hindered by traffic and road accessibility would be required to transport the samples, a drone can now be used which does not have to follow geographical routes. This method may reduce the price of testing for patients as the testing fee covers transportation of the samples [8]. This method may also improve the overall efficiency of the small parcel delivery system.

## 1.4 LABORATORY PROCEDURES

The Laboratory procedure requires a series of well-coordinated events in order to successfully treat patients in a timely manner. The inclusion of a drone in this process would require the adherence to the already established laboratory procedures.

The laboratory diagnostic procedure is made up of 6 stages [9]:

Stage 1: When a healthcare professional requires the laboratories assistance for clinical diagnostics, a collection request is placed for delivery to the nearest lab. In general, a doctor would use the same lab for all their specimens.

Stage 2: The healthcare professional begins by drawing the sample from the patient. The medical personnel then decide if the sample is urgent or routine. The lab then complies with the request and activates the appropriate collection methods.

Stage 3: The courier collects the sample and it is placed in a collapsible courier bag that is intended to protect the integrity of the samples. The courier often carries an ice pack as well. The samples are packed into small individual sleeves which contain both the sample and the request form. Samples are then transported either by foot, hospital ward to sample lab, or by vehicle.

Stage 4: Once received by the lab, the samples are processed. The receiving department opens the package and the request form is logged. The samples are then sent to the relevant section for processing.

Stage 5: Once the samples have been processed, the equipment which is interfaced with the electronic records company [10] publishes the results in order to print.

The printed report is used to notify the doctor, either via email or retrieved on the Laboratories smartphone application. Urgent or highly unusual results will be telephonically communicated to the doctor.

Stage 6: Serum samples are stored for a further seven days; histology samples however are stored for several years. The samples are then disposed of through a medical waste company.

Drone delivery is required to fit into the daily operation of the laboratory and intends to replace stage 3 of the specimen diagnostics system.

In order to achieve the desired results, the delivery method must be able to keep up with the current demand of samples that are delivered daily. A drone system must operate with either reduced staff, funds or time required to make the deliveries thus proving more efficient than the current method.

A unified modelling language (UML) diagram of the laboratory process is represented in figure 1.1.

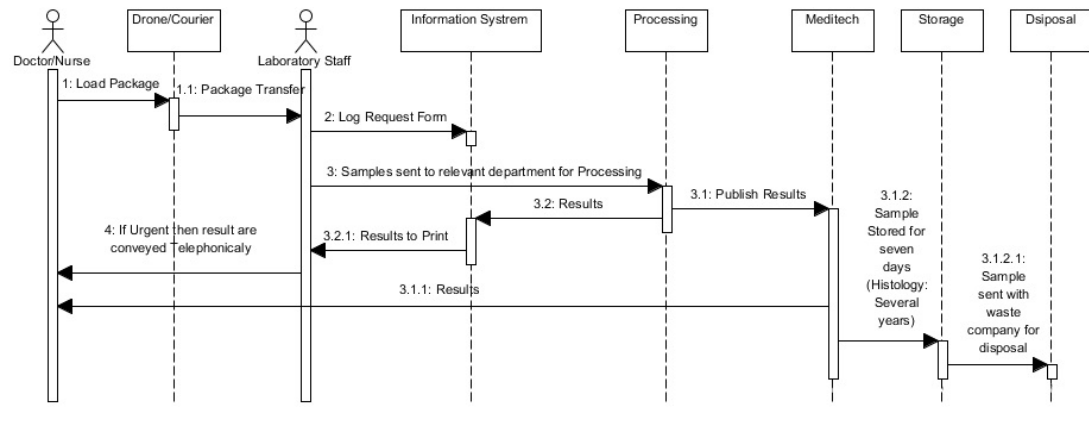


FIGURE 1.1: UML Diagram of Laboratory Process.

## 1.5 RESEARCH QUESTION

The primary objective of this research is to determine if it is possible to develop a framework for how future analysis of the feasibility of drone-based transport can be achieved, in the context of a rural environment. The reason for this, much like in many other fields, is that as technology improves, alternative methods are introduced and may prove more effective. In particular, the introduction of autonomous drones has opened up an abundant area of potential from photography to surveillance and now to the potential for package delivery. The research question thus comes to light, can a simulation model be developed which will allow for the testing of delivery scenarios so that future work can determine if this new found potential can be utilised to provide a more efficient means of delivery in the field of patient care?

This broader question is broken down into three sub questions:

- Do the physical characteristics of an autonomous drone in the form of a multi-copter allow for the transportation of specimens and POC devices?
- If so, can a simulation be developed in order to assess the capabilities of a drone delivery system in a rural environment? This system is to be used to compare drone delivery to current methods of delivery with regard to speed, efficiency and cost.
- Can this model be optimised, in turn providing the foundation for the development of a cheaper, more efficient method of delivery, that is scalable?

## 1.6 HYPOTHESIS

The review of current drone systems may indicate that the concept of drone delivery is not only possible, but potentially profitable as the method of airborne delivery may prove more efficient and economical. With the aid of optimisation algorithms and simulations, the proposed solution may improve greatly on turnaround times compared to current methods which may persuade stakeholders in the laboratory industry to develop such a system in the near future.

## 1.7 ASSUMPTIONS AND LIMITATIONS

The drone's physical characteristics will limit the overall system's turnaround time by the drone's maximum flight speed and carrying capacity. The drone's maximum payload capacity is set at 4 kg per drone with a maximum flight time of 30 minutes, this allows for a 10 km range in ideal wind conditions. This is a great deal lower than the range or capacity of current methods considering a road vehicle has in excess of 500 km range and 100 kg carrying capacity.

The drone is also at risk of collision or malfunction which could lead to specimen or package contamination. A courier company like FedEx produces a clinical pack that is secure for non-infectious clinical samples [11], but states that the outer packaging that is open to the elements must be constructed from a rigid material such as corrugated fibreboard, wood, metal or plastic. The primary inner receptacle must be water tight as to contain any spillage. Absorbent material must be placed around this packaging and a secondary watertight receptacle must be placed around that. Each sample must be individually wrapped as to not contaminate one another. These packaging regulations may make the transportation of infectious substances more difficult. The list below further illustrates the restrictions with regard to an overall solution.

- Implementing a drone delivery system requires initial outlay of monetary funds in order to purchase the components required to make up the drone. The system size is limited by the amount allocated. Purchasing larger drones or higher quantities of drones can expand the delivery system. The framework must therefore address scalability.
- Civil Aviation Authority (CAA) regulations limit the way in which the drones are operated and may reduce the maximum payload that the system is capable of transporting.

- Weather effects hinder the operation of flying units depending on the humidity and wind conditions. The simulation must therefore take wind conditions into account.
- Operation of the system relies on trained personnel to coordinate the transfers. The more operators available, the more drones can be operated.
- The technology requires sufficient facilities to operate. The functionality of the drones is constrained by the ground stations ability and the software and optimisation algorithms that accompany it.

### 1.7.1 Drone System Validation

A multi-copter delivery system can be a stand-alone operation that is outsourced by several laboratories or maintained in-house by an individual laboratory. The laboratory can designate staff to be the ‘pilots’ of these aircraft’s and they can load the attachment parcel as well as complete all pre-flight and in-flight checks in order to maintain the system in a safe manner.

The operator can maintain a permanent ground station located in an office that can include a transmitter tower to increase the range of flight control and flight data acquisition. The multi-copters fly a predetermined route mapped out to avoid public roads, crowds and restricted fly zones. The flight radius limit is set based on the location of the laboratory using the system.

### 1.7.2 Risk Assessment

The Federal Aviation Administration (FAA) regulation pose a risk for South African companies who wish to operate drones commercially as there is a possibility that the CAA may follow suit. This can result in the need to apply for clearance when testing autonomous drones in public air space.

The regulations imposed are for public safety and as with any vehicle there is a risk of collisions; especially those that are aerial. Collisions may be with structures or individuals and may cause harm to the environment. This project hopes to transport medical test specimens at a rapid rate and has the potential to save lives. In order to alleviate the risk as much as possible so that it is outweighed by the potential virtue, rigorous flight tests must be carried out in different scenarios.

In-flight malfunctions are a reality and often result in damage to the aircraft when colliding with the earth. Components may need to be replaced and the budget must accommodate for backup materials such as propellers, motors and ESC’s.

### 1.7.3 Legal and Ethical Issues

The Code of practice of south African Bureau of Standards, regulation SABS 0265:1999, clause 5, states with regard to hazard identification and hazard classification that the requirement of substances which are to be transported and classified as “harmful to health” and are identified as properties of substances that constitute as a risk from normal handling must be labelled accordingly. This is to protect the handler, general public and the environment. Clause 7 through 10 of regulation SABS 0265:1999 indicates the necessary pictogram and risk and safety phrases required when transporting these potentially harmful samples [12].

Should this mode of transport be used to traverse national borders the procedure would have to abide by the rules stated in the National Health Act, 2003 [13].

Drones or autonomous multi-copters not intended for recreational, sport or completion purposes are classified by the Civil Aviation Authority as Unmanned Aircraft System (UAS) and must adhere to the regulations set in place for flight in South African airspace [14].

The U.S. FAA recently proposed regulations concerning UAS's. For civilian operation, the drone must weigh less than 25kg to be classified as a small UAS/UAV. However, during operation the aircraft must remain in visual line of sight, which poses a problem for deliveries that are intended to be tens of kilometres away. Another concern is that the drones cannot be operated over persons not involved in the operation. In a suburban environment, this is near impossible to avoid.

Other regulations were also proposed such as maximum flying height of 500 feet (152.4 m) and maximum air speed of 100 mph (160.9 km/h). A full list can be found on the FAA web page [15].

South African CAA regulations released in June 2015 require a Remote Pilot License (RPL) when flying commercially. This can be obtained through flight school training, theory exam and practical demonstration test. An RPA Letter of Approval (RLA) and a certificate of registration with number displayed on each aircraft are also required. This is granted after an inspection and registration of the aircraft by the CAA has taken place. Each pilot must also obtain an RPAS Operators Certificate (ROC) that details the limitations exclusions for that specific pilot, RPAS and field of operation, acquired after applying for an RPL and RLA, along with an operator's manual detailing all tasks and safety measures. Finally a Restricted Certificate of Proficiency in Radio Telephony - Aeronautical must be obtained; this is a radio license to talk to full sized aircraft and air traffic control towers using a handheld air radio [16].

CAA Restrictions for commercial RPAS:

- The operator must carry a radio to communicate with aircrafts and ATC control tower
- The drone must operate below 121 meters roughly equivalent to a 40 story building.
- Operate up to 500 meters away from pilot, with unobstructed line of sight.
- Operate at least 50 meters away from buildings (unless special permission obtained).
- Operate at least 50 meters away from people (unless special permission obtained).
- No operation within 10km of an aerodrome / airport (unless special permission obtained).
- No operation within restricted or prohibited airspace (unless special permission obtained).
- No releasing of any payloads (unless special permission obtained).
- Always carry a fire extinguisher and first aid kit.

However, these regulations are the first implementation of its kind and are bound to change based on public pressure. The list of hurdles in order to fly commercially is long but can be overcome. The major concern is operation in line of sight which restricts autonomy to some degree but the testing of a prototype for the time being does fit in line with the above regulations.

### **1.7.3.1 Ethics in Drone Flight**

A multi-copter is an extension of the operator. So it is simple to say that anything socially or legally unacceptable when performed by a person is also unethical when accomplished with the aid of a drone. This is inclusive of recreational and commercial drone flights whether or not the operator has the intention of performing an unethical act.

A possible socially unacceptable operation of drone flight is the recreational operation in public spaces. This can result in the disturbance of public members who are within earshot and are affected by the noise pollution generated by the drone. A higher flight altitude may remedy this concern to some extent.

Multi-copters are often fitted with high-resolution cameras for surveillance or aerial photography. This poses major concerns with regard to invasion of privacy [17]. Operating



drones over suburban areas can result in inadvertently capturing images of people without their consent. In order to reduce the chance of this occurring, the camera should be powered off when it is not required for a specific flight path and if not required at all, a camera should not be fitted.

Commercial drone uses are becoming more common and as the number of companies that use drones increases. One such company is Amazon, whose primary objective is to deliver packages as quickly as possible to their clients. This poses a problem as the more drones there are in the air, the more chance of a collision or malfunction. This can be a danger to the public below. This is why autonomy may benefit the company in question as the operator would allow the drone to make altitude and flight path decisions based on available air space. The drones however would have to be equipped with wireless telemetry and communicate with one another.

## **1.8 SUMMARY**

This chapter proposes a new form of specimen and POC delivery that utilises autonomous drones as the transportation method. The proposed solution is to replace motorised vehicle delivery as this may improve the turnaround times and reduce the cost to the patient and stakeholders.

The proposed solution has never been used before in a commercial environment and it is therefore difficult to assess the full capabilities and limitations of the given solution. For this reason, a study must be undertaken in order to develop a framework that can be used for the simulation and future implementation of a system; this will aid in assessing a real world outcome, should the system prove feasible.

## Chapter 2

# BACKGROUND

### 2.1 INTRODUCTION

In recent years, Multi-copters have assisted in aid-and-relief for natural disasters such as the 7.8 magnitude earthquake in Nepal in 2015 [18]. The company, Global Medic, provided medical assistance in the form of drone surveillance in order to map the effected region and relay information to rescue workers [19]. This comes after the use of multi-copters for medical payload delivery in Papua New Guinea by Médecins Sans Frontières (MSF) in 2014 [20].

The inaccessibility of the clinic in the town of Malalaua, roughly 63 km from the Kerema hospital, led MSF to the trial use of drones for clinical sample delivery as kerema has the only functional microscopy equipment to sample these specimens [21]. The flight between Malalaua clinic and Kerema hospital took 55 minutes and required a battery change half way in the town of Tora. The journey would have taken four hours had a car been used to deliver the samples.

Global Medic and Médecins Sans Frontières have proven to the world that the inclusion of drones in delivery and surveillance can positively affect the lives of many people in underdeveloped regions and the like. It is thus necessary to investigate the impact that drones have on society, with medical delivery at the focal point.

This chapter introduces the attributes of multi-copters and other Unmanned Ariel Vehicles (UAV). Through the review of several implementations and drone system arrangements, a unique prospect can be obtained for the concept of medical specimen and POC device delivery.

### 2.1.1 Multi-copters

A multi-copter is a radio controlled aerial vehicle or rotary flying unit that contains multiple horizontal propellers on the frame's extremities.

Thrust of the unit is controlled by increasing or decreasing the speed of the rotors independently. The most common form of a multi-copter is the quad-copter whereby rotors on opposite corners of the frame spin in the same direction in order to provide stability during lift.

Pitch of a quad-copter is controlled by increasing the speed of the two rear motors relative to the speed of the two front motors. This allows the vehicle to move forwards or backwards. The greater the pitch angle the greater the speed in the given direction. Yaw of the vehicle can be altered by increasing the speed of the two opposite motors which destabilises the unit's horizontal rotation enabling it to rotate about its centre. By increasing the speed of two adjacent motors one can alter the angle of the aircraft to its lateral axis and produce roll of the aircraft [22].

Increasing or decreasing all four motors simultaneously controls the altitude as depicted in figure 2.1.

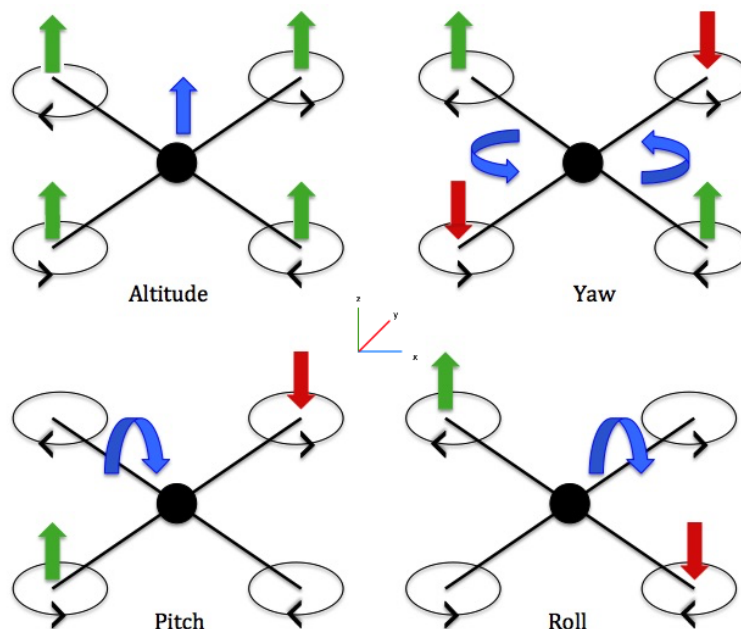


FIGURE 2.1: Flight orientation of quad-copter where arrows over the motors indicate the increase or decrease of the speed of the motors. All other arrows indicate the direction of motion of the quad-copter.

An on board computer is required to provide motor control for speed and direction as well as stability during flight. Additionally, peripherals such as GPS, gyroscopes,

accelerometers and sonar sensors are added to relay information such as position, altitude, speed and route mapping.

A multi-copter can be equipped with a payload in order to transport small objects autonomously. With regards to healthcare, the package can contain urgent specimens which may increase the rate of specimen delivery.

### **2.1.2 Unmanned Aerial Vehicles**

One of the early uses for the gyroscope, invented by Elmer Sperry, was to be used in World War I in an airborne drone for the U.S Navy [23]. The drone would be piloted remotely using ‘radio waves’ popularised by Nikola Tesla’s first remote controlled boat in 1898. The drone would be catapulted 1000 yards before crash landing into a designated target in order to trigger the equipped warhead. This was one of the first unmanned aerial systems.

In today’s time an Unmanned Aerial Vehicle (UAV) or a Remote Piloted Aircraft (RPA) is a flying unit often used by the military for battlefield surveillance. The aircraft is either completely autonomous or is given waypoint flight paths via a ground station. UAV’s vary greatly with respect to structure and overall size. A multi-copter can be referred to as a UAV when its hardware allows for autonomous flight [24]. The flight controller combines data obtained from the barometer, GPS, gyroscope and accelerometer to calculate its position and orientation during flight. It then follows a predetermined path set via a ground station.

## **2.2 REVIEWS OF CURRENT DRONE SYSTEMS**

Reviews of similar systems to the one proposed in this dissertation allow for an investigation into possible solutions as well as an indication of the capabilities of a drone delivery system. This will aid in justifying the framework’s development.

### **2.2.1 Drones in Medical Delivery and Aid Relief**

Zipline, a company associated with robotics based in Northern California [25] partnered up with UPS, a shipping and parcel service [26], and Gavi Vaccine Alliance, a non-profit organisation based in Rwanda [27], to develop a delivery drone called ‘Zip’.

The drone is a small fixed wing aircraft that carries up to 1.5 kg of payload in its fuselage and travels at a speed of 100 km/h [28]. The payload is focused on medical supplies such

as vaccines, medication and blood. The drone system can also be extended to disaster and humanitarian relief projects.

Zipline favours fixed wing drones over rotary flying units [29]. Rotary units only function in fair weather and the damage caused by a malfunction could be minimised by the aircraft's ability to glide. This is a major factor to consider when designing a system based on multi-copters.

The reason behind the development of Zip is the lack of adequate access to essential medical products in various locations around the world. Over 2.9 million children under the age of five die each year as a result of lack of treatment [25]. In addition 150,000 pregnancy related deaths could have been mitigated if the patients had access to blood according to Zipline [25].

A health worker places a text message which is used to ready the drone for delivery. The medical supplies are secured in a cardboard box within a compartment in the drone. Upon reaching the coordinates of the delivery point, the drone measures the wind and jettisons the package. The package is fixed with a parachute which deploys upon release. The drone then lands at the health facility in an open space.

The speed of the drone allows for a large supply radius and Zipline claims to be able to provide a national-scale coverage from a single home base. This also reduces the cost of the initial set up and any additional units as they can operate out of a single base station. The first location set for delivery is Rwanda where the government will pay for each delivery that Zipline makes [30].

