DURBAN UNIVERSITY OF TECHNOLOGY

Constructing Intelligent Drone Systems to Monitor Environmental Conditions

By

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Declaration

I, Ebrahim Asmal, declare that:

(i) The research reported in this dissertation, except where otherwise indicated, is my original research.

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I, begin in the name of Allah جلاله جل ,The Most Compassionate, The Most Merciful, and everlasting Blessings and Peace be upon Muhammad وسلم عليه الله صلى ,The Beloved of Allah. All praises directed towards me are for Allah and all faults are my own.

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Abstract

Durban is the third largest South African economic hub after Johannesburg and Cape Town. Durban houses the largest port harbour in Africa. The port generates massive road cargo to and from all over the continent. Furthermore, it is through the Durban South Basin that crude oil is imported, refined and then transported to the rest of the country by road or special dedicated pipelines. All of these have a significant impact on the local environmental. Durban University of Technology is one of 26 academic institutions producing future graduates for the nation. Literature informs that only Environmental Science students write or talk about the environment with authority. There is therefore a need to inculcate an environmental awareness by demonstrating actions have consequence to the environment that we work and study in.

The aim of the project is to develop a frugal mobile environmental data collector by embedding or installing sensors onto an Unmanned Aerial Vehicle, together with a microcontroller and transmission module for data collection and transmission to the user for viewing and analysis.

The main objective of this project is to assist in obtaining distinct environmental information from different layers of the atmosphere, from different areas through difficult terrains some of which are alternatively hazardous or populated spaces.

The research methodology and design was guided by the Agile Design Science Research Methodology because of the need to combine information technology, engineering and environmental science.

Furthermore, the use of data analytics-based algorithms in an environmental monitoring scenario was adopted for analysing and making educated decisions regarding environmental conditions. The k-means method was compared to the Silhouette index, Davies-Bouldin index, and Dunn's index, which are all well-known distance metrics. The evaluation's findings suggest that the well-known k-means algorithm performed effectively in the environmental condition dataset analysis, implying that the environmental condition of the collected data is normal.

The results show the construction of a frugal drone to undertake environmental data gathering as well as data analytics using artificial intelligence methods such as k-means is possible. The multidisciplinary model should be piloted in other environments located at hospitals, industrial zones, and the port itself.

Keywords

Drones, Unmanned Aerial Vehicle, Autonomous Drones, Intelligent Drones, 3D printing, Drone Flight Path, Waypoints, Environmental Monitoring, Clustering Algorithms, K-Means, Agile Design Science Research.

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List of Abbreviations

4IR	Fourth Industrial Revolution
ADC	Analog-to-Digital Converter
ADSRM	Design Science Research Methodology
AI	Artificial Intelligence
AMR	Anisotropic Magneto Resistive
BMP180	Barometric Pressure Sensor
BS	Base Station
BVLOS	Beyond Visual Line of Sight
CAD	Computer Aided Design
CH	Cluster Head
Cl	Cluster management
CO_2	Carbon Dioxide
CPU	Central Processing Unit
DaaG	Drone as a Gateway
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DHT11	Humidity and Temperature Sensor
DSR	Design Science Research
DSRM	Design Science Research Model
GCP	Ground Control Calibration
GIS	Geographic Information System

GPU	Graphics Processing Unit
hPa	Hectopascal
ICT	Information and Communication Technology
ID	Identification
IoT	Internet of Things
LAANC	Low Altitude Authorization and Notification Capability
LTE	Long-Term Evolution
MEMS	position of drones as MEMS accelerometers can sense movement
MQ135	Gas Sensor Module
NH_3	Ammonia
NO_2	Nitrogen Dioxide
O_2	Oxygen
ODBC	Open Database Connectivity
PEA	Pulseless electrical activity
PLA	Polylactide
PSL	Power Service Layer
ROV	Remotely Operated Vehicle
RPS	Remote Pilot Station
RPS	Remote Pilot Station
RTC	Real Time Clock
SDK	Software Development Kit
SOM	System on Module

SPI	Serial Peripheral Interface
UAS	Unmanned Aircraft Systems
UAV	Unmanned aerial vehicles
UDE	Uncertainty and disturbance estimator
WSAN	Wireless sensor-actuator network