Zipline intends on executing up to 150 deliveries per day to 21 health facilities across the western portion of Rwanda [28]. Currently there are less restrictions with regard to Rwanda's aviation regulations compared to that of the United States of America or South Africa which thus allows for real life field testing and eventual deployment in the region.

Another reason for Rwanda being the location of choice is the lack of supporting infrastructure for medication delivery. A large number of the roads in Rwanda are washed out annually by storms. In addition to this, the current percentage of the population living in urban settlements is only 15 % [31], which makes Rwanda one of the poorest countries in Africa [32]. This puts Rwanda into the category of 'underdeveloped' which indicates that it can benefit greatly from a system such as drone delivery where the Zipline concept excels.

In remote rural areas there are limited resources available to diagnose laboratory-intensive diseases. E-Juba [33], much like Zipline, is a UAV design from the National Health

Laboratory Service of Johannesburg that plans to transport a 500 g payload over a distance of up to 40 km using a fixed wing drone. E-Juba is also intended to transport urgently required medicine such as snakebite serum or packed red blood cells [33]. The issue of environment contamination as a result of collision is avoided by transporting the samples in dried spot format. The drone uses Global System for Mobile Communication (GSM) to communicate with its operator. The unit is battery operated and uses the 'MicroPilot' ground station. Successful autonomous take-off, guided flight and landing were accomplished.

The E-Juba is the first attempt at using drones to transport specimens in South Africa [34]. Prior to this drones were only used for military applications. Of the 300 audited test flights, only 2 were unsuccessful. No cargo or equipment was lost or damaged during the test flights [34]. The testing of the drone was possible after permission to fly from the CAA was granted. However, the drone had to be followed by a road vehicle at all times. This proved difficult as the drones flying altitude reduced visibility from the ground. The flying altitude had to be altered to accommodate for this. The team then employed local school children to collect the samples once the drone had landed and deliver them to the necessary clinic [34]. This provided additional jobs in an area where unemployment levels are high.

E-juba is a prime example of the drone delivery system that this dissertation proposes. However, the e-juba system is limited in some respects. Improvements to this design begin with the increase in payload. 500 g is very limited if multiple samples are required. Therefore, this dissertation focuses on the delivery using rotary flying units as opposed to fix wing. This can result in up to 5 kgs in payload capacity. Another advantage of rotary flying units is that the take-off and landing can be on a point and does not require a runway, hence a more accurate positioning overall. Since published in 2007, improvements in the technologies used in e-Juba have been made and enhanced ground stations and flight controllers can be added for increased accuracy.

A paper titled 'Autonomous Drones for Assisting Rescue Services within the context of Natural Disasters' [35], discusses the use of drones to aid in rescue missions to locate survivors or assess the magnitude of a situation . The drone is required to autonomously navigate buildings inside and out using a mounted camera. A camera is used as opposed to sensors because the drone is limited with its payload. The drone makes use of 'sparse3D' in order to compute distances and spatial locations [35]. Using regions of interest, the drone can also detect people. In this paper, Sensor weight is not a major concern as the drone is designed with sensors in mind. Therefore, sparse3D is not necessary and the guidance will be based on the sensors that are equipped.

The use of a fixed wing drone is not possible within this context as a fixed wing drone could not navigate within structures or hover above an inspection zone.

The MedizDroid project makes use of drones for mosquito vector control in the management of Malaria [36]. A hybrid system has been conceptualised in order to carry large payloads. The use of green energy could also improve flight time. Multiple drones conducting a single command may also reduce the need to transport heavy payloads. However this would require increased autonomy and drone-to-drone awareness for collision avoidance. The drone uses Service Orientated Architecture (SOA) which can communicate with MAVlink based ground stations [36]. The drones are still to be flight tested.

As flight time is a major concern, and the addition of batteries leads to a decrease in payload capacity, green energy such as solar may need to be considered in future developments of multi-copter designs.

### **2.2.2 Drones in Goods Delivery**

Amazon, a large internet-based reseller of commercial products has developed an autonomous delivery system using a hexa-copter called PrimeAir [37]. The intention of the company is to enhance their delivery service which is already provided to millions of customers by means of vehicle couriers. The service is not in operation as the aviation regulations in the USA do not permit autonomous beyond line of site (BLOS) drone operation [37].

Customers will be able to select the option of drone delivery on the Amazon website after purchasing a product that fits the criteria. This increases the company's autonomy with regard to service delivery.

Amazon envisions a fleet of drones delivering all their parcels that fit the size and weight restrictions in the near future. The weight limit has been set at 5 lb (2.26 kg) and the flight time is estimated at 30 minutes [37]. The unit will fly at an altitude of below 400 feet (121.29 m) to avoid altitudes of larger manned aircrafts. The unit itself will weigh 55 lb (24.94 kg) fully loaded and Amazon claim to be able to operate the drone from up to 10 miles (16.09 km) away. The drone also has sensors mounted to avoid collisions with other drones and structures.

A proposal outlined in Amazon's safe integration document discusses the use of segregated civil airspace below 500 feet [38]. Amazon suggests that the airspace available be segregated into flight 'levels' based on the capability of the vehicle in transit. This will

enable safe operations by providing a framework for airspace access based on the vehicles capability. The levels are separated as listed below [38]:

- “Low-Speed Localised Traffic”- This level is reserved for non-transit operations such as units operated for recreational, survey or inspection purposes. These units lack sophisticated sense-and-avoid (SAA) technology.
- “High Speed Transit” – This is the air space between 200 and 400 feet which is reserved for commercial high speed units that are well equipped with regard to sensor and performance hardware.
- “No Fly Zone” – This level is delegated to emergency flight services only.

Amazon have already tested over a dozen prototypes in order to be able to accommodate for different types of delivery environments. The development centres are located in the United States of America, United Kingdom, Austria and Israel [38] and give a broad perspective of various operating climates and weather conditions.

Unlike the drones previously mentioned in this paper, Amazon’s drone is purely a commercial based project with the intention of increasing the efficiency of their delivery department. Amazon will not be delivering medical specimens or blood and therefore do not have to consider the regulations involving these substances. The research at Amazon has proven that drone delivery is possible. However, the entire project is hinged on the aviation authority providing them with the necessary permission to fly autonomously, and carry a payload while doing so.

The well-known parcel delivery company DHL began using quad-copters in September 2014 for deliveries dubbed as “parcel-copters” [39]. The copters deliver small parcels to the German island of Juist. Deliveries include medication to the pharmacy on the island as well as other small items that are required urgently. This service is quicker than the ferry service previously used. The drone is equipped with a specially designed parcel housing that is weather- and waterproof [39]. The drone is monitored by a ground station and lands in a designated area on the island. From there a DHL courier delivers the parcel to the recipient.

An endurance test carried out by the company DJI, flew a tethered multi-copter for a period of 72 hours in order to determine if the components can handle the length of continuous flight [40]. This value was achieved and is regarded as the maximum continuous flight time, beyond which is not recommended before component breakdown. The drone’s maximum flight time between inspection and service is therefore 24 hours, a safe value below the 72 hour DJI test flight.



The reason behind the use of drones in these situations is the quick response time and large area coverage. The components required to build a multi-copter are readily available in large varieties and the inclusion and operation of a single drone within a system is a relatively simple task. This allows for almost immediate implementation in a crisis situation. However, the system does need to fit into the structures and guidelines already established by clinics and laboratories.

## 2.3 REQUIREMENTS BASED ON LABORATORY PROCEDURES

In a general case where a healthcare practitioner requires specimens to be tested, a drone would be requested from the dispatch office. Once the request is processed, a drone is sent on its way to collect the specimens. The drone lands in the dedicated area for the healthcare professional to load the specimens into the package. The drone then returns to the laboratory and the package is detached and processed by the laboratory. The delivery request procedure takes place as in figure 2.2.

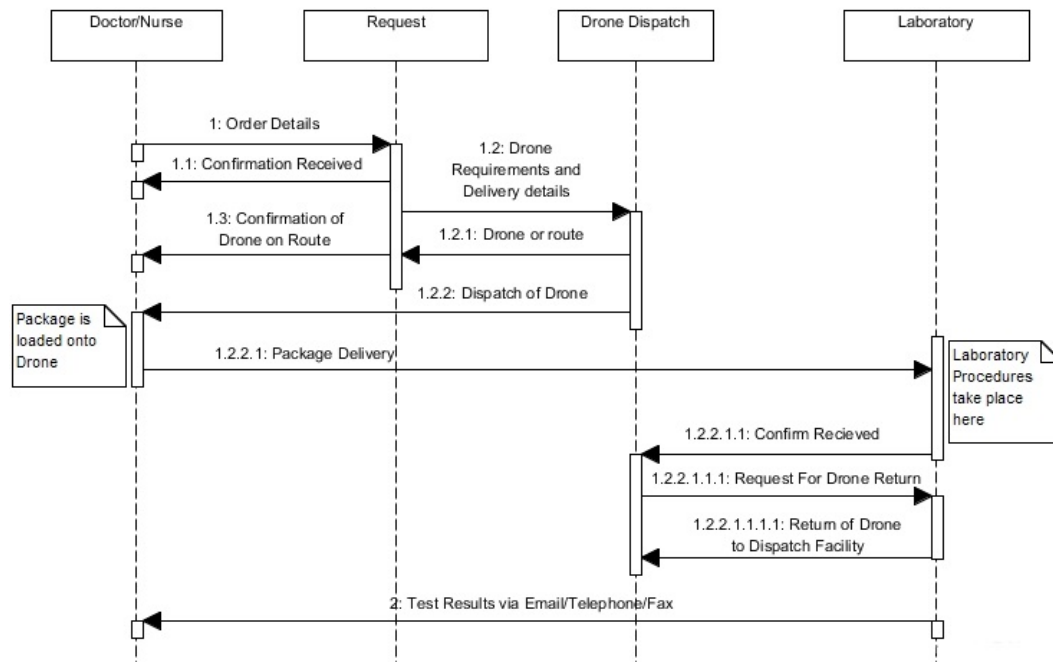


FIGURE 2.2: UML Diagram of Request for Delivery of Specimens.

Between the procedures of loading specimens onto the drone and offloading at a laboratory certain checks occur. The drone determines if a package has been securely fitted to the undercarriage, if a package is not secure, a warning indicator presents itself. Once secure, the healthcare professional indicates that the area is clear for take-off and the package is

ready for delivery. The drone then gathers GPS data and determines if it has a clear return path to the laboratory. At this stage weather effects should also be determined as well as battery percentage. Indicators must be equipped to notify the operator if either of these values is inhibiting the drone's operation. If all the above checks are passed the drone can proceed with the delivery.

During the flight, weather and battery checks continue to run and the operator is updated accordingly. On arrival the package is released and the sample is processed by the laboratory. Once results are made available, the doctor is notified via email. The procedure described is illustrated in figure 2.3.

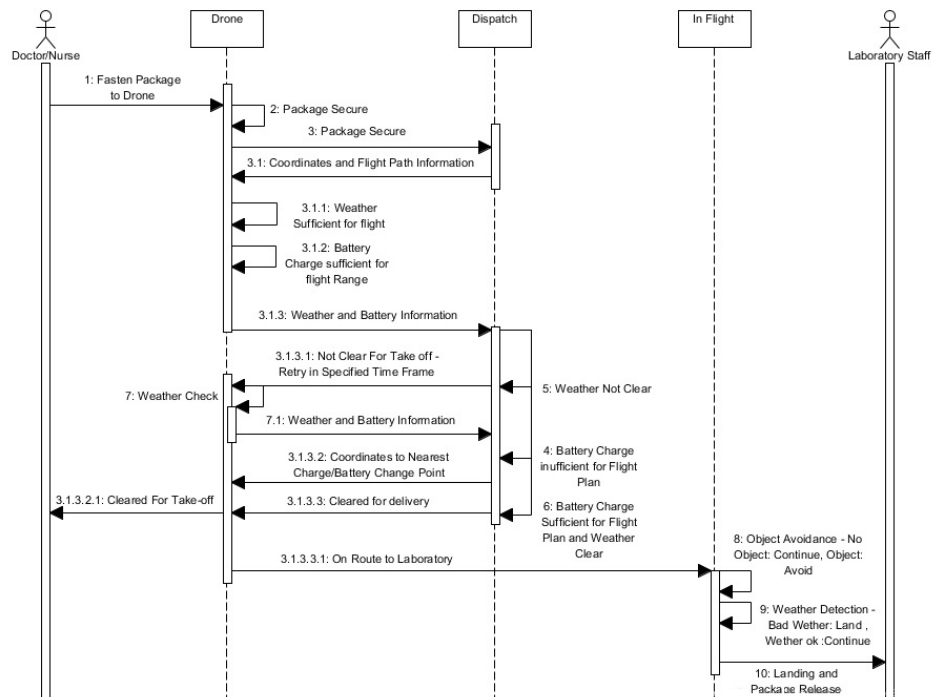


FIGURE 2.3: Flight plan of drone delivery system.

## 2.4 SUMMARY

The review of drones, particularly multi-copters, suggests that the inclusion of such units in a delivery system is possible within their context.

The preferred drone is a rotary drone over fixed-wing as it has the ability to land on point and carry a greater payload. The disadvantage of rotary drones over their fixed winged counterparts is the flight range, which can be overcome by using battery changes and stop over points.

In addition, aviation regulations pose restrictions which may limit the use of such a system in various locations around the world. However, the system does abide by the guidelines used in laboratories and clinics.

Furthermore, a drone delivery system can fit within the guidelines of the already established laboratory procedures which indicates that a framework is necessary in order to assess such systems should they be required in the near future.

## Chapter 3

# POINT OF CARE

### 3.1 INTRODUCTION

The introduction of a form of testing referred to as Point of Care (POC) may negate the need for drone delivery as the results of the testing are almost immediate and transportation to and from laboratories are no longer required. For this reason a full investigation must be conducted into POC testing in order to determine if it can be a viable replacement for general laboratory testing.

Limited access to laboratories in sub-Saharan Africa has led to the increase of POC testing. POC testing is a form of laboratory testing that allows an individual to obtain clinical results by means of patient self-management (PSM), patient self-testing (PST) or general blood tests [41]. This decreases the turnaround time for tests such as blood glucose, anticoagulation, cardiac markers, haematology or urine screening.

In order to reduce the risk of blood clots, patients will take anticoagulation therapy with the aid of anticoagulants such as warfarin [42]. However, if the wrong dose of medication is ingested it can result in excessive bleeding. In order to prevent this, the patient must be monitored by a clinician who tests the International Normalised Ratio (INR) using the POC device and adjusts the dose accordingly [43].

The POC method of testing has numerous benefits such as the ability to test on demand. It would be near impossible for a diabetic to monitor their blood glucose level at the predetermined intervals if there was a requirement to enter a laboratory for each and every test. The monetary cost of the test can be lower as the supply costs are less than what the laboratory would charge and the cost of transport is reduced. It is even possible that in the case of glucose testing, the full POC test will take less time than collecting a sample to transport it to the laboratory.

One form of POC is where a patient can perform a blood test with a blood glucose meter or urine strip test to obtain a result and alter their medication dosages at home.

Another assisted type of test [44] is where the clinician uses a POC device to determine the outcome which requires trained personnel to operate the equipment. The test still takes place at a location convenient to the patient, but specialised equipment is required such as an Ultrasound monitor, an ECG machine, a pulse-oximeter monitor or a heart-rate monitor .

Some hospitals and clinics contain a laboratory-like setup where a patient can walk in and get a POC test done in the clinic. This allows trained nurses to monitor tests and make sure the correct procedure takes place. This also provides an easier platform for managing the POC results.

POC contrasts with centralised laboratory testing where the results are loaded into a database and retrieved by the medical personnel who requested the testing. The results can take up to a few days to be made available depending on the test. This may indicate that POC testing has the potential to mitigate the need for laboratory testing, in turn rendering the drone sample delivery system redundant.

## **3.2 RESEARCH UNDERPINNINGS**

### **3.2.1 Costs Associated With POC Devices**

As of 2015, low cost glucose monitors in South Africa retail for between R150.00 - R200.00 per device with the requirement of purchasing test strips for between R110.00 and R130.00 per pack of 50 [45]. A patient monitoring their blood sugar levels on a regular basis could easily use up to 100 strips per month. This is a minimum of R370.00 in the first month and R220.00 per month following.

Laboratory CD4 count tests range between R314.00 - R557.00, where 83 % of the overall cost comes from the assisting products such as the consumables [46]. However, the cost per test is reduced as the volume of tests carried out increases.

The delivery of POC devices to and from laboratories adds to the overall cost. The cost per kilometre of a hatchback delivery vehicle is approximately R0.64, a scooter R0.24 and a drone R0.17 [47][48]. However, these costs are divided between the quantities of devices that are delivered. In the case of a motor vehicle carrying large quantities of devices it becomes more cost effective. This information limits the drone to urgent and small quantities of equipment which are less than the specified package weight of 4 kg.

However, for packages less than 4 kg, the drone is the favoured transportation method as it adds minimal costs when transporting these devices.

The general perspective of laboratory professionals is that POC testing is more expensive than centralised laboratory testing. This is partially due to the fact that each test is conducted individually and that bulk tests are less frequent. Adding to this is the high cost of labour. An estimated two-thirds of POC test cost is accredited to clinical personnel necessary in administering the procedure or monitoring the outcome [49]. This is obviously reduced when PSM is used.

An analytical cost of central laboratory glucose tests estimates the total cost of tests performed in the U.S.A using the following equation [49]:

$$\text{Cost per Test} = \frac{(\text{Equipment Cost} + \text{Supplies} + \text{Labour})}{(\text{No. of Patient Glucose Specimens})} \quad (3.1)$$

Of the 445 institutions, the cost per test for glucose was lowest in central laboratories and highest in low-volume bedside glucose testing, averaging \$1.18 and \$4.66 respectively [49]. This indicates that using drones to deliver POC devices may prove costlier than laboratory testing.

However, POC cost comes with added benefits such as the possibility of an overall improvement in the patient's outcome as the patient is able to respond immediately to the test results. In the instance of blood glucose tests, one can adjust one's insulin dose depending on the POC test with immediate effect and hence reduce the risk of permanent or prolonged illness and avert an emergency or life threatening situation. For this reason, it appears as though simply looking at costs to determine the preferred method of testing is insufficient.

### 3.2.2 Laboratory Testing

The use of antiretroviral (ARV) in pregnant women is the key prevention of mother-to-child transmission of human immunodeficiency virus (HIV) [50]. Even though the mother is diagnosed to be HIV-positive, the unborn child does not necessarily share this virus. Antiretroviral therapy can be used to prevent this if the condition allows for it. The eligibility of the mother is determined by her CD4 cell count [50]; this is the number of white blood cells per cubic millimetre of blood. If the cells that play a major role in fighting off infection drop below 350 cells/mm<sup>3</sup> [50], ARV therapy is recommended.

In order to test for the CD4 count at clinic POC, an ‘Alere Pima Analyser’ may be used [51]. The device is a bench-top unit which provides an absolute CD4 count in less than 20 minutes.

521 women took part in a study [52] with an average gestation age of 23 weeks. Laboratory devices recorded their median CD4 cell count at 388 cells/mm<sup>3</sup> whereas the POC device recorded a median CD4 cell count of 402 cells/mm<sup>3</sup>. In women of 36 weeks gestation age the discrepancy was even higher.

Accurate results play a crucial and vital role when it comes to clinical tests such as CD4 count. It is imperative that these tests are done at a clinic laboratory to obtain an accurate clinical diagnosis upon which a trained clinician would immediately be able to respond to the obtained result.

The timely and accurate administration of ARVs can mean the difference between a mother passing on HIV to her unborn foetus or preventing the transmission of the virus.

### 3.2.3 Proportional Approach to Testing

When considering the various forms of testing, the evidence points towards the use of both POC devices as well as laboratories for obtaining the necessary results. What needs to be determined is when it is appropriate and cost effective to use the POC methods or laboratory testing and whether or not they are interchangeable.

From what has been explored in this chapter, POC devices are highly beneficial when it comes to frequent, on-the-go testing such as blood glucose tests for diabetics or cardiac monitors for someone with a heart condition. Generally, POC testing often remains inferior to laboratory testing when it comes to accuracy. Therefore, for tests such as CD4 count and anticoagulation it is preferable, where possible, to obtain results via laboratory testing and have a clinician oversee the procedure and advise the patient on how to respond to the test results.

The publication, “From access to adherence: the challenges of antiretroviral treatment Studies from Botswana, Tanzania and Uganda” [53], assessing the challenges that comes with ARV treatment in Northern Africa, discusses the reasons for skipping medication amongst patients with HIV. Beyond the common reasons such as forgetfulness and the stigma associated with someone who has HIV, cost also plays a major role. Logistical cost as well as the distance needed to travel in order to acquire medication accounts for 1.9 % and 13 % of missed doses respectively [53]. ‘Cost and logistics’ is a summation of all the costs accrued to the patient when collecting the medication. The following needs to be taken into account - the cost of transport, wages lost due to the patient being absent

from work in order to collect their medication from the clinic and other treatment related outlays. On a logistic level, workers reported a lack of transport availability as well as the lack of funds required for transport as the reasons behind missing clinical treatment [53]. The large distance the patient has to travel to the clinic also poses difficulties as the patient must take off many hours from work resulting in lost wages.

One of the main reasons behind POC is to grant access to laboratory facilities in areas that are not easily accessible due to lack of infrastructure. A case in point would be that of a person living with HIV in an inaccessible rural area who has difficulty gaining access to transport to and from a clinic on a regular monthly basis in order to collect their supply of ARVs. Laboratory diagnostics may be the best form of accurate diagnosis, but when it comes to ARV treatment, visiting a clinic once a month may not be possible. Therefore, an alternative means of ARV delivery must be found for people in this predicament. A faster more reliable alternative is needed that can access areas that are inaccessible for various reasons.

An Unmanned ARV carrier (U-ARV) may be a possible solution to urgent medication delivery. This can reduce the number of patients that skip medication as a result of not having regular access to the clinic due to their socio-economic situation and rural location, such as in the cases of Tanzania and Uganda. Not only will this U-ARV deliver medication, but also deliver the POC devices needed by the patients that are easily transportable and do not require technical over-site.

The aspects that inhibit the delivery of medication such as ARVs are the drone system's limitations, such as the amount of medication that the drone can carry. A common combination of ARV treatment is 300 mg of zidovudine (AZT) and 300 mg of lamivudine (3TC) every 24 hours. Other dosages such as Saquinavir (SQV) can be as much as 1600 mg combined with 100 mg of Ritonavir [54]. This can equate to 52.7 g for every 30 days of treatment. If it is assumed that packaging weighs an additional 50 g a single drone with the ability to carry 4 kg per trip would be able to transport roughly 30 days of treatment for 38 patients. If the drone is packed to capacity, it will not be able to carry any additional samples and a more sensible loading limit for medication would be half the maximum limit; 30 days of treatment for 19 patients.

It must be emphasised however that the delivery of medication is restricted to urgent supplies where clinic stock has run low. This would be the case in a region that lacks storage facilities or if the short shelf life of the drug is accompanied by a low rate of demand.



### **3.3 SUMMARY**

POC testing proves costlier than laboratory testing and the latter is preferable with regard to result accuracy. This indicates that in order to improve on efficiency, it is not always monetary costs that must be reduced, but also turnaround times and accessibility to patient care. Therefore, a proportional approach to clinical testing and POC must be achieved. For this reason, it is necessary to include within the framework, a simulation that takes multiple variables into account.

Now that it has been established that the current methods of sample delivery can benefit from supplementary methods, it is essential to evaluate the type of regions where this method would be most beneficial.

## Chapter 4

# MPUMALANGA CASE STUDY

### 4.1 RESEARCH DESIGN AND METHODOLOGY

In order to assess the capabilities of a drone system, if it were to be implemented in the future, a consideration must be given to the development of the system in a theoretical scenario. In order to accomplish this, a sample population must be selected based on their residing region; this will allow for the demarcation of a test region for the case study. The criteria and infrastructure of the region plays a vital role in its selection.

Once the region location is determined, the established laboratories and clinics must be indicated on a map in order to measure their distances from one another. This will grant a direct comparison between delivery requirements and the drone's capabilities.

As cost and turnaround times are presented as the initial considerations; they must then be minimised. This can be done by finding the shortest path between all the laboratories and clinics. In this way, if all the points on the map are to be visited on a daily basis, the system has a predefined route. The route optimisation will be developed in MATLAB which will allow for an overall time frame of the visits in the region and ultimately quantify the number of locations that a drone can visit per time frame selected.

### 4.2 PROBLEM AND PURPOSE OVERVIEW

The aim of this chapter is to classify the people that would otherwise go without patient care if not presented with alternate methods of delivery. This can be achieved by investigating various demographics and applying a theoretical framework to the appropriate data set.

A limited case study of a particular region can assess the detailed considerations of the developing delivery process. Given the regions infrastructure, a case can be presented whereby an aerial delivery vehicle transporting clinical samples in the region can be simulated. From the analysis one can determine if the region has the potential to adopt the system in question and further expand the process to alternate terrains.

### **4.3 POPULATION AND SAMPLE**

#### **4.3.1 Optimum Demographic**

A U-ARV may be used to deliver medical samples under certain strict conditions where safe transport methods have been adhered to, from the patient to the clinic. This would be an ideal method of transport and interaction between the clinic and patient in low socio-economic areas and remote inaccessible locations or regions where transport and other conventional delivery methods are cumbersome.

Maslow's hierarchy of needs states that a person's physiological and biological needs must be fulfilled in order to be self-motivated [55]. If one lacks the basic necessities or one's health is poor the potential for growth is suppressed. This applies to the 45.5 % of people living in poverty in rural areas in South Africa [56]. Easy access to medication grants a population the ability to thrive in a case where their health would otherwise stagnate or decline. A much greater impact can be achieved in lower socio-economic regions as compared to middle or upper class sectors and thus a system implementation such as the drone delivery could have a larger impact on rural areas.

Due to the lack of investment in a specific region, the transportation infrastructure is often lacking. This hinders the ability to trade with the region as would be the opposite in an affluent society. The lack of trade lowers the diversity of supplies and medication. Because of the reduced influx of trade or access to the region, it can be considered as 'remote'. A remote location thus lacks the supporting architecture to facilitate the treatment of major diseases. From this one can see the importance of selecting a region that is underdeveloped in order to meet a delivery systems full potential.

#### **4.3.2 Region Selection**

Mpumalanga has one of the lowest incomes of all South African provinces and has an estimated 7 % of its total population [57]. None of the areas in Mpumalanga have the status of metropolitan areas and therefore all the urban areas are considered small towns.

59.6 % of people in Mpumalanga live in rural areas compared to the national average of 37 % [57]. This makes Mpumalanga a good choice when considering case study regions in South Africa. The low population density of 53 people/km<sup>2</sup>, compared to Gauteng of 675.1 people/km<sup>2</sup> [58], is also favourable as densely populated areas would cause concerns to arise such as the increased probability of injuring of a bystander during a flight malfunction.

### 4.3.3 Region's Supporting Infrastructure

The area selected has supporting roads and some regions are accessible by railway lines but limited public transport is available [59]. Independent minibus taxis service some areas but do not run on a set schedule. The times and routes of the minibus taxi service are based on the area congestion at certain times of the day [60]. If it is not profitable to travel along a route, it may be avoided in which case the client must make their way to a taxi rank in order to gain transport to a clinic or laboratory.

The area is fully covered by the MTN, Vodacom and Telkom 2G and 3G networks which allows for the transmission of results via email or SMS from a laboratory to a clinic in the surrounding area [61]. If need be the SMS can be directed to the patient directly if the patient has access to a mobile device.

## 4.4 ASSUMPTIONS AND VARIABLES

The MATLAB algorithm simulates an ideal scenario in order to determine a base value for the number of delivery points a drone could potentially service within a given time frame. Therefore, external elements such as changes in weather conditions and drone malfunctions are assumed to be a non-occurrence.

The request points are also assumed to be in fixed positions on the map and contain a fixed number of specimens. Each specimen has the same weight and the drone is assumed to be able to visit all locations without overloading its payload capacity. Table 4.1 lists the simulation variables.

TABLE 4.1: Case Study Variables.

Object	Variable
Clinics	Clinic Number, Location
Laboratories	Laboratory Number, Location
Drones	Position, Maximum Range, Total Travel Distance (Route Cost)
Region	Border Locations
Distances	Distances Between Laboratories and Clinics, Distances between Drone and Clinics , Distances between Drone and Laboratory

## 4.5 DATA COLLECTION AND INSTRUMENTATION

### 4.5.1 Mapping the Region

The towns surrounding Whiteriver, roughly 100 km South West of the Kruger National Park, are the centre-point for this Mpumalanga case study as they are less populated than their neighbouring towns. The region borders the towns of Dullstroom, Amanda, Komatipoort and Swaziland and has limited transport infrastructure between them. The neighbouring towns have laboratories and clinics and the necessary infrastructure for their requirements. However, they are few and far between and the limited public transport poses major difficulties to people in need of clinical diagnostics. It is not a random selection of an area that determines the case study route location, but rather the area's infrastructure that allows for the possibility of the systems implementation which makes this region favourable for investigation.

A basic laboratory search is done using Google Maps. This allows for pinpointing the laboratories and clinics within the region. The outlined area in figure 4.1 illustrates the search results of 6 Lancet Private Laboratories and 13 general clinic locations in the area specified above. From the figure it is apparent that there are fewer laboratories than clinics and the distance between them are relatively large. The coordinates of the enclosed case study region as well as the Laboratory and clinic coordinates are tabulated in table 4.2.

Clinics are not always able to collect as well as process samples and must forward samples to a laboratory to be processed. It is therefore necessary to map out a travel route for the delivery vehicle that would allow for transportation between clinics and laboratories. The route must be optimised for the shortest path which will provide the shortest turnaround time. This will reduce the overall monetary costs involved in delivery. The results of the tests can be telecommunicated or delivered on the return route of the delivery vehicle.

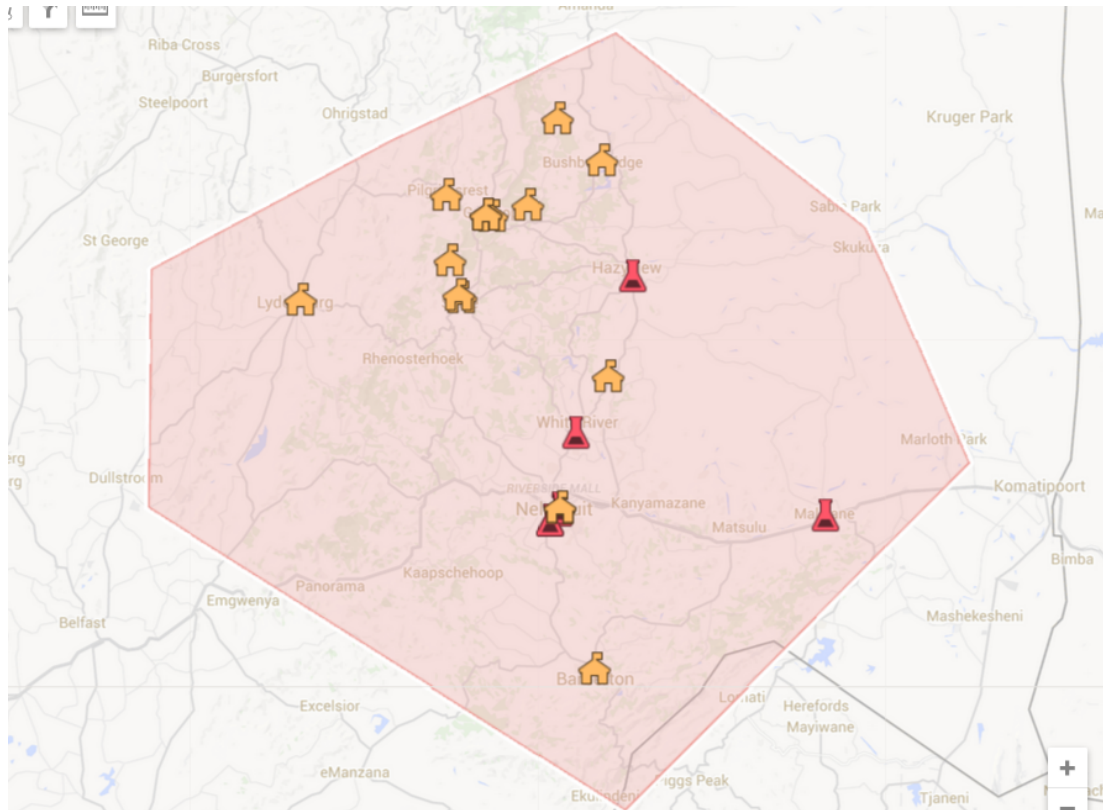


FIGURE 4.1: Map of area selected for research case study. Laboratories represented by glass flasks and clinics are represented by houses [62].

#### 4.5.2 Optimisation Objectives

As the system would need to be sustained, the costs involved in operating the drones must be reduced as much as possible. This means that non-essential delivery routes cannot take place in order to avoid unnecessary wear and tear on the units. Therefore, the flight routes must be optimised for shortest time between two points. This will provide the shortest delivery time and the fastest potential turnaround time.

The coordinates of the laboratory and clinics in the outlined region are extracted from the map and presented in table 4.2. The Laboratories latitudes and longitudes are placed in adjacent columns one beneath the other followed by those of the clinics. Using the distance formula, the distance between two coordinates can be found. This is done between every laboratory and clinic resulting in a total of 156 values. Duplicate paths are immediately eliminated such as the distance between laboratory ‘A’ to clinic ‘1’ and clinic ‘1’ to laboratory ‘A’.

The average distance between laboratories and clinics is 54.48 km and between clinics and other clinics is 43.05 km. The resultant mean value is 48.76 km. This value is higher than the maximum flight range of 22.5 km based on an estimated half hour flight [63] at

TABLE 4.2: Coordinates of points in case study region.

Enclosed Area Coordinates	Laboratory Coordinates	Clinic Coordinates
-25.47390, 30.14989	25.04645, 31.12774	-24.75728, 30.97617
-25.03651, 30.15542	25.33277, 31.01451	-24.83333, 31.06666
-24.60260, 31.09519	25.47057, 30.97811	-24.91666, 30.91666
-24.95936, 31.60077	25.47581, 30.97763	-24.93333, 30.83333
-25.39207, 31.80959	25.48333, 31.51666	-24.89785, 30.75342
-26.02586, 31.11436	25.49355, 30.96188	-24.93689, 30.84500
		-25.01844, 30.76085
		-25.08174, 30.77730
		-25.08632, 30.78228
		-25.09013, 30.45857
		-25.22802, 31.07718
		-25.46815, 30.98132
		-25.76227, 31.05040

45 km/h and hence only distances smaller than 22.5 km can be considered. This leaves 27 out of a possible 156 flight paths (17 %) and reduces the potential operating points to 5 laboratories and 11 clinics. The laboratory to clinic distances and clinic to clinic distances are tabulated in figure 4.2 and figure 4.3 respectively, where all unreachable flight distances are highlighted in red.

Distances Between Laboratories and Clinics (km)											
A1	35.5	B1	63.87	C1	79.01	D1	79.6	E1	97.61	F1	81.57
A2	24.4	B2	55.57	C2	71.15	D2	71.73	E2	85.11	F2	73.9
A3	25.71	B3	47.14	C3	61.67	D3	62.24	E3	87.16	F3	64.07
A4	32.26	B4	47.87	C4	61.28	D4	61.83	E4	91.95	F4	63.4
A5	41.23	B5	54.9	C5	67.36	D5	67.9	E5	100.62	F5	69.25
A6	31.02	B6	47.07	C6	60.62	D6	61.18	E6	90.81	F6	62.78
A7	37.16	B7	43.2	C7	54.66	D7	55.17	E7	91.92	F7	56.39
A8	35.57	B8	36.67	C8	47.59	D8	48.09	E8	86.74	F8	49.26
A9	35.13	B9	35.96	C9	46.91	D9	47.42	E9	86.05	F9	48.6
A10	67.69	B10	62.14	C10	67.19	D10	67.52	E10	115.2	F10	67.58
A11	20.75	B11	13.21	C11	28.66	D11	29.22	E11	52.51	F11	31.62
A12	48.99	B12	15.36	C12	0.42	D12	0.93	E12	53.86	F12	3.43
A13	79.68	B13	47.72	C13	33.12	D13	32.57	E13	56.11	F13	31.07
Average	39.6223		43.8984615		52.28		52.7231		84.28076923		54.0708
Total	54.4792										
Average											

FIGURE 4.2: Distances between laboratories and clinics with highlighted cells indicating distances that are too large to travel.

By using the laboratories as central hubs and the clinics as access points, it is possible to use the points on the map as a network and reduce the overall travel expense. A flight path is chosen by taking the shortest route between two points. It is assumed that stop overs are allowed at any point specified on the map; in reality this stop-over would

Distances Between Clinics (km)																	
1,2	12.45																
1,3	18.71	2,3	17.74														
1,4	24.31	2,4	26.03	3,4	8.605												
1,5	27.38	2,5	32.41	3,5	16.6	4,5	8.972										
1,6	23.96	2,6	25.15	3,6	7.568	4,6	1.241	5,6	10.2								
1,7	36.26	2,7	37.08	3,7	19.36	4,7	11.96	5,7	13.43	6,7	12.4						
1,8	41.28	2,8	40.17	3,8	23.11	4,8	17.44	5,8	20.59	6,8	17.5	7,8	7.23				
1,9	41.48	2,9	40.17	3,9	23.22	4,9	17.77	5,9	21.16	6,9	17.8	7,9	7.85	8,9	0.71		
1,10	63.98	2,10	67.62	3,10	50.03	4,10	41.59	5,10	36.61	6,10	42.5	7,10	31.5	8,10	32.1		
1,11	53.32	2,11	43.9	3,11	38.21	4,11	40.95	5,11	49.11	6,11	39.9	7,11	39.5	8,11	34.3		
1,12	79.05	2,12	71.11	3,12	61.67	4,12	61.3	5,12	67.43	6,12	60.6	7,12	54.7	8,12	47.6		
1,13	112	2,13	103.3	3,13	94.98	4,13	94.72	5,13	100.6	6,13	94.1	7,13	87.7	8,13	80.5	12,13	33.4
Average	44.52		45.88		34.34		32.88		39.9		40.7		38.1		39		33.4
Total Average	43.05																

FIGURE 4.3: Distances between clinics with highlighted cells indicating distances that are too large to travel.

mean the hub or access point would contain the necessary facilities to support the use of the drones in their operation. These facilities include battery changes, battery chargers, spare parts and general maintenance. Trained personnel to load and offload packages are also required. The resultant possible flight ranges are shown in figure 4.4. If the resulting flight ranges are overlaid with a mapped network it is reduced to the diagram shown in figure 4.5. As expected, fewer points are visible as fewer paths are applicable. In this case the mean value of the combination selected is 11.8 km.

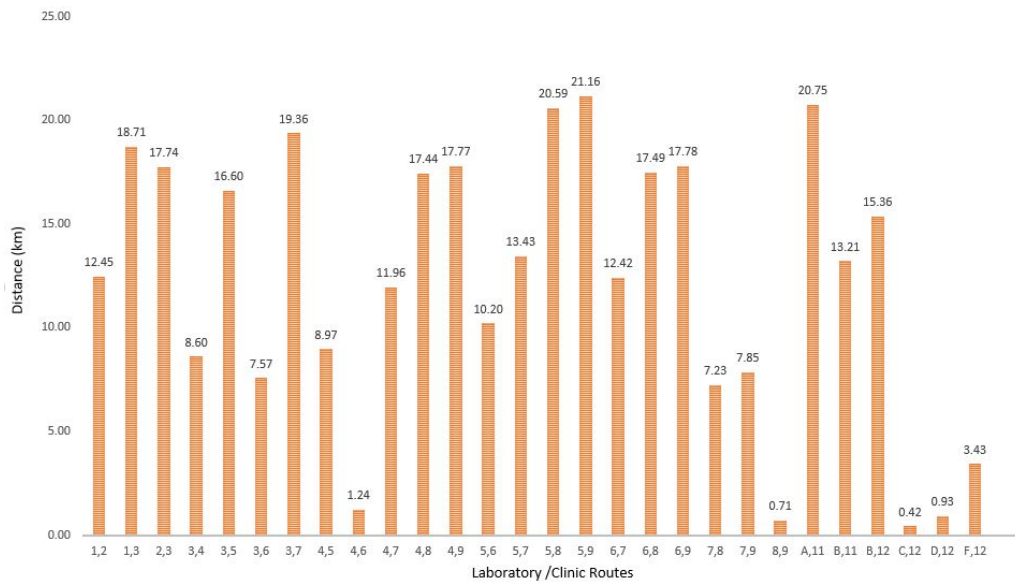


FIGURE 4.4: Point to point distances between Laboratories and Clinics irrespective of path.