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Chapter One: Introduction

2.1 Introduction

Due to the rapid rise in the human population, which exerts additional strain on an already stressed ecosystem, environmental monitoring has become increasingly important. This is a result of agricultural runoff and rainwater contaminated with air pollutants, most surface soils, ice caps, and water bodies have traces and high amounts of inorganic compounds, while water also contains significant quantities of pesticides (Elmqvist, Folke and Nyström, 2003; Giones and Brem, 2017). There is therefore a need to improve, extend, expand, and automate the collection of environmental data in a safe and secure manner. Automed data collection, which recommends the usage of drone technology, might be used to achieve this optimization.Durban is the third largest South African economic hub after Johannesburg and Cape Town and it houses the largest port in Africa. The Durban port generates massive road cargo to and from the continent. Furthermore, the Durban South Basin imports and refines crude oil which is then transported to the rest of the country by road or dedicated pipelines. All of these have a significant impact on the local environment. This study aims to develop a frugal mobile environmental data collector by embedding/ installing sensors onto a UAV, together with a microcontroller and transmission module for data collection and transmission to the user for viewing and analysis.

This chapter discusses the research's background and problem statement, as well as the study's aim, objectives, significance, and structure.

2.2 Background of the study

Knowledge-Based Environmental Monitoring is defined as the observation of the presence of harmful factors such as toxins, bacteria, chemicals and other pollutants in a specific location (Rao, 2002; Batzias and Siontorou, 2006; Hussain and Nath, 2013; Batzias and Kopsidas, 2019). Thus, environmental monitoring is a multidisciplinary science requiring skills from the disciplines, inter alia, ICT, engineering, physics, biology, and statistics. The multidisciplinary nature provides the basis for extending the consideration to intelligent drones. Daley (2020) asserts that drones and Artificial Intelligence (AI) are a match made in technological heaven. Pairing drones' unmanned capabilities with real-time AI technology empowers ground operators with the equivalent of a human-eye-in-the-sky. In addition, drones already play a crucial role in critical sectors, such as security and defence, agriculture, natural disasters, and construction by improving safety and increasing efficiency (Brown, 2015; Daley, 2020).

Drones or more formally unmanned aerial vehicles (UAV)[1] are airborne systems modelled around an aircraft. They are operated remotely by a human operator or autonomously by an onboard computer. The earliest evidence of UAVs was in military combat and the application of drone technology has disrupted almost every sector. The invention, sophistication and widespread use of UAVs has supplanted the need for humans to engage during risky ventures such as surveillance and monitoring while simultaneously reducing the cost and accuracy of such exercises (Biber, 2013; Brown, 2015).

The defence sector invented and deployed drones in 1937. This provided the initial investment in research and design which is why the most sophisticated drones are found in the military and security industry (Sullivan, 2006; Drone Life, 2018; Choudhary, 2018). A few practical areas of drone applications are presented below:

Emergency response and disaster management: Remotely controlled drones with transmitting cameras or surveillance abilities can travel for long distances even under extreme weather. In these situations, UAV’s are applied to determine the extent of damage, locate victims and also deliver necessary aid and help, such as blood, basic food and medicine (Drone Life, 2018; Choudhary, 2018).

Healthcare: The world is continuously experiencing instances of life threatening diseases. These demands increased the need on modern medicine to deliver on-demand life-saving solutions and medication particularly hard to access rural areas. Drones are emerging as a timely intervention to deliver medicine, blood and medical technology to areas that are largely inaccessible, such as Zipline International's blood delivery in Rwanda and South Africa (Choudhary, 2018; SANBS, 2019).

[1] This research will use the term UAV and drones interchangeably as is common practice.

Weather forecasting: Most current climatic data is gathered by satellite images. Drones deployed by meteorological departments gather data to understand and physically follow changing weather conditions. Drones can also be equipped with multiple weather-related devices such as pressure and humidity sensors, thermometers, and wind gauges to gather environmental information (Drone Life, 2018; Choudhary, 2018).