From this network the best travel path between two points can be derived, allowing for the shortest turnaround time. This can be achieved by applying route optimisation methods.



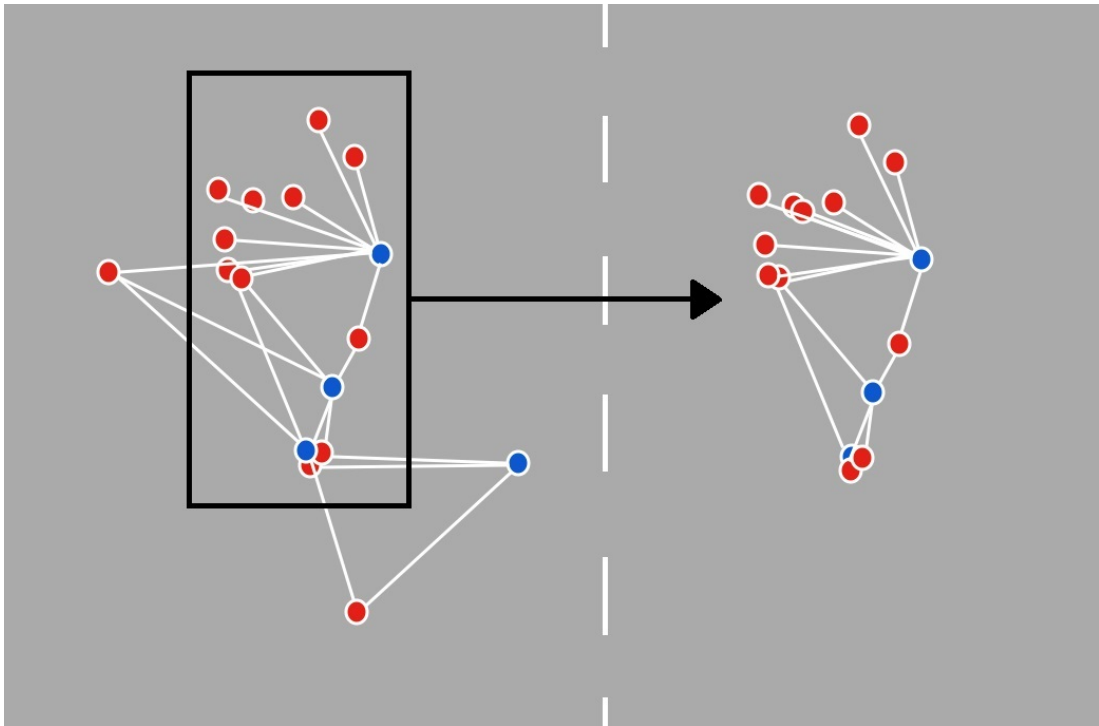


FIGURE 4.5: Representation of reduced laboratory-clinic network. Blue markers indicate Laboratories, Red markers indicate Clinics.

### 4.5.3 Classifying the Type of Routing Required for Optimisation

Vehicle delivery such as waste disposal or paper routes, use routing algorithms. There are three main routing algorithms used by these companies based on the type of delivery [64]. High density routing, point to point routing and paired routing are some of the methods used.

Examples of routing that use high density routing algorithms are paper delivery, waste disposal, postal delivery and meter reading [64]. These routes are common in that there are a large number of stops on the same schedule over a contiguous route. Point to point delivery however is more significant for smaller numbers of stops where boundary is of less importance than schedule and sequence.

Paired routing is similar to point-to-point routing but requires an additional point to be paired with the original collection. An example of this is a shuttle service that collects a person and transports them to their desired location but then returns the passenger to their original point. Until now the assumption has been made that a route optimisation method is needed in order to determine the shortest possible delivery route. However, not all route optimisations problems can be solved using the same optimisation algorithm and the required algorithm must be identified. The algorithm for the optimisation of

routes must be designed based on the systems attributes. The attributes of a general optimisation route are Schedule, Boundary and Sequence [65].

#### **4.5.3.1 Identifying the Schedule**

The schedule is the time frame of delivery. With most deliveries taking place between the hours of 8:00 am and 5:00 pm where visibility is at its finest, this seems to be the preferred window of delivery. However, the collection of samples should be done earlier in the day in order to make it in time to the laboratory to be processed that same day. Additionally, the issue of public safety can be reduced when flying in the early hours of the morning or even at night when less activity is taking place in public areas. Most major clinics and hospitals run a 24-hour facility or emergency unit that can attend to these deliveries at any given time.

#### **4.5.3.2 Identifying the Boundary**

The route boundary is the geographical extent of the route and is a major factor in determining the range of delivery. A boundary can be in the form of country, region or even a complex of dwellings. In the Mpumalanga case study, this boundary has been clearly marked to include the towns where the laboratories necessary for the processing of the medical samples are located.

#### **4.5.3.3 Identifying the Sequence**

The stop sequence focuses on the order of importance for delivery and/or collection. In the case of high density routing the order of the sequence can affect the travel time greatly. For the Mpumalanga clinics and laboratories, point priority is not the main concern as the starting point can be any point with the available drone facilities.

For the Mpumalanga case study, the boundary conditions and the number of points along the path are known. In addition, the points are not paired with a delivery and collection point but rather any specimen collected can be delivered to a laboratory further along the predetermined route. This classifies the drone delivery routing problem as a high density route even though the number of points in this situation is relatively low.

#### 4.5.4 Classifying the Optimisation Method

A special case of the vehicle routing problem is the ‘Travelling Salesman Problem’ (TSP) [66]. Much like the Mpumalanga case study, the TSP is used to determine the shortest possible route in a situation where a graph of specified points is given.

The algorithm computes the route between ‘N’ points regardless of point priority as long as every point is accessed along the route at least once. The ‘cost’ involved can now be calculated based on how difficult it is to traverse the region between two points or simply the distance or time it takes to get there. This ‘cost’ or expense must be minimised throughout the route. So simply moving to the next closest point may result in an extended overall route.

This is referred to as an NP-hard problem [67]. The difficulty of obtaining the lowest cost increases exponentially as more points are added to the route. The most expensive solution would be to try every possibility, but in the case of ‘N’ points the possibilities are (N-1) factorial. For 100 stops on a map there would be  $9.3 \times 10^{157}$  possible solutions. The computational cost would outweigh the delivery cost.

For smaller solutions of 40-60 points, a branch and bound approach can be used [68]. This is for a more real world solution where a state space search can determine the optimum state using a routed tree. A tree is an undirected graph with a single vertex between two points, but can have multiple vertices extending from each node. The algorithm finds the shortest path between two points and then expands to find the next shortest path between the remaining points.

A heuristic approach can be used to approximate larger sets by making certain assumptions. One heuristic approach is by gathering information on the surrounding nodes such as the quantity or density of points and choosing the higher value even though the other node may contain a shorter vertex. This way, more points can be visited in a smaller region. This encourages cluster visits as opposed to lowest cost routes.

Since the number of points in the Mpumalanga case study is fixed at the relatively small value of 17, the branch and bound approach or nearest neighbour (NN) of similar attributes can be used over multiple iterations to approximate a low cost solution. The variable that can be changed in order to alter the data set is the starting point which may provide a shorter route based on its location.

#### **4.5.5 Link Between TSP and Drone Delivery**

Applying a TSP approach to the Mpumalanga case study may answer the second question of the dissertation as to whether or not a simulation can be developed in order to assess the capabilities of a drone delivery system in a rural environment.

A TSP simulation could potentially formulate the shortest route between delivery points, whereby providing a baseline for delivery turnaround times. In addition, a TSP simulation may quantify the number of points and area size that a drone can service per time period. This is once step closer to assessing the feasibility of the drone delivery system.

Once these values are determined, an optimised approach can be taken in order to minimise the costs involved in drone delivery through an optimisation simulation.

## **4.6 SUMMARY**

The Mpumalanga case study presented new information on clinics and laboratories in rural and urban areas. The distances between the testing stations and the infrastructure connecting them allow for the direct comparison between traditional methods of delivery and autonomous methods. Given the current data on the required region and the classification of delivery method falling under high density routing, a simulation can now be completed in order to optimise the delivery route using the chosen TSP algorithm.

## Chapter 5

# TSP SIMULATION

### 5.1 INTRODUCTION

Chapter 4 outlined the type of region and demographic that would predominantly benefit from supplementary medical care systems. If a drone delivery system were to be implemented in the Mpumalanga region outlined in the case study, the flight route would need to be optimised based on the classification of the routing. Optimising the route will estimate the turnaround times expected from a region of similar scale and laboratory density.

It was established that a drone delivery system would fall into the category of high density routing and therefore the TSP algorithm is recommended as the optimisation method. From here a MATLAB simulation can be developed using the TSP algorithm within the Mpumalanga region.

### 5.2 SIMULATION

#### 5.2.1 Applying TSP to the Case Study

In order to determine the optimum route of travel between laboratories and clinics using the travelling salesman algorithm a few steps are needed.

The data required for the algorithm to run effectively is the precise locations of the delivery points. This is obtained in coordinate format using Google maps. The starting point can be any point on the map and is chosen as the furthest West point with the starting direction facing north.

From there the ‘cost’ can be calculated between points. In this case the cost is the distance between points as it is directly proportional to the delivery flight time. The flow diagram in figure 5.1 adapted from a general TSP algorithm [69] represents the basic flow model of the TSP using the branch and bound approach where the selection of the next location is based on the distance between the two points only. Satisfactory route costs are determined by comparing the drone’s physical capabilities, such as maximum flight time and operating range, to the algorithms route cost output.

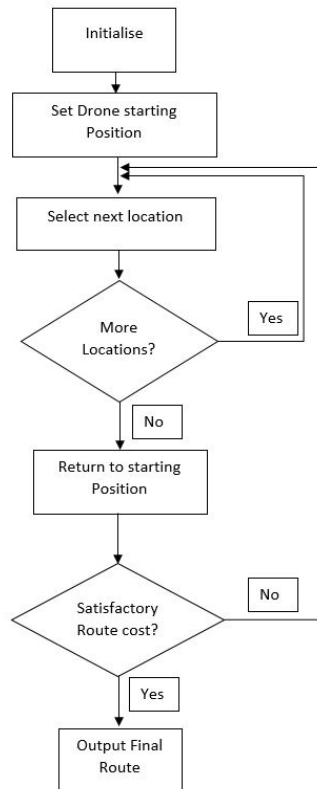


FIGURE 5.1: Flow diagram of the Travelling Salesman Problem using the branch and bound approach.

### 5.2.2 MATLAB Configuration

- Firstly the demarcated area in Mpumalanga is outlined using its coordinates from Google maps. This is done by loading the boundary coordinates into a matrix in MATLAB.
- An additional matrix is created in order to contain all the laboratory and clinic coordinates within the boundary. These coordinates are displayed within the boundary as in figure 5.2.

- All distinct routes between laboratories and clinic coordinates are then generated. For example the route from point ‘A’ to point ‘B’ must be drawn but route ‘B’ to ‘A’ can be ignored as it is duplicate information.
- The distance of each route is then calculated by using the distance formula between two coordinates.
- The distance values larger than 22.5, with no clinics or laboratories closer than that value are removed from the matrix and excluded as the drone cannot travel further without stopping over to recharge. Conventional forms of delivery must be used in these circumstances.
- The cost function used to minimise the total route is calculated as the sum of all route distances along the tour. This cost function must be reduced to the minimum possible value.
- Each path between two points is given a binary value. Where 1 represents a path added to the route and 0 represents one that was removed from the route.
- In order to ensure that the final route includes all necessary stops, the number of paths must be the same as the number of points on the map and each point is limited to a single arrival path and a single departure path.
- The problem is then optimised using the ‘optimoptions()’ function which returns a set of default options for the TSP algorithm, displayed in figure 5.2-A.

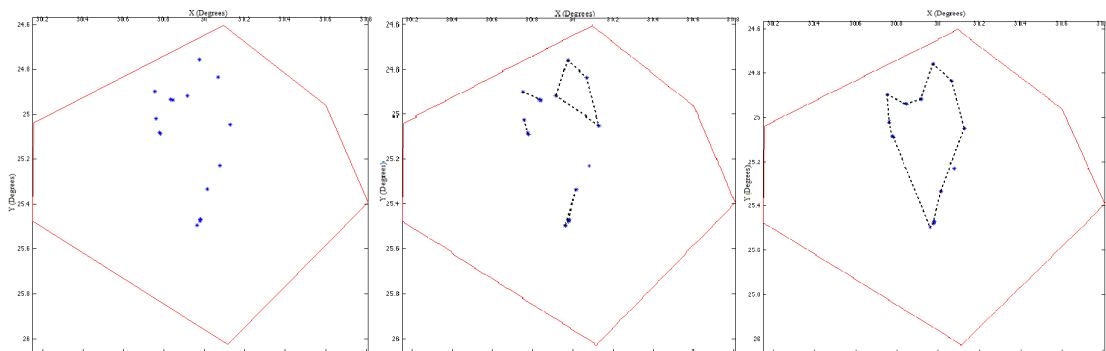


FIGURE 5.2: A) Graph representation of demarcated area with laboratory and clinic coordinates. B) Solution of routes with sub-tours. C) Final route solution with sub-tours eliminated.

What can be observed from figure 5.2-A is that there are multiple sub-tours as they provide the lowest distance value. This can be a solution in itself for using multiple drones for different sub-tours. But if the system is limited to a single drone as in the

case of an initial start-up phase, all the points on the map would need to be included in a single route.

In order to do this the ‘detectSubtours()’ function is used to return a cell array of vectors containing all the stops in each sub-tour. The sub-tours are then eliminated using the linear inequality constraints mentioned earlier with the function ‘spalloc()’. This function creates an all zero sparse matrix which clears the sub-tours. This is repeated until only one sub-tour remains. This final sub-tour is the optimised route for delivery shown in figure 5.2-B.

The route displayed in figure 5.2-C allows the drone to begin its flight at any point on the map and follow the route until it returns to the same point. This way every clinic will be visited and the samples can be offloaded on-route at a laboratory for processing. Once results are made available the drone can collect them on its next trip. The estimated route length is 198 km.

For urgent delivery of samples or medication to a specific clinic, the shortest route can be calculated using these methods. The drone would avoid unnecessary stops but would often require at least one stop for a battery change at distances higher than 22.5 km. An additional “urgency” drone can be deployed for this type of scenario. The full TSP MATLAB code can be found on the accompanying disk in the folder *Traveling Salesman Problem*.

## 5.3 DATA ANALYSIS

### 5.3.1 Efficiency and Turnaround Times

A blood-result turn-around time survey highlighting the turn-around times between clinics and laboratories [70] delves into the reason behind the hospitals not being able to treat patients in a timely manner. Nkomazi Health Ward in the Eastern Transvaal has 19 surrounding clinics between 5 km and 70 km away [70]. The clinics are in radio contact with the Shongwe hospital which has a laboratory facility that services the clinics. It was identified that blood test turnaround time was the leading cause of untreated woman with positive syphilis serology. Of the 220 batches that were tested, 41 % took up to 13 days for the results to be obtained by the clinic. The turnaround time was broken down to 17 % retrieving the specimens, 47 % laboratory procedures, 13 % obtaining results for distribution and 23 % returning results [70]. However, no direct correlation was found between clinics of further distances to longer turnaround times as the transportation of specimens contributes to less than 1 day (21.6 hours) of the 13 days in most cases .



From these results, 21.6 hours is obtained as the base value for specimen, ARV or POC device delivery. From the point of collection from clinic 1 to clinic 11, then delivery to a laboratory thereafter, the total hours of delivery should not exceed 21.6 but the upper maximum limit is set at 24 hours to account for minor delays.

The total route of the calculated flight path accumulates to approximately 198 km. If it is assumed that there is minimal headwind then we can use the aerial velocity from of 45 km/h discussed in chapter 4. At this speed it would take 4.4 hours of continuous flight to circle the entire route. Time for loading specimens, take-off, landing, offloading specimens and battery changes can be taken into account and a fair estimate is 5 minutes per stop over. As there are 5 laboratories and 11 clinics the leeway time for stopovers is 80 minutes. The total time assumed for an entire route is approximately 5.7 hours, below our base value of 21.6 hours. If it is only necessary to visit a single laboratory for the flight duration, this value can be reduced further. Additionally if more drones are used the total flight time is divided between them and the method of multiple sub-tours can be considered.

These results indicate that the method of drone delivery is within the boundaries of current delivery methods and has the potential to improve on turnaround times. This model provides a foundation for a drone delivery simulation.

### **5.3.2 Deliveries Exceeding the System's Capabilities**

The Mpumalanga case study presented flight optimisation routes for clinics and laboratories that are within the flight range of the delivery drones. However, three delivery locations were beyond this range and had to be excluded. This left these locations inaccessible to the surrounding areas that they currently service. Therefore, an alternative for these three locations must be presented.

Motorised delivery presents itself as the fall-back option when drone delivery is unavailable. However the investigation into POC devices in comparison to laboratory testing in chapter 3 would lead to the use of POC devices for testing when available. This is due to the inaccessibility of these locations and the high cost involved in the transportation of specimens in low volume.

## **5.4 SUMMARY**

The region mapped out in chapter 4 was optimised in a MATLAB simulation using the travelling salesman algorithm. A path was mapped out for the delivery route of a

single drone over a time frame of 24 hours with an upper limit set at 21.6 hours. This simulation allowed for assessing various scenarios with different flight distances. Three of the 19 points on the map were too far to be accessed by the drone and would require conventional means of delivery.

The optimisation methods that were used determined that the flight range of the designed multi-copter was within the boundaries of the routes mapped out in the case study. The calculated delivery time of 5.7 hours was also below the mean value of current methods. This model indicates that the autonomous method can be a viable replacement for land based delivery with probable improvement on laboratory turnaround times; resulting in enhanced quality of patient care.

From here, a framework can be constructed which will facilitate future analysis of drone systems; in turn, identifying the problems that will need to be taken into account in future development of analytical approaches.

## Chapter 6

# SIMULATION DEVELOPMENT

### 6.1 INTRODUCTION

In order to facilitate the development and testing of a drone delivery system, a simulation is constructed that fits within the framework. The aim of the simulation is to find the global minimum of a systems cost function; this entails using the appropriate algorithm that satisfies the overall objective. The global objective is defined as the weighted combination of the overall cost, urgency, minimisation of losses and shortest delivery time. The algorithm is able to determine the next best move of the drone given the global considerations and ground conditions. A full consideration of the systems limitations is required in order to simulate a request process comparable to the real world state space.

In order to maximise the various scenarios, all key factors are established and the simulation is run over a number of iterations. Each iteration is based on the initial number of requests generated.

The simulation results provide the necessary information for the planning of real life implementation. The scenario results quantify the most effective implementation values such as number of drones per location and maximum distribution potential per region.

### 6.2 PROBLEM AND PURPOSE OVERVIEW

The Mpumalanga case study highlighted the key values when implementing a system in an isolated region with a fixed number of request points and drones. The case study was an ideal situation where all specimens were of equal weighting. In addition, the delivery times between collections were not of major concern. However, in reality this is not the case and often clinics will request urgent collections where the delivery time is

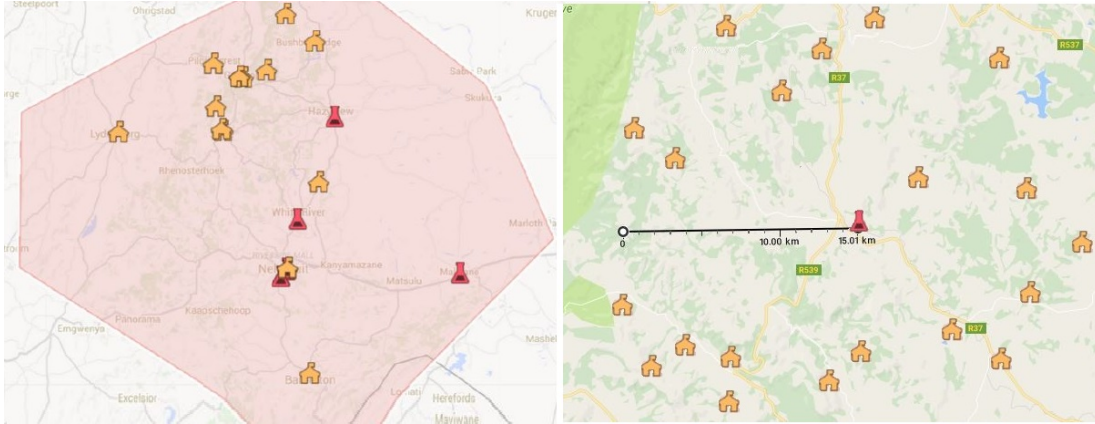


FIGURE 6.1: Left: Map of the region used in the Mpumalanga case study. Right: Map of the modified region used for the optimisation simulation.

the primary concern. Therefore, the request must take priority even though it may be further from the destination point. For this reason an optimisation simulation must be developed based on global minima that include delivery time.

In addition, the Mpumalanga case study is used to get a lay of the land. However, a notional region containing 20 clinics and one laboratory is better suited in order to provide a more extensive approach to the problem. A Set of clinics spread more uniformly throughout the plane will provide a more widespread framework while only a single laboratory is necessary for a drop off point. The modified region, based off of the Mpumalanga case study values can be seen in the figure 6.1.

### 6.3 SIMULATION FRAMEWORK

A software platform is developed in order to simulate a given situation where each clinic or laboratory can generate requests. Each request has specific properties. These properties are weighted and a priority is assigned to the request based on these weightings. Each drone in the scenario is assigned a request based on the drone's own properties and the requests are then queued for collection.

The platform used for the simulation is MATLAB and the scenarios are plotted on a graph for a visual representation of the optimisation process. This ensures that given any scenario, the outcome can be determined; limited by the simulation variables. The MATLAB code can be found on the accompanying disk in the folder *Inspection Algorithm*.

## 6.4 SIMULATION ALGORITHM

This dissertation solves a global solution based on maximizing a reward function, in turn minimising cost. The Inspection based optimisation algorithm uses a number of drones, each performing their own task in a search space in order to achieve an overall solution. The drones make use of an exploration factor that enables them to explore distant areas of the landscape [71]. The units then use exploitation to optimise the already visited areas by re-sampling the points and improving the solution.

The drone delivery network uses a combination of tasks to perform a structured event. A drone delivery system is based on multiple units, which are required to collect and deliver specimens to their destinations in the most efficient manner.

The methods used in this dissertation is a reward based selection and elimination process used to find the next best move for the drone. The algorithm leans heavily towards the exploitation factor and less towards the exploration factor as the drones are required to collect as many samples as possible within the shortest range while taking priority into account. The velocity and inertia of the drones remain constant throughout the simulation.

### 6.4.1 Future Scenario Impact of Optimisation Approach

All the static scenario variables are recorded in a history table containing a corresponding scenario number. The scenario number is incremented for every simulation that is completed.

On completion of the simulation, the optimised approach with corresponding scenario number is saved in a results table. The results table is then used for future simulations.

When a simulation is initiated, the history table is scanned for a matching scenario. If a scenario with identical static variables is found, the corresponding results table is used to populate the route of the drone. Hence, the optimisation algorithm is not required.

As the scenario has been calculated previously, there is no need to recalculate as the simulation is already aware of the optimum route. In both cases, the resulting routes will be identical. However, if the scenario has previously been explored, the optimisation algorithm will not be triggered.

## 6.5 ASSUMPTIONS AND VARIABLES

The conditions for selecting a request point for delivery are outlined in equations 6.1, 6.2, 6.3 and 6.4. These conditions must be met in order for a route to be considered possible. Once the route's possibility is determined, the cost factor must be minimised in order to select that route as primary. Once the route is selected the drones transition into their next state. This allows the simulation to act as a state machine.

$$R_i - d_i \geq 0 \quad (6.1)$$

$$S_i + C_i \leq 100 \quad (6.2)$$

$$P_i \geq P_1, P_2, P_3 \dots P_N \quad (6.3)$$

$$T_i = (T_{current} - T_{generated}) \cdot e^2 \quad (6.4)$$

Where:

$R_i$  = Range of drone.

$d_i$  = Distance between drone and request point.

$S_i$  = Number of specimens.

$C_i$  = Current payload capacity of drone (max. 100).

$P_i$  = Priority of specimens.

$T_i$  = Time elapsed.

$T_{current}$  = Current simulation time.

$T_{generated}$  = Time of specimen generation.

If the above conditions are met, then the cost factor must be minimised. This is in a case where:

- The drone has enough battery charge to fly the distance between its current position and a request point.

- The drone's payload capacity is not full and is able to collect the specimens at the request point.
- The priority of the request point is higher than the surrounding requests.

### 6.5.1 Routing Rewards

Equation 6.5 calculates the reward that a request point is assigned based on the number of specimens it contains, the specimen priority as well as the delivery distance. The 'cost' remains to be the monetary cost of charging and replacing the battery as well as the flight time which is a parallel factor to the aforementioned. The drone therefore receives a penalty for longer delivery times and specimens that remain uncollected. The reward value aims at reducing the penalty value or cost function and is therefore used to guide the drone to the best possible route. The drone's decision is now based on the maximum reward it can achieve in the given scenario.

$$r = T_i + P_i + S_i; \tag{6.5}$$

$r$  = Reward Value.

### 6.5.2 Penalty Values

When a drone's primary concern is the priority of the specimens, it does not weigh up the consequences of travelling a far distance or of collecting minimal samples. Similarly when a drone's objective is to minimise distance or maximise specimen collection, the priority of the specimens may be neglected.

For this reason, a penalty must be issued on the drone whenever a compromise is made. The penalty value takes into account the above mentioned as well as the request points that were not visited as a result of the drone's decision.

A penalty function is introduced in order to validate the optimisation algorithm. This will allow the simulation results to be compared with other policies. The total penalty value is the sum of the penalties accrued by a drone throughout the simulation. This can be seen in equation 6.9. The penalty equation for priority of request points over distance and number of specimens can be seen in equation 6.6.

$$P_P = \frac{T^2}{\sum_{i=1}^n P_i} \quad (6.6)$$

$P_P$  = Penalty based on priority.

$T$  = Delivery Time.

$n$  = Number of visited delivery points.

The penalty equation for maximum number of specimens over distance and specimen priority can be seen in equation 6.7.

$$P_S = \frac{T^2}{\sum_{i=1}^n S_i} \quad (6.7)$$

$P_S$  = Penalty based on number of specimens.

The penalty equation for minimising the distance between the drone and request point over priority of specimens and number of specimens can be seen in equation 6.8.

$$P_D = \frac{\sum_{i=1}^n d_i}{T^2} \quad (6.8)$$

$P_D$  = Penalty based on distance.

$$P_T = P_P + P_D + P_S \quad (6.9)$$

The penalty values are based heavily on the reward function. A penalty is issued if a possible reward was not obtained. For example, in response to the drone not selecting the shorter travel distance, the penalty equation 6.2 would result in a higher value. This penalty value is then used to gauge the efficiency of the optimisation method.



A flow diagram illustrating the reward based inspection algorithm for the drone delivery system can be seen in figure 6.2.

## 6.6 DATA COLLECTION AND INSTRUMENTATION

A scenario is compiled where an initial ‘N’ number of requests are defined and allocated a properties matrix. This matrix consists of the coordinates of the location, the number of specimens per location and a priority of the specimens. The coordinates lie within the radius defined on start up. The number of specimens and priority of the specimens is defined between the values of 1 and 10. The priority scale is descending where 10 is high and 1 is low.

The number of drones, ‘K’, is defined and the drone criteria matrix is generated. Each drone in the scenario is given an initial position within the defined radius. The drone’s states are set at zero. The maximum distance the drone can travel is 22.5 km. In order for the battery to never be fully depleted this value is reduced to 22 km. The generated drones are given their initial range of 22 km and an initial payload of 0 %. If the drone is unable to reach the destination based on its range it must locate the nearest charge point which may be the nearest clinic. If the drone has no clinics or charge points within the range it is considered to be out of commission.

Once the drone is assigned its respective request, it must make its way to the location to collect the samples. Upon reaching the location the drones range is considered to be reduced by the distance between the request point and the drone’s initial position. The battery is then replenished as a battery change is scheduled and the range of the drone is now set to its maximum of 22 km or a flight time of just under 30 minutes. However, upon collection of the specimens, the drone’s payload is increased as it has now collected a number of specimens. This affects the next possible route as the drone must complete its delivery before the payload capacity limit is reached.

Once the drone reaches the request point it ‘loads’ up the specimens by adding the number of specimens at the request point to the drone’s payload capacity value. If the drone capacity is verging on maximum with no request points within range containing low numbers of specimens i.e. no possible routes, the drone must travel to its delivery point and offload. When the drone offloads at the delivery point the payload is reset to 0 % and the range is reset to 22 km.

The initial scenario is plotted on a graph with red stars indicating the initial request locations and blue X’s defining the drone’s initial position. The properties matrices are assigned and the requests as well as drones are given a defining value from 1 to N and 1

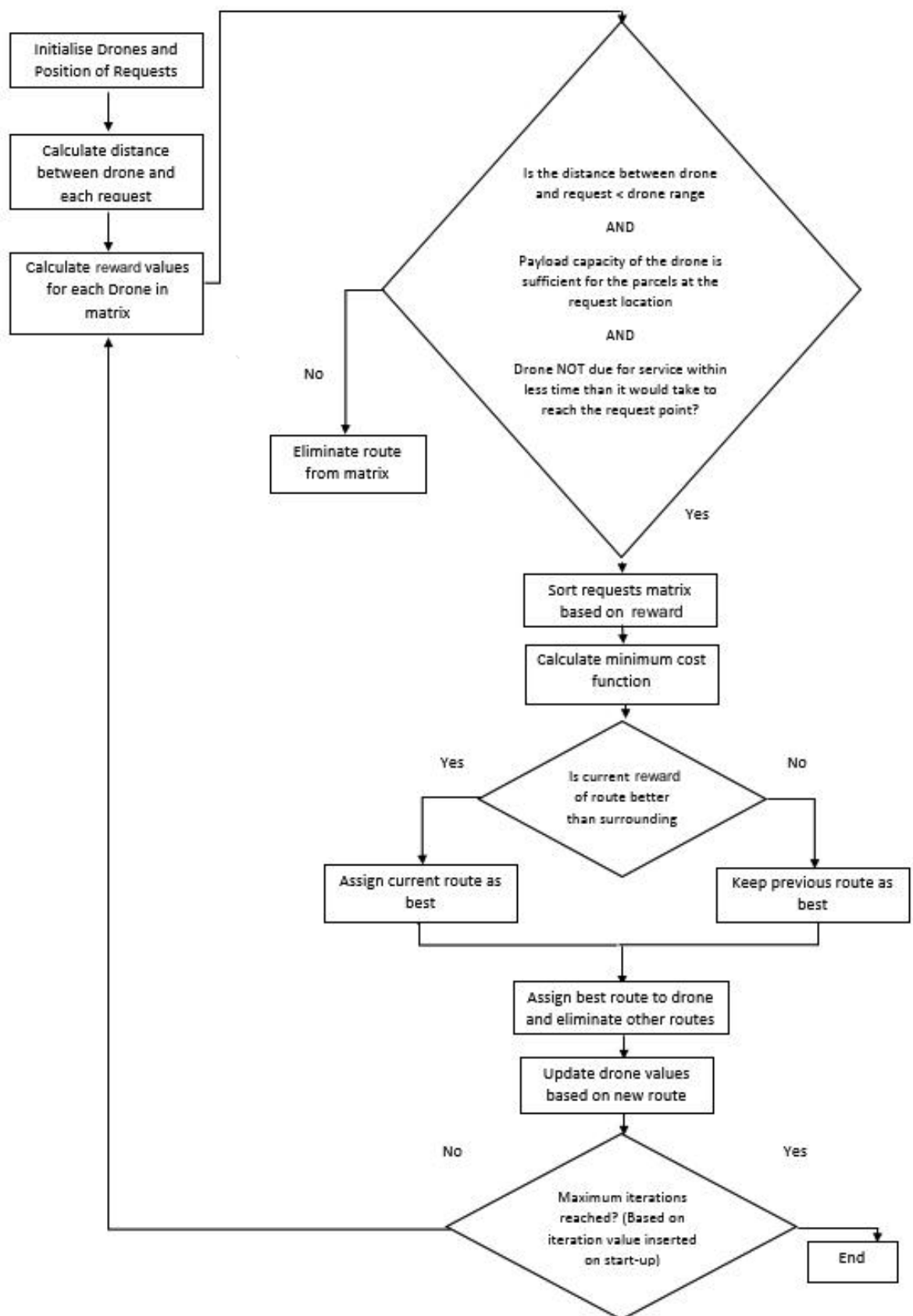


FIGURE 6.2: Flow diagram of Inspection Algorithm for a Drone Delivery Service.

to  $K$  respectively for reference purposes. The drone's velocities are constant at a rate of 1 km per time period which is defined at start up as 1 minute and 20 seconds equating to a speed of 45 km/h. All points plotted on the graph are overlaid with text labelling their properties. The object properties are listed in table 6.1.

TABLE 6.1: Object properties.

Object	Assigned Properties
Requests	Location, Number of Specimens, Urgency Rating
Drones	Position, Range , Payload Capacity
Region	Radius, Specified number of Drones, Specified number of initial request points

# Chapter 7

## SIMULATION OPTIMISATION

### 7.1 SIMULATION

The following scenarios are used to assess the simulation algorithm. The system's ability to produce accurate results are evaluated based on the input variables reflecting real life scenarios.

The variables can be configured according to the criteria of a region under assessment. The input variables are based on the known values of the region under question. The simulation automates the properties of the drones and request points while running through each iteration. Once the simulation is complete, the output variables are presented on a graph depicting as a map of the region as well as a log file of the output variables. The simulation variables can be found in table 7.1.

TABLE 7.1: Key Variables.

Input Variables	Automated Values	Output Variables
No. of Request Points	Initial Payload Capacity	No. of Specimens Collected
No. of Drones	Initial Flight Range	No. of Points Visited
Radius of Search Space	Request Rewards	Total Distance covered
No. of Iterations	Penalty Values	Total Flight Time
No. Specimens per location		
Specimen Urgency		

An example of the log output, found in the accompanying disk, labelled “Log Files.PDF”, is as follows:

*“RequestXY = (23,6) DroneXY = (27,6) Coordinate = 10 Drone = 1 Distance = 4.00  
No.Specimens = 2 Req.Priority = 3 Drone Range = 22 Drone Capacity = 85 Route  
Possible = 1 Reward = 37.72”*

*“Accumulated Distance Travelled = 103.53 Kilometers , Time Elapsed = 139.21 minutes,  
No.Point Visited = 19 No.Specimens Collected = 87”*

## 7.2 OPTIMISATION CONFIGURATION

The simulations below assess the optimisation method devised in this dissertation. Once the optimisation method is validated based on its overall solution, a series of scenarios can be simulated in order to compare specimen delivery times in various conditions.

### 7.2.1 Scenario 1: Case Study Comparison

In order to test a sample scenario similar to that of the Mpumalanga case study, the parameters are configured in scenario 1, according to table 7.2. The initial request-point value is set to 20. The number of drones is set to 1 for the initial run, however this value will be varied in order to compare the effects of additional drones on the delivery routes.

The drone’s starting positions as well as the request coordinates remain constant in order to fix parameters across the various simulations.

The radius is set to 15 km in order to allow for circumstances where the request points are out of range of the drone’s 22 km flight range.

TABLE 7.2: Input Variables.

Input Variables	Value
No. of Request Points	20
No. of Drones	1
Radius of Search Space	15 km

In scenario 1, the drone was able to collect all the samples in the search space. A full flight breakdown and collection log can be found on the accompanying disk, labelled “Log Files.PDF” - log file 1. The output variables can be found in table 7.3 which is depicted graphically in figure 7.1.

TABLE 7.3: Output Variables.

Output Variables	Value
No. of Specimens Collected	87
No. of Points Visited	20
Total Distance covered	103.53 km
Total Flight Time	139.21 Minutes
Penalty Value	855.07

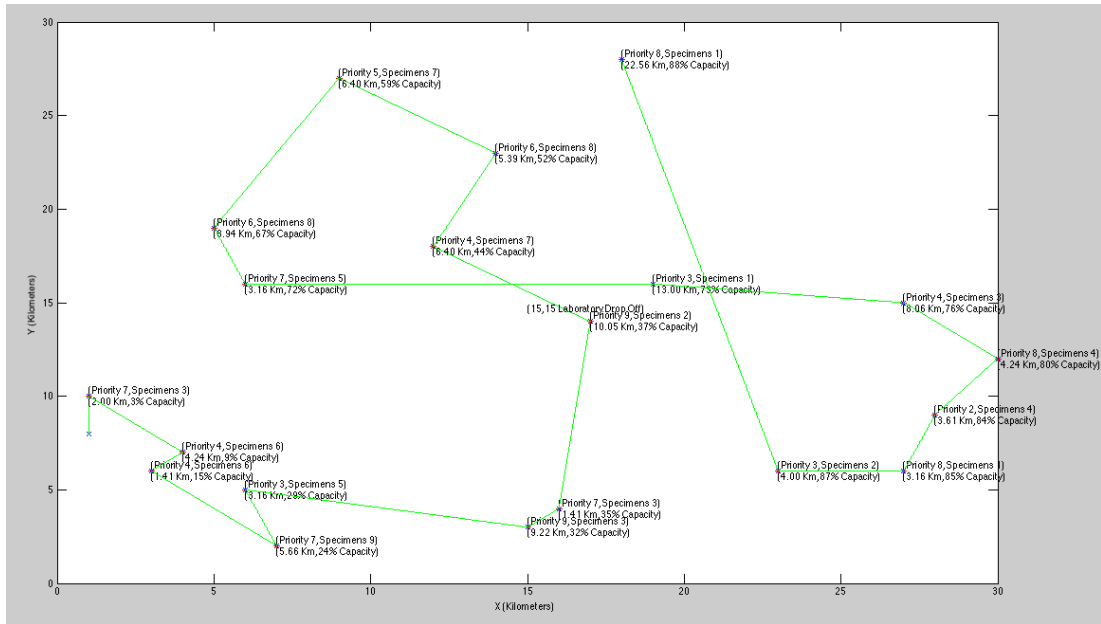


FIGURE 7.1: Plot of request search space with 1 drone and 20 request points within a radius of 15 km.

## 7.2.2 Scenario 2: Inclusion of a Second Drone

Scenario 2 simulates two drones in an environment similar to that of the case study. This allows one to compare the effects of multiple drones on a search space.

The simulation is run for two drones and 20 initial request points as shown in table 7.4. The radius is also set at 15 km as in scenario 1.

TABLE 7.4: Input Variables.

Input Variables	Value
No. of Request Points	20
No. of Drones	2
Radius of Search Space	15 km

In this instance all request points were visited as can be seen in figure 7.2. The output values for drone 1 and 2 can be found in tables 7.5 and 7.6 respectively. The graphical representation can be seen in figure 7.2.