Photography/audiometry: Present drones capture photographs by mounted or inbuilt cameras enabling them to collect photographic images of weather patterns, people, land or even ocean cycles. A drone can fly at heights of about 200 meters, unobstructed by cloud, for an extended period taking high resolution photographs, making drones suitable for environmental monitoring and aerial mapping of terrains. Such drones already mapped an area of approximately 4.32 million square kilometres (Taylor-Smith, 2018).

Drones capture sounds through mounted listening sensors. The combinatorial audio-visual capability has made drones invaluable for modern surveillance or other uses that relies on data collection, recording or transmission (Biber, 2013; Brown, 2015; Daley, 2020). Research problem statement

Environmental monitoring necessitates the safe, frequent, accurate, longitudinal measurement of several variables simultaneously over extended periods. Continuity is crucial as data gaps impair the evaluation of environmental variability that is frequently shaped by occasional key events (Biber, 2013; Brown, 2015). Furthermore, missing data and geographic proximity of the data collection aggregator impacts data quality. This compromises the results of a particular monitoring program to the extent of affording opponents an opportunity to challenge the monitoring validity or its recommendations. Longitudinal data collection is also crucial as some environments exhibit subtle trends requiring adequate time for identification. As a result of these challenges, sophisticated means of collecting data with the use of drones is proposed (Biber, 2013; Brown, 2015). This research aims to implement a frugal intelligent drone system that helps monitor environmental conditions in monitoring scenarios to curb the gap faced by other UAV systems.

Environmental conditions is subject to an array of occasional impacts from natural and human sources such as flooding and chemical overflows respectively. Long periods of data collection is required to establish links between such environmental consequences. (Biber, 2013; Brown, 2015).

This study undertook a life cycle design of constructing a proof-of-concept drone solution that could read atmospheric environmental data by on-board reading sensors, a microcontroller and storage capabilities. The experiment comprises the drone, the three sensors and SD card connected to a microcontroller which is housed in a secure container attached to a 3D printed part together were mounted onto drone. The study will refer to this as the experiment.

2.3 Aim and Objectives

The aim of the project is to develop a frugal mobile environmental data collector by embedding sensors, a microcontroller and transmission module in to a UAV, for data collection and transmission to the user for viewing and analysis.

Tthe following objectives were set:

- To comprehensively review relevant publications based on the use of UAVs in monitoring environmental conditions in order to compare well known systems to our proposed system
- To design and implement the proposed frugal intelligent drone system that helps monitor environmental conditions
- To analyse and evaluate accumulated environmental condition data using clustering algorithms.

2.4 Research Methodology

The research uses the Agile Design Science Research Method (ADSRM) which is a combination of the ICT Agile method along with the Design Science Research (DSR) paradigm to demonstrate that a drone may be purposefully, economically designed and constructed to fly safely and autonomously through a predetermined flightpath using several waypoints. The drone will store quantitative atmospheric data in an onboard storage device collected through specific sensors. The sensors will store in a specially engineered and built 3D printed payload container which will be mounted on the drone.

Stored data from frugal drone will be downloaded after each flight for analysis. In order to interpret the data a clustering algorithm will be utilised. The design choice was deliberate to demonstatre that AI techniques could be used in environmental data analysis.

2.5 Significance of the study

Although the army was the first to deploy drones (Gregory, 2011; Van Tilburg, 2017), this technology now allows for better environmental monitoring and protection. Drones have been used in places where human transit is too dangerous, time-consuming, or expensive, or when the terrain is inaccessible. Almost every industry is experimenting with drone technology, with varying degrees of success ranging from rudimentary to advanced. In addition, AI and drone technologies are being used to perform intelligent evaluations (Laksham, 2019).

The objective of the concept for this study was to modify commercial drones that could operate in an urban area without interfering with everyday life. This is only possible if drones are made intelligent which became the research goal.. Ddrones could not easily be fitted wirth sensors and microcontrollers to make them smarter because it was a non-trivial engineering problem, which this study overcame with 3D printing technology. Second, automation allowed for the drones to fly through pre-programmed waypoints in order to collect comparable geo spatial data points (Brown, 2015; MIT Robust Robotics Group, 2021). This research serves as a proof of concept.

2.6 Contribution of the Study

Drone technology and applications will continue to gather pace as their capacity and capability is enhanced. This study contributes to the body of knowledge by showing how a frugal drone can be sourced, configured, repurposed with other technology using an agile design science research method to solve real world problems. The addition of sensors was made possible through re-engineering and printing of a special housing using 3D technology. The project also demonstrated that automated multivariable real-time data collection is possible safely in a urban area. Some Artificial Intelligence clustering analytics is added to show the perceived value to stakeholders such as environmentalists.

2.7 Delimitations

The combinatorial audio-visual tuple capability of drones with camera and microphones has extensive possibilities on data collection, recording, interpretation and transmission. This is delimited for future research work (Biber, 2013; Brown, 2015). The environmental data is not interrogated with any environmental expertise. However an AI clustering method was applied. This non-trivial analytical system was deliberately chosen to stress that sophisticated analytics that may be performed. Thus expert-level interpretation of the gathered data is delimited and deferred to environmentalist as this is their domain.

In a complete system, a drone does not act in isolation; as it may be networked to a server to maintain seamless connectivity whereby the captured images, videos or sound may be transmitted and stored. The transmission process makes use of wireless technologies including ZigBee, Wi-Fi, WiMAX, and LTE (Yanmaz, Rinner, Yahyanejad & Hellwagner, 2017). In this study an onboard storage device is mounted on the drone and data is transferred when the drone lands. The intelligent drone is an AI-enabled drone and its developmental progress mirrors building robots such as "Sophia" which communicate with human beings. Drones, will hold constructive command-driven conversations with humans, for example returning a useful answer to a question (Brown, 2015; Simons, 2017). This is delimited for further research.

2.8 Structure of the thesis

The thesis is organised as follows:

Chapter One: Introduction

This chapter introduces the research topic providing details on the background of the study, the research problem, and aim of the study, significance of the study, and the research objectives and research questions.

Chapter Two: Literature Review

This chapter provides a comprehensive literature review of drones, its use cases, opportunities and challenges. Subsequently, it explores drones and environmental concerns, focusing on two major Durban catastrophes that drones may have averted.It further reviews the value of AI when used with drone technology.

Chapter Three: Research Methodology

This chapter discusses and motivates the Agile Design Science Research Method (ADSRM) choice which is a combination of the ICT Agile method along with Design Science Research (DSR) method. Various aspects of this quantitative study pertaining to data collection such as the validity and reliability using sensors, a microcontroller and further computational processing are detailed in this chapter.

Chapter Four: Data Analysis and Discussion

This chapter uses the ADSRM framework to describe the drone construction process and describe how the data will be analysed as a proof of concept. It describes the processes and challenges over drone identification, construction and experiment design.

Chapter Five: Conclusion and Recommendations

This chapter presents a summary of the study, describing the process followed, listing the results as well as the contribution of the study to knowledge in research and practice. The chapter provides recommendations for further future research.

2.9 Conclusion

This chapter presented a brief overview of drone technology, its application in environmental monitoring and protection. The background of the study and the problem statement was discussed in this chapter. In addition, the research question as well as the study's aim, objectives, and relevance was highligted.

The next chapter examines important theory and discussion on the use of drone technology in order to identify the research gap and clarify the study's theoretical foundation.

Chapter Two: Literature Review

3.1 Introduction

This chapter reviews literature related to environmental monitoring, modern day drones and technological advancements such as Fourth Industrial Revolution (4IR). Key words and concepts are explored to gain insight on drones and environmental monitoring. It then chronicles two Durban environmental disasters wherein drones could have provided much needed environmental data. It further reviews the value of AI when used along with drone technology.

3.2 Environmental Monitoring

Environmental monitoring is a multidisciplinary science that requires various physics, biology, and statistics skills, among others. In their seminal ecological paper, Lovett, Burns and Driscoll (2007:253) define environmental monitoring as "*a time series of measurements of physical, chemical, and/or biological variables, designed to answer questions about environmental change*". These measurements may be taken at one or at multiple locations. The multidisciplinary nature of EM is the basis for considering the use of intelligent drones.