TABLE 7.5: Output Variables: Drone 1.

Output Variables	Value
No. of Specimens Collected	45
No. of Points Visited	10
Total Distance covered	41.55 km
Total Flight Time	56.38 Minutes

TABLE 7.6: Output Variables: Drone 2.

Output Variables	Value
No. of Specimens Collected	42
No. of Points Visited	10
Total Distance covered	67.19 km
Total Flight Time	94.49 Minutes

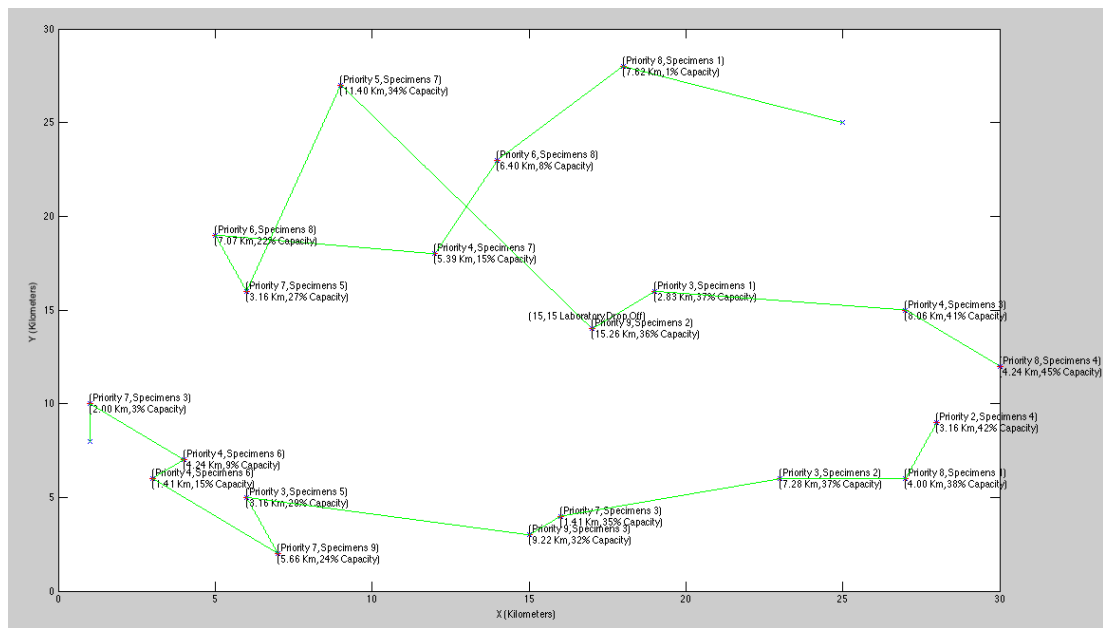


FIGURE 7.2: Plot of request search space with 2 drones and 20 request points within a radius of 15 km.

This scenario has given a base value for the optimum drone system implementation in order for all samples to be collected. Scenario 2 has indicated that in order to improve on collection time, additional drones can be deployed. A full flight breakdown and collection log can be found on the accompanying disk, labelled “Log Files.PDF” - log file2.

### 7.2.3 Scenario 3: Inclusion of a Third Drone

As the previous scenario was successful in terms of all the request points being visited with multiple drones, the scenario can now test an additional drone to confirm the findings. The input variables for scenario 3 are tabulated in table 7.7.

TABLE 7.7: Input Variables.

Input Variables	Value
No. of Request Points	20
No. of Drones	3
Radius of Search Space	15 km

A full flight breakdown and collection log can be found on the accompanying disk, labelled “Log Files.PDF” - log file 3. The output values for drones 1, 2 and 3 can be found in tables 7.8, 7.9 and 7.10 respectively. The graphical representation can be seen in figure 7.3.

TABLE 7.8: Output Variables: Drone 1.

Output Variables	Value
No. of Specimens Collected	33
No. of Points Visited	7
Total Distance covered	35.75 km
Total Flight Time	51.36 Minutes

TABLE 7.9: Output Variables: Drone 2.

Output Variables	Value
No. of Specimens Collected	25
No. of Points Visited	6
Total Distance covered	36.70 km
Total Flight Time	51.63 Minutes

TABLE 7.10: Output Variables: Drone 3.

Output Variables	Value
No. of Specimens Collected	31
No. of Points Visited	6
Total Distance covered	48.81 km
Total Flight Time	64.65 Minutes



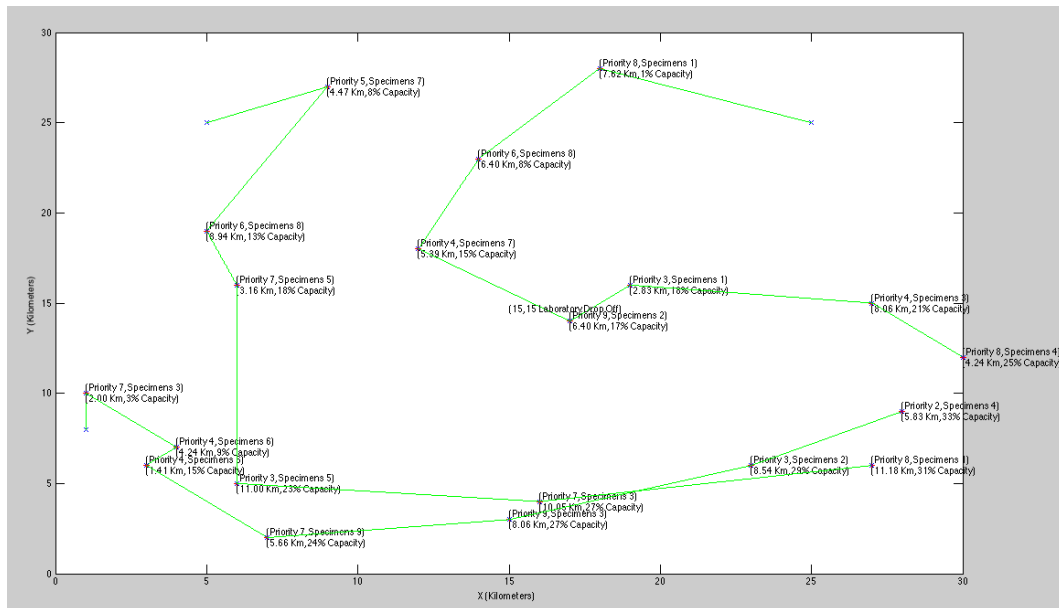


FIGURE 7.3: Plot of request search space with 3 drones and 20 request points within a radius of 15 km.

From what can be observed from the figures above is that when multiple drones are used, more path options are available and the shorter the total collection time per specimen. This is as a result of the delivery routes being split between the drones.

The simulation prioritises urgency and does not take into account the possibility of collecting samples that already lie on the path of collection. For example, if three points A, B and C existed in a straight line and point C was highest priority, the initial route suggestion would ignore points A and B and head straight for C.

This solution does give a desired result as the point designated for collection is visited. However, it is not the most efficient method as the points A and B could have been visited at minimal cost and the overall solution would be of greater proportion. This can be altered by increasing the weighting of ‘distance’ in the reward function.

### 7.3 Manipulating the Reward Function

In order to collect samples along routes which may increase efficiency, the reward function can be manipulated. As stated in section 6.5.1, the reward function takes into account distance, priority, and number of specimens. By increasing the weighting of one of these variables, the drones approach can be altered.

### 7.3.1 Scenario 4: Manipulating Reward Function with Distance as Primary

The primary objective in scenario 4 is to reduce the overall travel distance, in turn reducing the delivery time. This is done by assigning the distance variable in the reward function as the primary objective. In order to assess the outcome, the scenario is configured in the same way as scenario 1, as in table 7.11.

TABLE 7.11: Input Variables.

Input Variables	Value
No. of Request Points	20
No. of Drones	1
Radius of Search Space	15 km
Reward Function Primary	Distance

The results are tabulated in table 7.12. The total path distance, compared to the initial reward function used in scenario 1, was reduced by 16.02 %. The graph can be seen in figure 7.4.

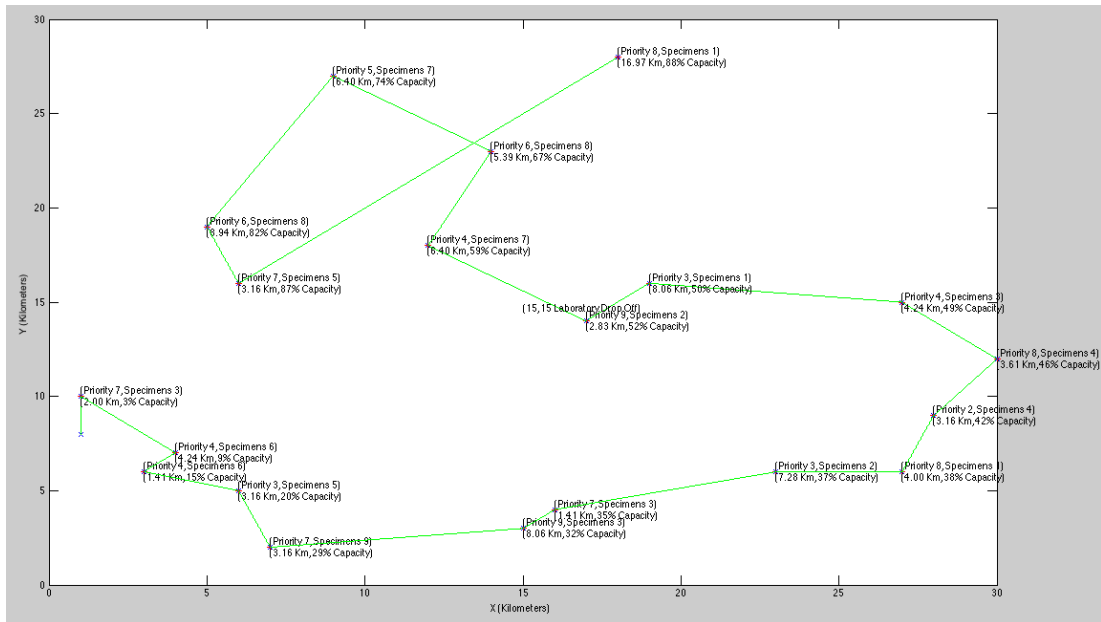


FIGURE 7.4: Plot of request search space with 1 drone and 20 request points within a radius of 15 km and 'distance' as primary value in reward function.

TABLE 7.12: Output Variables: Drone 1.

Output Variables	Value
No. of Specimens Collected	87
No. of Points Visited	20
Total Distance covered	86.94 km
Total Flight Time	115.92 Minutes
Penalty Value	281.21

### 7.3.2 Scenario 5: Manipulating Reward Function with Priority as Primary

The objective in scenario 5 is to navigate the delivery schedule based on the priority of the request point. This is done by assigning the priority variable in the reward function as the primary objective. In order to assess the outcome, the scenario is configured in the same way as scenario 1, as in table 7.13.

TABLE 7.13: Input Variables.

Input Variables	Value
No. of Request Points	20
No. of Drones	1
Radius of Search Space	15 km
Reward Function Primary	Priority

The results are tabulated in table 7.12. The total path distance, compared to the initial reward function used in scenario 1, increased by 107.06 %. The graph can be seen in figure 7.5.

TABLE 7.14: Output Variables: Drone 1.

Output Variables	Value
No. of Specimens Collected	87
No. of Points Visited	20
Total Distance covered	214.37 km
Total Flight Time	285.82 Minutes
Penalty Value	2154.71

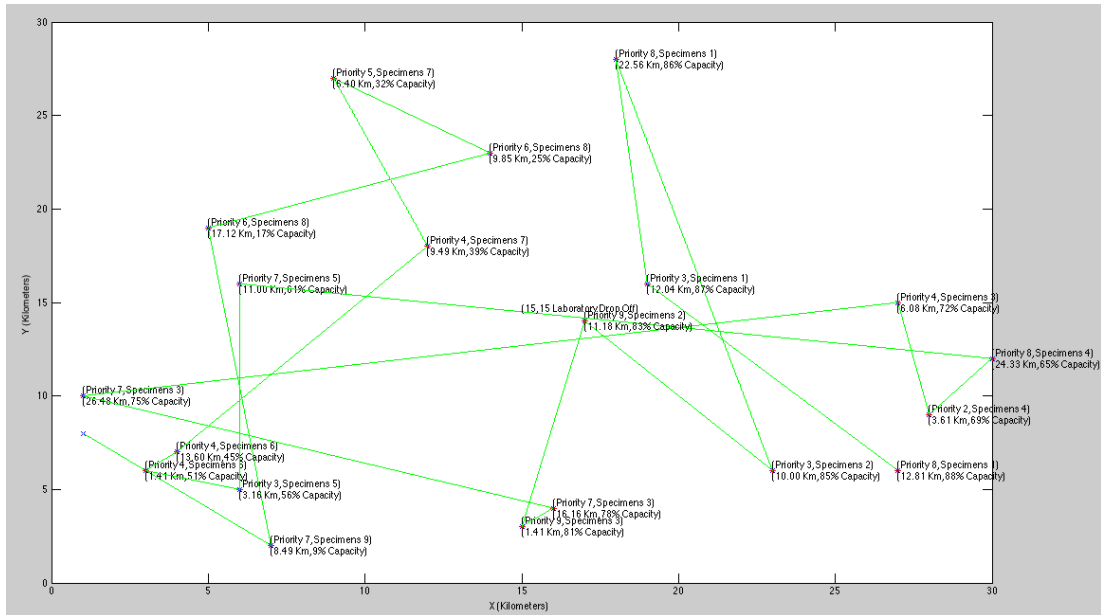


FIGURE 7.5: Plot of request search space with 1 drone and 20 request points within a radius of 15 km and 'priority' as primary value in reward function.

### 7.3.3 Scenario 6: Manipulating Reward Function with Specimens as Primary

The objective of scenario 6 is to navigate the delivery schedule based in the the number of specimens located at the request point. This is done by assigning the specimen variable in the reward function as the primary objective. In order to assess the outcome, the scenario is configured in the same way as scenario 1, as in table 7.15.

TABLE 7.15: Input Variables.

Input Variables	Value
No. of Request Points	20
No. of Drones	1
Radius of Search Space	15 km
Reward Function Primary	Specimens

The results are tabulated in table 7.16. The total path distance, compared to the initial reward function used in scenario 1, increased by 168.68 %. The graph can be seen in figure 7.6.

Scenario 4 indicates that in order to decrease the total turnaround time, the distance variable must have a large weighting in the reward function. In addition, scenario 5 and 6 indicate that using a single variable as primary, such as priority or specimens does

TABLE 7.16: Output Variables: Drone 1.

Output Variables	Value
No. of Specimens Collected	87
No. of Points Visited	20
Total Distance covered	278.17 km
Total Flight Time	370.89 Minutes
Penalty Value	1946.10

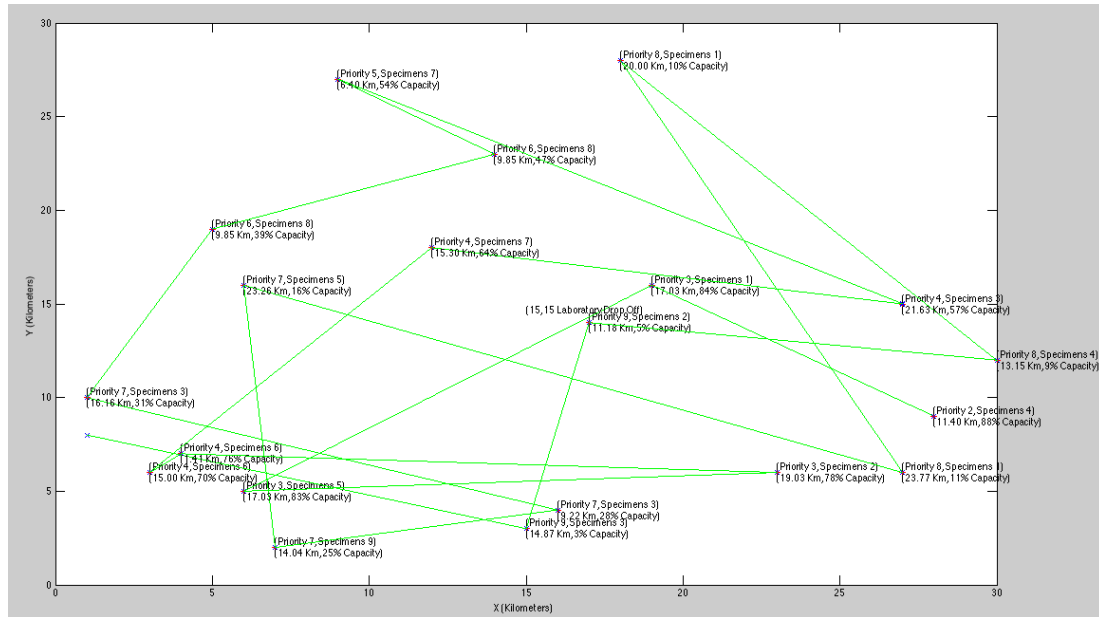


FIGURE 7.6: Plot of request search space with 1 drones and 20 request points within a radius of 15 km and 'specimens' as primary value in reward function.

not result in an optimum solution and therefore a combination of the three will give the greatest overall solution.

### 7.3.4 Scenario 7: Random Walk

This scenario tests the reward functions optimisation efficiency by comparing it to a random selection of request points. This is done by assigning a random reward to each request point. In order to assess the outcome, the scenario variables are configured as in scenario 1, table 7.17. The overall travel distance and time can then be assessed.

The results are tabulated in table 7.18. The total path distance, compared to the initial reward function used in scenario 1, increased by 189.51 %. The graph can be seen in figure 7.7.

TABLE 7.17: Input Variables.

Input Variables	Value
No. of Request Points	20
No. of Drones	1
Radius of Search Space	15 km
Reward Function Primary	Random

TABLE 7.18: Output Variables: Drone 1.

Output Variables	Value
No. of Specimens Collected	87
No. of Points Visited	20
Total Distance covered	299.74 km
Total Flight Time	399.65 Minutes
Penalty Value	3428.12

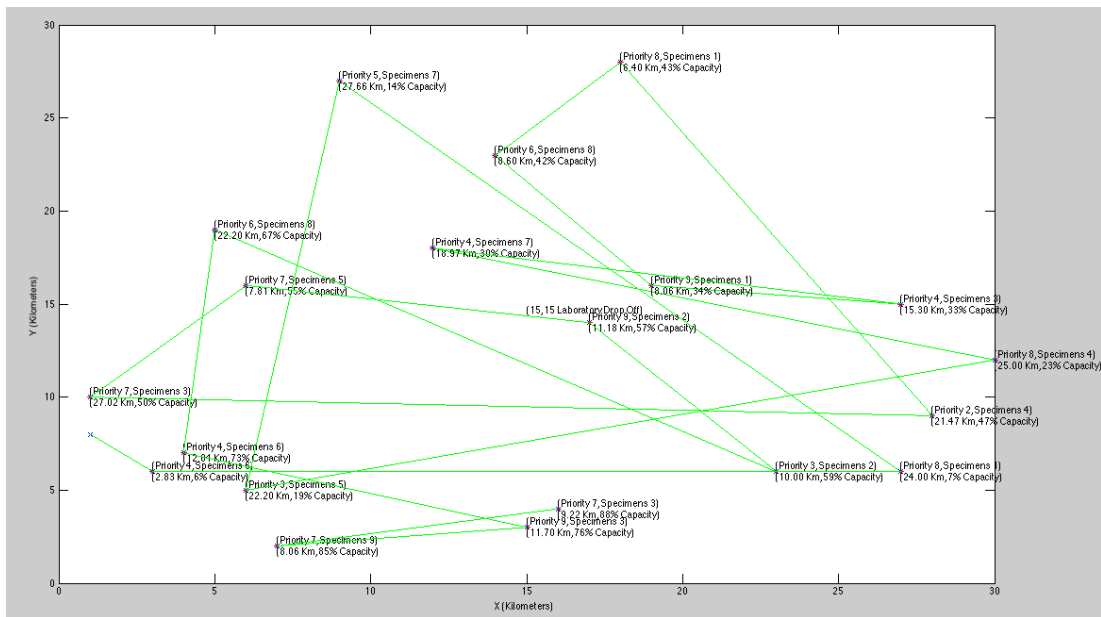


FIGURE 7.7: Random Walk Plot of request search space with 1 drone and 20 request points within a radius of 15 km.