Many examples of harmful ecological changes, some unanticipated or even unintended, arise from the increasing population and intensified human activities. For instance, the American agricultural, industrial revolutions in the 20th century generated tons of waste products released into the environment without any study of their consequential impact (Thompson, 1968; Conejo, Birat and Dutta, 2020). Similarly, in various parts of the developing world, raw waste is still disposed of in the environment without treatment or consequential monitoring.

Environmental monitoring has revealed that most surface soils, ice caps, and water bodies contain traces and high levels of inorganic chemicals and nuclear-fallout materials (Chaudhry, and Malik, 2017). Also, most surface waters like lakes and rivers contain traces or high concentrations of pesticides due to agricultural runoff and rainwater contaminated with atmospheric pollutants.

The possible danger associated with environmental measurement and data acquisition lends itself to using drones for data acquisition. Drones have evolved from sophisticated automated toys to business tools (Giones and Brem, 2017). The 4IR era has allowed multiple technologies to be combined producing exponential technology. The drone is an exemplar of this (Thakur and Asmal, 2021). Drones may now be used as airborne environmental inspectors which neutrally acquire data with speed and vigilance. Drones may even be combined with appropriate data acquisition Internet of Things (IoT) sensors. These may be analysed with AI or other 4IR technologies to deliver real-time value.

3.2.1 Knowledge-Based Environmental monitoring

i. Knowledge-Based Environmental monitoring is defined as the observation of the presence of harmful factors such as toxins, bacteria, chemicals and other pollutants in a specific location. Rao (2002) defines Environmental monitoring as a means of collecting a representative portion of water, waste or air from a specific area in order to ascertain its quality and characteristics. This leads to the notion of knowledge-based environmental monitoring (Rao, 2002; Batzias and Siontorou, 2006; Sahu, Sahu and Sahu, 2018). Knowledge-based environmental monitoring is beneficial because it helps in the:protection of water supplies. This protection includes identifying water pollution sources, monitoring ground and surface water, and wastewater treatment (Biber, 2013, Naves, Samper and Pisani; 2021).
ii. management of radioactive, non-hazardous, and hazardous waste. This management includes reuse, proper disposal, and probable environmental and human health implications (Gamulescu, Rosca, Panaite, Costandoiu and Riurean, 2020).
iii. protection and management of natural resources including monitoring soil and land degradation, water supplies like lakes and rivers, monitoring forests for wood harvesting, and food supply (Biber, 2013; Naves, Samper and Pisani; 2021).
iv. forecasting the weather which involves anticipating disasters as well as long- and short-term climatic conditions (Teague and Gallicchio, 2017).
v. monitoring natural disasters such as floods or fires or man-made environmental disasters such as gas explosions (Gamulescu, Rosca, Panaite, Costandoiu and Riurean, 2020).
vi. monitor during civil or criminal riotous acts (Singh, Patil, and Omkar, 2018).

The aim of this study is to monitor urban air quality and the perceived impact of industry on air quality.

Lovett, Burns and Driscoll (2007) informs that Environmental monitoring is often criticised as being unscientific, expensive, and wasteful. This study responds to this criticism by addressing the issues with drone-based monitoring.To achieve this, three typical types of knowledge-based monitoring methods are suggested namely visual examination, analytical monitoring, and compliance monitoring (Ho, Robinson, Miller and Davis, 2005; Feenstra, Papapostolou, Hasheminassab *et al.*, 2019). The following environmental cases demonstrate why these methods are critical in the environmental monitoring field.

3.2.2 Examples of environmental case studies

Two Durban-based case studies of significant relevance, namely the massive refinery explosion (4 December 2020) and agrochemical fire (12 July 2021), are presented to illustrate the importance of real-time data acquisition and continuous analysis. These cases were selected due to its academic resonance and is the geographical area where data collection for this study was conducted.