Scenario 7 illustrates that a random selection of flight paths has the lowest optimisation value when compared to previous scenarios. This result is expected as the scenario has no optimisation applied and is therefore assumed to be the least efficient method.

### 7.3.5 Inclusion of Wind Effects

For increased simulation accuracy simplified wind effects are taken into account with the inclusion of a wind speed function, which can be found in MATLAB code on the accompanying disk in the folder labelled *Inspection Algorithm*.

The wind speed vector can be altered and its units are in km/h. The heading can therefore be calculated with equation 7.1. The ground speed can then be calculated using the equation 7.2 and finally the flight time can be calculated using the equation 7.3.

$$\Theta_{Heading} = \Theta_{Track} + \arcsin\left(\frac{WS \cdot (\sin(\Theta_{Track} - \Theta_{Wind}))}{TAS}\right) \quad (7.1)$$

$$GS = TAS \cdot \cos(\Theta_{Heading} - \Theta_{Track}) + WS \cdot \cos(\Theta_{Track} - \Theta_{Wind}) \quad (7.2)$$

$$T = \frac{D}{GS} \quad (7.3)$$

$D$  = Distance between two points.

$T$  = Travel Time.

$GS$  = Ground Speed.

$\Theta_{Track}$  = Bearing of destination from starting point e.g. Bearing of clinic B from A.

$TAS$  = True Air Speed. (45 km/h)

$\Theta_{Heading}$  = True Heading Angle.

$WS$  = Wind Speed.

$\Theta_{wind}$  = Wind Angle.

The flight range is reduced based on the headwind. If a specific headwind value is known, the simulation can act as a worst case scenario by providing the maximum headwind effects with that value. The maximum headwind accepted as an input is 45 km/h at a  $0^\circ$  relative to the ground in which case the drone remains stationary and does not reach any collection points. The average windspeed throughout the year in Mpumalanga is 4 km/h with a maximum value ever recorded of 35 km/h [72]. This will be the wind speed range for the simulation.

Future work could include the use of weather pattern data to guide the flight paths and minimise potential accidents. Thus pre-empting the need for a backup delivery service in cases of higher projected wind speed. For the simulation however, live weather pattern data is not used as the simulation is developed to illustrate the principle of drone delivery.

### 7.3.6 Scenario 8: 10 km/h Wind Speed

In order to test the effects of wind on the drones in the simulation, scenario 1 is repeated as in table 7.19 with an inclusion of a wind speed of 10 km/h at a bearing of 30 degrees.

TABLE 7.19: Input Variables.

Input Variables	Value
No. of Request Points	20
No. of Drones	1
Radius of Search Space	15 km
Wind Speed	10 km/h
Wind Angle	30 degrees

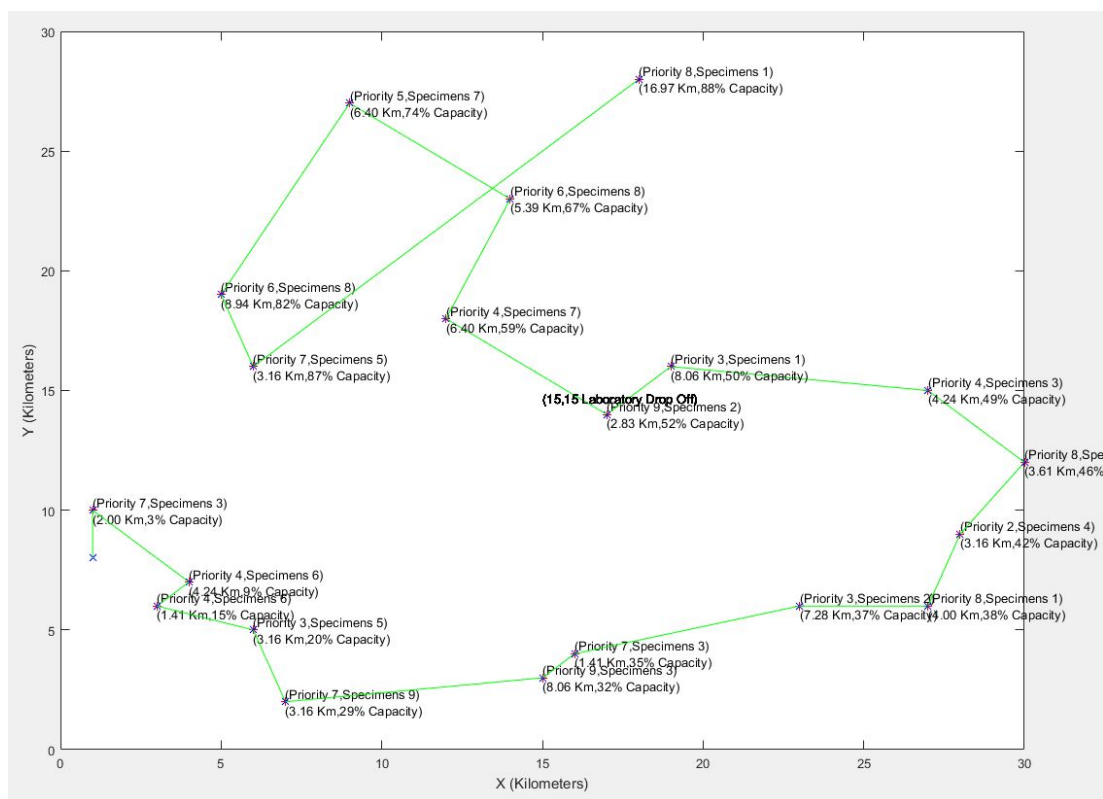


FIGURE 7.8: Single drone, 20 Request points - 10 km/h wind speed at 30 degree bearing.

The drone manages to complete all 20 collections and all available samples. The entire route takes 169.71 minutes and covers 120.87 Kilometers. This is a similar time-frame to scenario one.



### 7.3.7 Scenario 9: 25 km/h Wind Speed

Increasing the wind speed to 25 km/h at a bearing of 120 degrees as in table 7.20 results in an extended flight path as the optimum route is no longer available.

TABLE 7.20: Input Variables.

Input Variables	Value
No. of Request Points	20
No. of Drones	1
Radius of Search Space	15 km
Wind Speed	25 km/h
Wind Angle	120 degrees

The drone manages to complete the entire route as in scenario 1. However, a different approach is taken by the drone as seen in figure 7.9. Some paths are not available as a result of the headwind. The drone travels 140.51 Kilometers in 296.61 minutes, in contrast to the 139.21 minutes in ideal conditions.

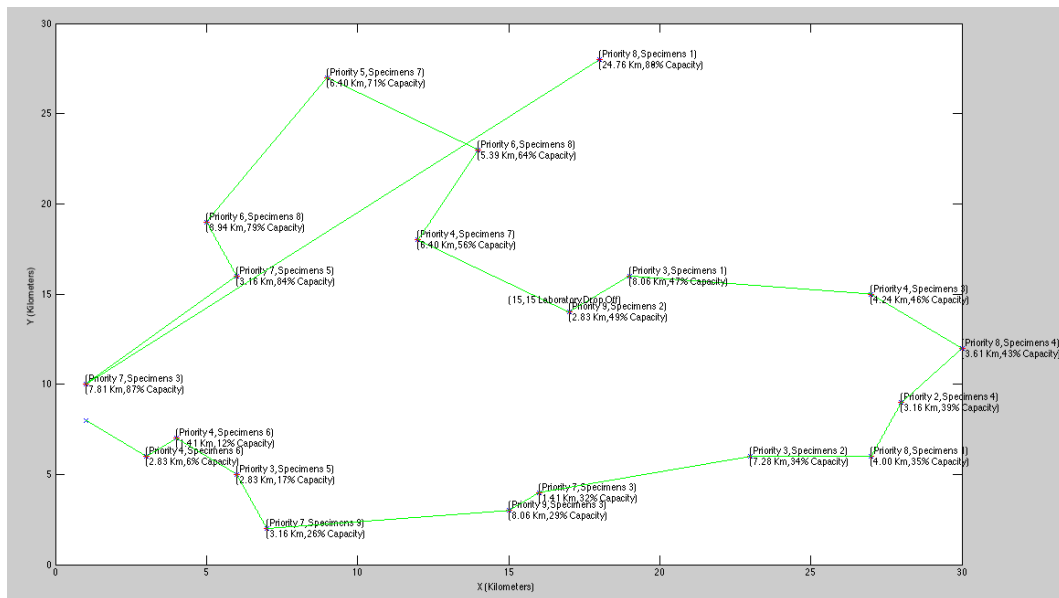


FIGURE 7.9: Single drone, 20 Request points - 25 km/h wind speed at 120 degree bearing.

### 7.3.8 Scenario 10: 40 km/h Wind Speed

Increasing the wind speed to 40 km/h at a bearing of 90 degrees as in table 7.21 results in an extended flight path as the optimum route is no longer available.

TABLE 7.21: Input Variables.

Input Variables	Value
No. of Request Points	20
No. of Drones	1
Radius of Search Space	15 km
Wind Speed	40 km/h
Wind Angle	90 degrees

The drone manages to complete the entire route as in scenario 1. A different approach is taken by the drone as seen in figure 7.10. Most initial paths are not available as a result of the headwind. The drone travels 134.45 Kilometers in 598.81 minutes, in contrast to the 139.21 minutes in ideal conditions.

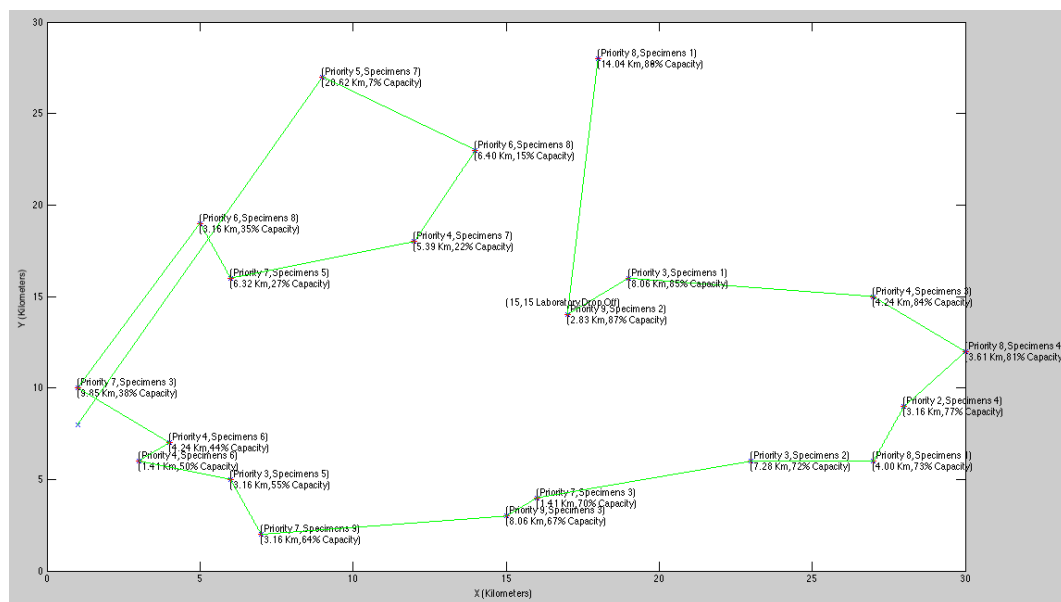


FIGURE 7.10: Single drone, 20 Request points - 40 km/h wind speed at 90 degree bearing.

### 7.3.9 Scenario Outcome Summary

Table 7.22 summarises simulation scenarios 1 through 10, carried out using the inspection algorithm developed in this dissertation.

TABLE 7.22: Simulation Results.

Scenario	No. of Drones	Wind Speed (km/h)	Total Route Distance	Route Time (min)	Penalty Value
1: Case Study Comparison	1	0	103.53 km	139.21	855.07
2: Multiple Drones	2	0	108.74 km	150.87	-
3: Multiple Drones	3	0	121.26 km	167.647	-
4: Distance As Primary	1	0	86.94 km	115.92	281.21
5: Piority As Primary	1	0	214.37 km	285.82	2154.71
6: Specimen As Primary	1	0	278.17 km	370.89	1946.10
7: Random Walk	1	0	299.74 km	399.65	3428.12
8: Inclusion of Wind Speed	1	10 $\angle$ 30°	120.87 km	169.71	-
9: Inclusion of Wind Speed	1	25 $\angle$ 120°	140.51 km	296.61	-
10: Inclusion of Wind Speed	1	40 $\angle$ 90°	134.45 km	598.81	-

## 7.4 CONCLUSION

Scenario 1, 2 and 3 produce optimised routes that can be used for regions similar to that of the case study. However, when prioritising ‘priority’ or ‘number of specimens’ the total flight time is considerably greater.

The results of table 7.22 indicate that the optimum algorithm configuration occurs when the distance of the drone’s route is prioritised, thus leading to a reduced delivery time. The penalty value of prioritising distance confirms this conclusion.

The algorithm fairs well in various wind conditions and a full turnaround time comparison using the optimisation algorithm can be developed.

## Chapter 8

# TURNAROUND TIMES

### 8.1 INTRODUCTION

Clinicians suggest that turnaround time is one of most important factors to take into account when considering adequate health care [73]. A rapid and reliable delivery method can improve the speed and quality of laboratory services.

The quality of the drone delivery system is defined by its ability to service a cluster of clinics in an acceptable measure of timeliness. The operational cost of the system is weighed up against its ability to satisfy the needs of the patient and improve on laboratory turnaround times.

The needs of the patients encompass impact and urgency. The patients are to receive their results in a timely manner in order to benefit from the outcome. Therefore, the delivery of the specimens must be within an acceptable time frame. In addition, the system must provide a service that can manage large volumes of requests in a consistent manner.

The aim of this chapter is to provide a consolidated source of data in order to benchmark the system's delivery times, thereby validating the quality of the delivery system.

### 8.2 SIMULATION

The effects of wind speed, wind angle and dynamic request point generation can be compared using a series of histograms formed from the simulation results. The delivery time or turnaround time is the interval between a request generation and specimen drop-off.

The simulation scenarios are run for a period of 12 hours. Each clinic can generate a request, with a number of samples, based on a Poisson probability distribution. The Poisson probability distribution occurs during the fixed time period and actions at every 5 minute interval.

The wind speed is increased from 5 - 25 km/h in steps of 5km/h intervals. For each wind speed scenario, the wind angle increments from 90 - 360° in 90° intervals.

These simulations are repeated for a request point generation rate of 2 requests per hour, 3 requests per 2 hours, 1 request per hour, 1 request per 2 hours, 1 request per 4 hours and 1 request per 6 hours. Over a 12 hour time period, these values equate to 2, 1.5, 1, 0.5, 0.25 and 0.166 requests per hour respectively. This combination of wind and average request rates result in 120 different scenarios. A full delivery time table for all scenarios can be found on the accompanying disk, labelled "Delivery-times.xlsx".

As per section 7.3.9, table 7.22, the most effective reward function for this application prioritises delivery time. The algorithm ensures this by calculating the flight path of each request point while taking into account distance, drone speed and wind conditions.

### 8.2.1 Assumptions and Variables

All the clinics in the search space have the same fixed average rate of request generation during a scenario. However, in reality, the geographical region as well as the facilities, time of day and seasonal change would often determine this distribution. Future research could include an in depth study of seasonal request rates and weather patterns that can be applied to the simulation. In this way, wind speeds and directions could be more realistic as it would be based on actual weather data for the region rather than a flat distribution as assumed during the simulations in this study.

The topology of the region in question is assumed to be relatively flat with no steep projections that may obstruct the drone's flight path. In future work, a more realistic simulation would include the topology so that potential collisions could be circumvented.

As turnaround time is the main concern for patient care in rural environments, the delivery reward value increases exponentially as the time delay of the generated request increases. A limit of 3 hours is placed on requests that remain uncollected or in transit in order for the delayed samples to be given priority. This ensures a turnaround time within an acceptable range should a patient have to remain at a clinic to obtain their results. An internal 60 minute [73] laboratory turnaround time is assumed, resulting in a maximum of 4 hours waiting period.

The loading time as well as the time for the drone to reach its designated flying altitude is incorporated in the handling time of the clinic. The turnaround time to re-launch the drone after each stop is likely to be relatively short as it simply involves changing the battery and loading or unloading specimens, To retain simplicity, this has not been taken into account in this study, however this should be included in future work.

## 8.3 RESULTS

### 8.3.1 Delivery Time Distribution

Simulations are run for 12 hours, however only deliveries where the requests were generated during the first 9 hours are included in the analysis, even though these requests may still be delivered up to 12 hours. The reason for this is to ensure that requests that are generated just before the end of the simulation are not erroneously recorded as not delivered simply because the simulation ended. The following histograms display a clear comparison between high and low rates of request over the first 9 hours of the 12 hour period.

Figure 8.1 displays delivery times for 5 km/h wind speeds at wind angles of  $90^\circ$  to  $360^\circ$  and request generation rate of 2 requests per hour. Figure 8.2 depicts delivery times for 25 km/h wind speeds at wind angles of  $90^\circ$  to  $360^\circ$  and request generation rate of 2 requests per hour.

Figure 8.3 represents delivery times for 5 km/h wind speeds at wind angles of  $90^\circ$  to  $360^\circ$  and request generation rate of 1 request per 6 hours, while figure 8.4 represents delivery times for 25 km/h wind speeds at wind angles of  $90^\circ$  to  $360^\circ$  and a request generation rate of 1 request per 6 hours.

### 8.3.2 Delivery Times

Table 8.1 indicates that as the wind speed increases and the average request rate decreases, the number of possible deliveries decrease, resulting in a lower number of samples delivered. However, the delivery times for these samples are reduced as less points are visited.

It is also evident from table 8.1 that an increase in wind velocity does not have a proportionate affect on delivery times. This may be in relation to the fact that the wind direction is randomised and in certain scenarios the tailwind improves on turnaround time as opposed to the assumption that an increased wind speed would hamper delivery times.

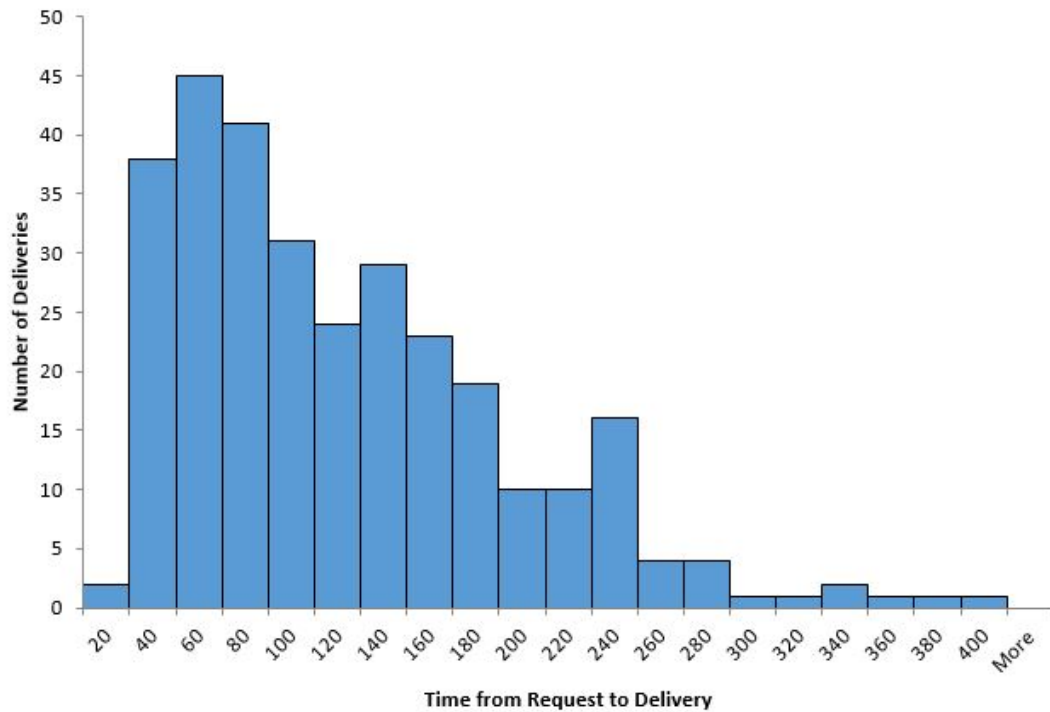


FIGURE 8.1: Histogram of delivery time frequency for 5 km/h wind speeds at wind angles of  $90^\circ$  to  $360^\circ$  and a request generation rate of 2 requests per hour.