3.2.2.1 United Phosphorus Limited fire on 12 July 2021

United Phosphorus Limited (UPL), a multinational agrochemical company based in Durban, South Africa, is a timely case study with significant relevance. UPL was accused of failing to implement critical regulatory safeguards against environmental and health hazards at its warehouse, which became apparent when the warehouse was set on fire during civil unrest (van Rensburg and Comrie, 2021). The long-term consequences of this will be felt by inhabitants, vulnerable wetlands, rivers, and beaches for many years to come (Kuenzer and Renaud, 2012).

The immediate consequence occurred when first responder firefighters, dispatched to extinguish the blaze during civil unrest, entered a hazardous chemical fire, completely unaware that they were putting their lives in danger (van Rensburg and Comrie, 2021). Firefighting efforts were further hampered by the fact that the contents of the warehouse were kept secret, further complicating the situation. When one considers that the warehouse is directly across the street from Redham School, which has a few hundred students, the issue becomes even more difficult. Masta 900, an insecticide containing a strong neurotoxin that may be deadly when applied to the skin, inhaled through dust or spray, or swallowed, was among the chemicals stored. Masta 900 is a neurotoxin that can be fatal when applied to the skin, inhaled through dust or spray, or swallowed (van Rensburg and Comrie, 2021).

The contents of the facility revealed that UPL was not compliant with environmental and risk studies as legally prescribed by the National Environmental Management Act (NEMA) as well as the Occupational Health and Safety Act (OHSA).

Figure 3.1: Fire after UPL Explosion (Mbele, 2021)

The case suggests a motivation for deploying drones during real-time disasters such as fires. Such environmental monitoring is already occurring in Thailand (Iwai, Pratad, Sereepong and Noller, 2008); Tanzania (Lema, Machunda and Njau, 2014); Ghana (Fianko, Donkor, Lowor, and Yeboah, 2011) and Bangladesh (Rahman and Debnath, 2015). These were however non-drone data acquisitions. This study argues that drones are an innovation that will neutrally acquire data during normal regularas well as disaster periods.

3.2.2.2 Durban Refinery explosion on 4 December 2020

A massive explosion occurred at the Engen Oil Refinery located at Tara Road, Durban, on 4 December 2020 at 7 am, during morning peak-hour traffic. The black smoke made visibility and breathing complicated (Figure 2.2). At least seven people were treated for smoke inhalation.

Figure 3.2: Fire at Engen Oil Refinery (Engen Explosion 1, 2020)

The sirens blared twice, signaling a severe condition (Marriah-Maharaj, 2020). The refinery explosion is consequential of a lengthy environmental battle with the recipient of the prestigious Goldman Environmental Prize, Desmond D’Sa claiming his community is slowly being poisoned (Erasmus, 2020).

Figure 3.3: Fire at after Engen Explosion (Engen Explosion 2, 2020)

There is a legal and civil investigation ensueing over this explosion. An official investigation into the incident is also underway in the South African parliament (Parliament, 2020).

As human settlement and industry become increasingly intertwined, it is inevitable that these sorts of environmental disasters will occur with greater regularity in the future. This strengthens the legal, social, and commercial rationale for the use of drones to collect impartial data. it is congected that drones may be utilized to support or disprove charges made by citizens in various ways.

3.3 Drones

An unmanned aerial vehicle (UAV), also referred to as a drone, is an aircraft without an *onboard* human pilot, crew or passengers. UAVs are a component of an unmanned aircraft system (UAS), which include a ground-based controller *with* a system of communications with the UAV (Sharma, Vanjani, Paliwal, 2020). In this study, unmanned aerial vehicles (UAVs) are employed. This research makes use of unmanned intelligent drones. Drones are classified as either manned or unmanned, as well as intelligent or unintelligent, as discussed further below.

3.3.1 Manned vs. unmanned environmental systems

A manned system of droning is an aircraft system that is completely handled manually by a pilot for monitoring various environmental conditions (Horowitz, Krepsand and Fuhrmann, 2016). However, drone technology is one of the best examples of unmanned systems. Aircraft that are exceptionally managed and handled by software systems, AI and other technological advancements are known as unmanned systems. Unmanned aircraft including drones are connected to ground-level software with data exchange taking place between ground-level aircraft stations and the device as illustrated in Figure 2.4.

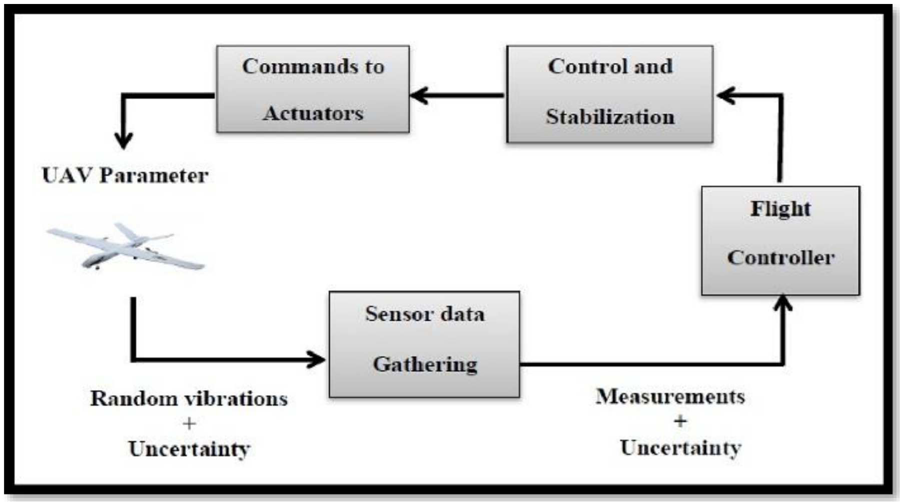

Figure 3.4: Control unit of the unmanned system (Greene, Segales, Waugh, Duthoit and Chilson, 2018)

The spending of the South African government on technological advancements for developing unmanned aircraft for supervision has increased to 133.57 billion dollars (Statista, 2020). The environmental conditions have witnessed a massive degradation in the past few years. According to estimation, the Global warming of South Africa has increased by 1.5% and it has contributed to raising the world's air pollution graph by 33% (Korombo, 2019).

In such situations using unmanned technology to monitor environmental conditions is vital. A manned aircraft is mainly used for contesting environments where autonomy is essential, policy restrictions have existed and command and control are limited (Horowitz, Krepsand and Fuhrmann, 2016). However, an unmanned aircraft does not consist of aircrew for limiting endurance and range or has the risk of being captured. A UAV is dependent on a GPS module, transmission module, ground control system, software and camera along with the person who controls the drone.

3.3.2 Intelligent vs. unintelligent drones

A drone is termed intelligent and unintelligent. Unintelligent drones cannot operate in urban environments, or get useful things done, or interact with people. Intelligent drones are more autonomous and can avoid crashes and collisions, as well as sense what is going on around them.

Intelligent drones can avert obstacles; they can understand and distinguish what is safe and what is not secure and understand the environment. They can understand how humans need them to do certain things and understand their behaviour regarding performance and reliability (Yawson and Frimpong-Wiafe, 2018).

Drones, are controlled remotely by human or fly automatically through software-controlled flight procedures in their embedded systems. They are used together with GPS and smart sensors onboard. Drones, sensors and intelligent systems were originally employed in missions which were very dangerous repetitive or unhealthy for humans. Their use has since expanded to scientific, commercial, agricultural, recreational and other applications such as surveillance, security, logistical product delivery, peacekeeping and photography (Yawson and Frimpong-Wiafe, 2018)

The choice of unmanned intelligent drones for this research was based on safety and costs with a view of encouraging adoption for environmental monitoring.

3.3.3 Components of a drone

Figure 2.5 shows a typical drone and its components. Each component is described.

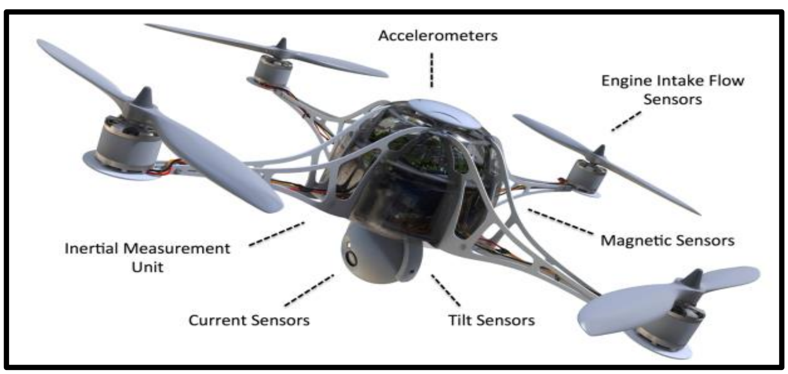

Figure 3.5: Sensors in Intelligent Drone (Bhuvaneshwari, Saranyadevi, Vani and Manjunathan, 2021)