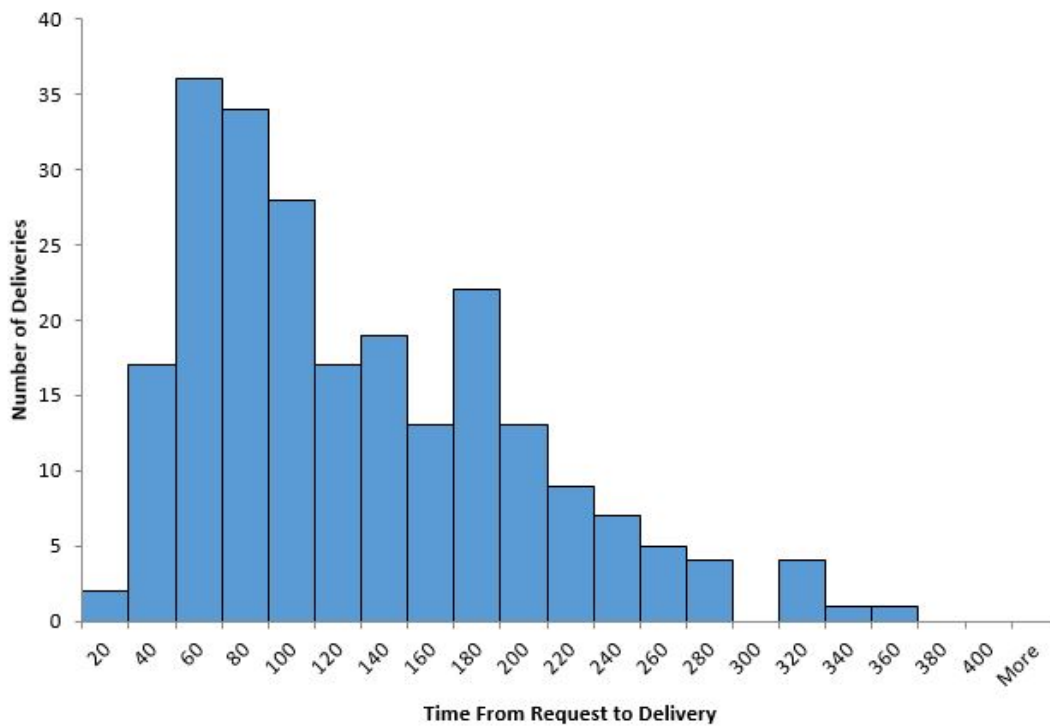


FIGURE 8.2: Histogram of delivery time frequency for 25 km/h wind speeds at wind angles of  $90^\circ$  to  $360^\circ$  and a request generation rate of 2 requests per hour.

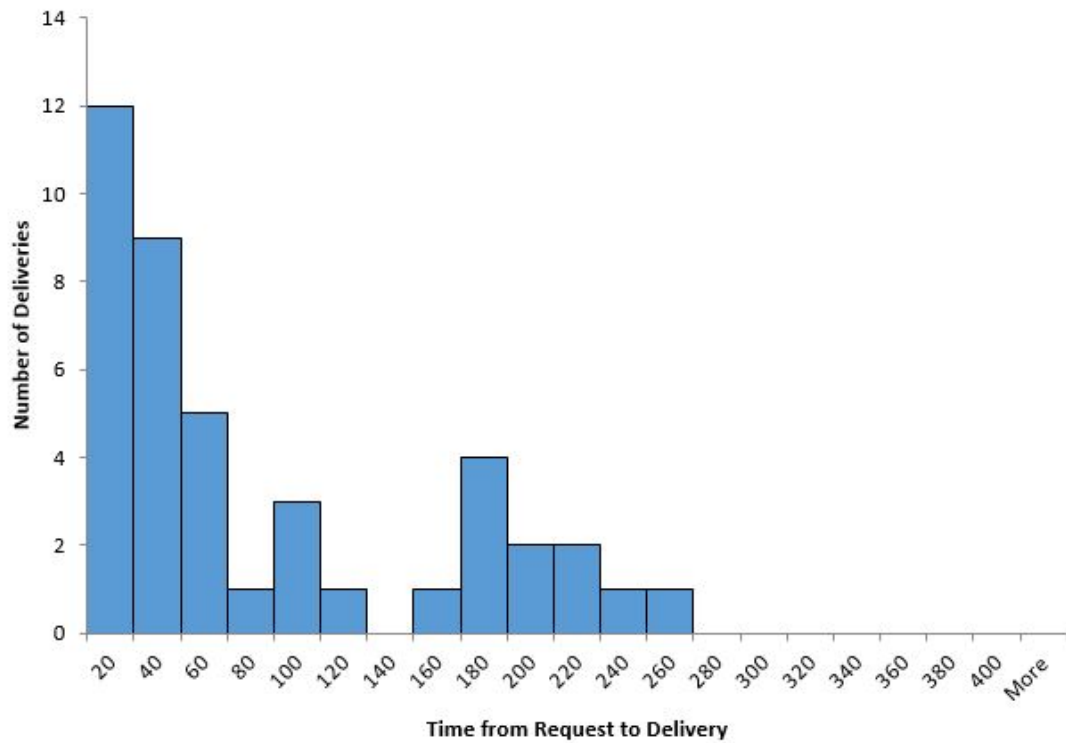


FIGURE 8.3: Histogram of delivery time frequency for 5 km/h wind speeds at wind angles of  $90^\circ$  to  $360^\circ$  and a request generation rate of 1 request per 6 hours.

In addition, table 8.1 indicates that less than 30 % of the total requests are those that take longer than 3 hours for delivery. However, the table does present a larger value in a case with a generation rate of one request per 4 hours. Future work could incorporate previous scenario data in order to flag irregular values in order to reinstate the scenario.

The average scenario delivery time of 93.94 minutes is well under the 3 hours (180 minutes) suggested for processing a patient's results. therefore one can conclude that for a drone system consisting of a single drone or multiple drones in regular wind conditions, similar to those observed throughout the year in Mpumamalanga, the system proves feasible for implementation with regard to turnaround times and resilience to external wind conditions. However, one must include a minimal handling time in the final estimate.

## 8.4 DATA ANALYSIS

### 8.4.1 Limitations and Future Work

In the first implementation of the algorithm, the path searching method re-initiated for every step that the drone made between its initial position and the request point. Each



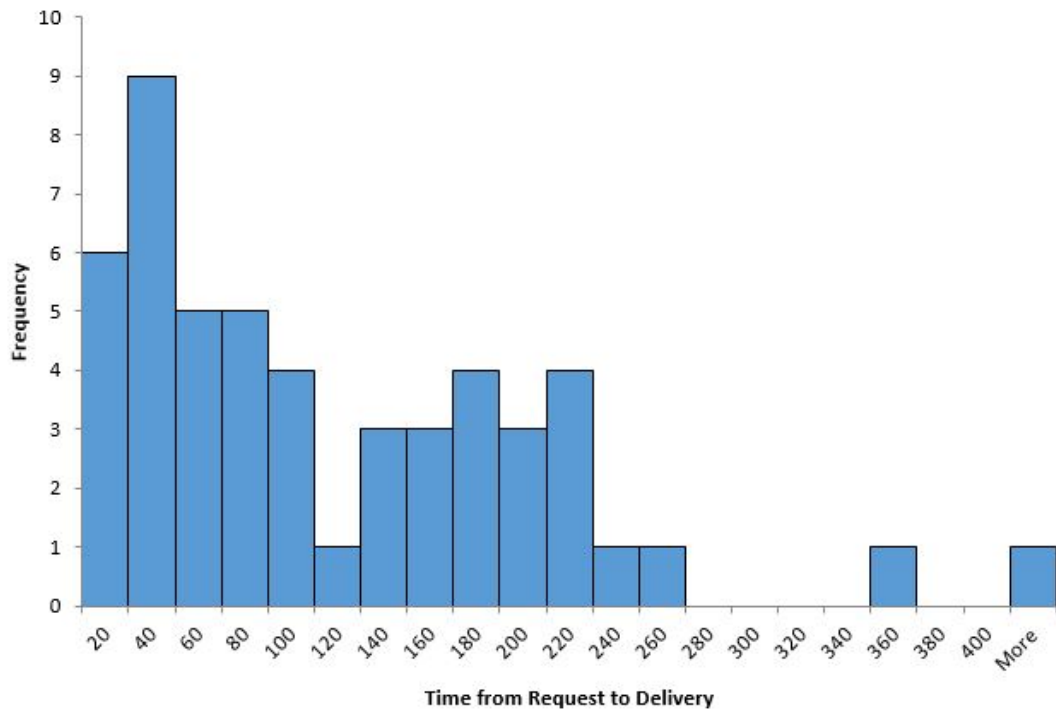


FIGURE 8.4: Histogram of delivery time frequency for 25 km/h wind speeds at wind angles of  $90^\circ$  to  $360^\circ$  and a request generation rate of 1 request per 6 hours.

step was considered to be a 1 km interval, but after much consideration, the algorithm initiates after the drone has moved to its desired position. The reason behind this is that the drone's path changes too often resulting in a 'zig-zag' configuration. This proves very inefficient. The system is also required to simulate real world conditions and if a request is sent for collection and a response is made then it is expected that the delivery will take place within the allocated time period. However, if the drone were to re-evaluate the next best move and land up selecting a new destination then the previous stakeholder who initiated the request would be dissatisfied with the service. Therefore if the request is accepted it must follow through with the service.

Collisions and target misses, such as a drone blown off course, are not taken into account as a collision would simply constitute as a drone out of commission and a target miss is assumed to be unlikely when simulating in ideal conditions.

The simulation does not allow for backtracking and if a drone wandered too far from its drop off point it could cause the simulation to fail. This can be overcome by reducing the search space radius or adding additional drop off points. Future work can include backtracking but this would reduce efficiency as the drone could cover the same route multiple times without making a collection.

TABLE 8.1: Delivery times for a single drone at varying wind speeds and average request generation rates. Wind Angle range: 90° - 360°.

Average Request Generation Rate	Wind Speed (km/h)	Average Request Delivery Time (min)	Number of Requests Generated (First 9 Hours)	Percentage of Requests Delivered within 1, 2 and 3 hours (%)	Percentage of Requests with delivery longer than 3 hours (%)
2 Requests per hour	5	113,50	210	28, 60, 83	17
	10	104,34	198	30, 68, 87	13
	15	122,53	194	17, 60, 79	21
	20	113,25	190	27, 62, 81	19
	25	119,87	175	24, 58, 81	19
3 Requests per 2 hours	5	97,70	200	32, 74, 91	11
	10	103,26	189	36, 68, 91	9
	15	93,94	175	35, 73, 92	8
	20	105,80	151	35, 67, 85	15
	25	129,85	137	24, 60, 75	25
1 Request per hour	5	81,74	192	47, 80, 93	7
	10	86,72	168	44, 76, 90	10
	15	83,19	172	42, 80, 95	5
	20	102,09	169	31, 73, 86	14
	25	90,80	125	39, 74, 90	10
1 Request per 2 hours	5	77,13	75	53, 78, 90	10
	10	70,45	106	51, 90, 97	3
	15	81,44	118	53, 80, 91	9
	20	85,27	68	47, 73, 92	8
	25	99,08	77	46, 70, 79	21
1 Request per 4 hours	5	73,18	36	56, 76, 87	13
	10	74,73	62	56, 77, 86	14
	15	76,29	44	57, 78, 93	7
	20	89,51	47	35, 68, 85	15
	25	117,04	39	31, 46, 57	43
1 Request per 6 hours	5	72,50	33	62, 74, 86	14
	10	82,28	37	52, 71, 88	12
	15	81,24	25	46, 66, 89	11
	20	86,35	24	58, 66, 82	18
	25	103,15	27	39, 59, 78	22

The simulation also falls short in cases where the request point's specimen quantity is too high and the drone does not have the available payload capacity. On occasion requests are not visited at all in high request volume scenarios. In these circumstances the solution to the delivery system would be additional drones or a combination of drone delivery and on the road vehicle delivery. Future research into the algorithm could include scenarios of system breakdown where the limits of the drones and clinics are reached and further assessed.

Future work could also include an investigation into the handling and loading times of the specimens in question, which would allow for a more accurate representation of turnaround times.

## 8.5 SUMMARY

The resulting case study values were used for the input of a dynamic simulation based on a reward system. Request points were generated in MATLAB and a number of drones were given a location and flight properties. The drone's delivery routes were optimised to minimise a cost function in order to find a global objective. This was done by prioritising routes based on factors such as time, cost, number of specimens and urgency.

The simulation was able to quantify a search space area for different numbers of drones as well as determine their most efficient routes, which can be used to coordinate a swarm of drones that communicate with one another in a real life scenario.

This simulations concluded that a small drone system is feasible as long as wind conditions are within the normal range of between 0 km/h to 25 km/h, however this does decrease the number of specimens that can be delivered in a given time period. The simulation can be used in various optimisation scenarios for future development and can be expanded to larger regions and increased number of drones.

## Chapter 9

# CONCLUSION

### 9.1 INTRODUCTION

The concept of drone-based specimen and urgent medication transport was introduced as a result of the need for increased laboratory access in underdeveloped regions. New prospects and alternate forms of deliveries were investigated in order to build a framework which will aid in the assessment of future implementations of similar solutions. The proposed concept of using drones to transport specimens, ARV's and POC devices has the potential to increase the service range of laboratories and clinics and has a major impact on laboratory turnaround times.

### 9.2 FINDINGS

The investigation into current laboratory delivery procedures uncovered the need for alternate methods of transport for urgent medication such as ARV's and POC devices in developing regions. The proposed delivery method proved more effective with regard to efficiency and cost as a drone system is not limited by geographical routes and roadway congestion.

The consideration that POC devices may be a viable alternative to laboratory testing, on the assumption that POC may mitigate the need for drone delivery, proved otherwise as the results achieved through laboratory testing is more accurate. With the new found information on POC testing, the inclusion of these devices in the drone delivery system further improves on turnaround times but runs the risk of reduced accuracy when compared to specimen-to-laboratory transport.

The focus on developing areas led to a case study analysis that was conducted over a relatively isolated region in Mpumalanga. Clinics and laboratories in the area were selected and a theoretical flight route was optimised between them using the Travelling Salesman Algorithm. It was determined that drone delivery can be more cost effective when servicing up to 14 laboratory locations per region for a single drone. However, the system is limited by the travel distance of the drone (22.5 km) as well as the maximum load capacity (2-4 kg).

A limited number of laboratories or clinics can be serviced per day by a single drone in a single region. The case study quantified this number and the results can be expanded to regions of similar topography and laboratory density. Larger regions can be serviced by increasing the number of drones used in the delivery system, but as the TSP algorithm used in the case study was developed for a single drone, the analysis lacked this capability and required the reward based inspection algorithm that followed. Other regions to consider for implementation are the Eastern Cape and the Limpopo Province as they are similar in nature with regard to population density, infrastructure and vehicle accessibility.

As the case study was limited with regard to the number of laboratories on the map as well as their predetermined locations, the need for dynamic route optimisation methods was presented. A simulation was developed to find the global minimum of the system's cost function by maximising the reward of the given scenarios. This entailed using an inspection algorithm to perform an overall objective. The global minimum was defined as the weighted combination of the overall cost, urgency, minimisation of losses and shortest delivery time.

The simulation was able to determine the next best move of the drone given the search space conditions. The drone managed to visit all 20 request points in the scenario and reduced the travel distance to 103.53 km.

Further scenarios were presented whereby the number of drones were increased. The algorithm handled the increased number of variables with ease and the delivery time improved in proportion to the number of drones that were added. This was the expected result.

The reward function was assessed by manipulating the terms such as distance, priority and number of specimens. In each scenario, a single term was prioritised and the resulting delivery route was sub optimal. A random walk scenario was introduced as a baseline comparison which proved inefficient based on the large penalty value of 3428.12, in contrast, prioritising distance resulted in the relatively low penalty value of 281.21. Prioritising distance is a viable substitute for situations where the shortest delivery route is required.

Wind speed variables were included in the simulation and it was observed that the delivery time of the drone increased from 139.21 minutes to 296.61 minutes with a wind speed of 25 km/h at a  $120^\circ$  angle to the drone's heading.

For the algorithm validation, the random walk scenario route of 299.74 km was compared to the optimised route of 103.53 km. The results confirmed the findings of the case study and a framework was thus established for any given drone delivery scenario.

The penalty values achieved by the inspection algorithm was 855.07 for the final solution, 1946.10 when prioritising number-of-specimens, 2154.71 when prioritising specimen-priority and 281.21 when distance was the primary concern. This policy comparison validated the modified inspection algorithm but showed that prioritising distance, when travelling along one long route with no stop overs, is a viable alternative.

The specimen turnaround times were then assessed using 120 scenarios of varying wind speed and rate of request generation. The delivery times were then plotted on histograms for wind speeds of 5 km/h and 25 km/h and rate of requests of 2 requests per hour and 1 request per 6 hours. In conditions similar to those observed in Mpumalanga, the average delivery time was 93.94 minutes which is well below the 3 hour limit previously discussed. The results indicate that as less requests are generated or become available due to high wind conditions, less clinics are visited resulting in reduced turnaround times.

### 9.3 IMPLICATIONS AND FUTURE RESEARCH

The inspection algorithm simulation can be scaled up to any number of drones or request points which allow for the testing of various landscapes. The simulations are used to determine the most efficient drone-to-request ratio in order to minimise the cost of implementation of a system. Limited scenarios were simulated in this dissertation and future work includes increasing the number of iterations in order to determine the average point of failure over a set time period. The maximum size limit of the service area can also be determined by increasing the number of request points until system breakdown.

Live weather pattern data can be used to determine the safest route for delivery. This will further prevent specimens from not reaching their destination.

The reward based inspection algorithm fares well for the current task at hand but improvements to the algorithm could include the use of particle swarm optimisation (PSO) or reinforcement learning (RL).

Particle Swarm Optimisation (PSO) [74] is an optimisation method used to solve a global solution based on minimising a cost function. The PSO algorithm uses a swarm of

'particles' each performing their own task in a search space in order to achieve an overall solution.

Much like a drone delivery network, PSO uses a combination of tasks to perform a structured event. A drone delivery system could include multiple units, comparable to particles, which are required to collect and deliver specimens to their destinations. This dynamic solution could be a viable alternative to the inspection algorithm.

The research paper by Janusz A. Starzyk et al. discusses optimising a particle's route using a reinforcement learning (RL) approach [75]. The principles of reinforcement learning are used to control the particle's steps in order to explore the search space. The algorithm does not require prior knowledge of the optimum solution and may potentially improve on delivery routes when run over multiple iterations.

### **9.3.1 Summary**

Through case study analysis and optimization algorithms a proportional approach to patient care was determined whereby POC and clinical specimens can be transported via drones and conventional methods remain as a fall-back in cases where larger delivery distances are required. A feasibility study aided by a system implementation model highlighted the most cost effective and safest method of specimen delivery and patient care in the most efficient manner. The problem presented in this paper is not solved, but rather a way forward is presented whereby realistic scenarios can be simulated. The system outlined in this paper can thus be used to implement a real-world prototype of a drone delivery system.

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