3.3.4 Drones and AI

This research supports the use of drones in conjunction with AI for environmental monitoring. To fulfill environmental duties, drones require extra technology and software systems. Daley (2020) is eloquent, asserting that drones and AI are a match made in technological heaven. Pairing drones' unmanned capabilities with real-time machine learning technology provided by AI empowers ground operators with the equivalent of a human eye in the sky. These eye-in-the-sky drones play a crucial role in supporting critical sectors like security and defence, agriculture, natural disasters, and construction. As their capability to improve safety and increase efficiency increases, drones have become essential tools for many users, ranging from firefighters (Daley, 2020).

AI software allows drones to process data and report back in real-time. In specific contexts, drones with a "digital brain" through the pairing with AI is compelling (Vattapparamban, Güvenç and Yurekli, 2016).

3.3.5 Drones and IoT

Jovanovska and Davcev (2020), noted drones are IoT-based with the the potential of inferring above the cloud-based environmental conditions through smart sensors from aerial surfaces. Therefore, data on varied environmental conditions can be obtained through the application of strong network sensors as compared to human-driven current techniques.

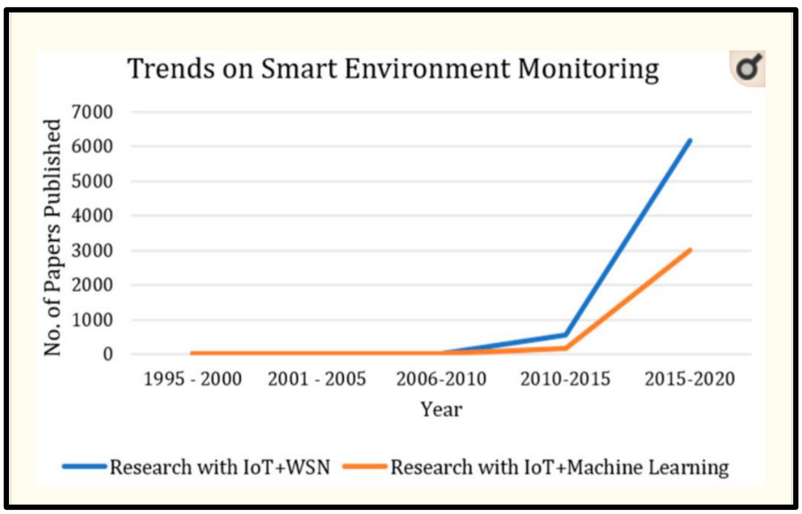

Figure 3.6: Smart Environment Monitoring Trends (Ullo and Sinha, 2020)

From Figure 2.6, it can be highlighted that in the last five tears adoption of drone technology has bennrapidly increasing. However, the application of machine learning incorporated within drone technology has only been able to increase from 1000 to 2500 over a period of 15 years. Drone and current monitoring and capturing systems

This section discusses drones in the context of environmental monitoring systems which includes drone data capture.

3.3.5.1 Challenges with the current monitoring environmental systems

Environmental monitoring needs to measure different variables over extended periods and has to be both long-term and continue to be successful (Stow, Carpenter and Webster, 1998; Elsawah, Filatova, Jakeman and Kettner, *et al.*, 2020) . Continuity is crucial as data gaps impair the evaluation of environmental variability that is frequently shaped by occasional but critical events. Missing data compromises the results or integrity of particular monitoring programs. For instance, flood gauge information might not be available because floodwaters destroy a specific gauge. As a result, critics use missing data to challenge the monitoring program's authenticity or the recommendations based on the data (Stow *et al*., 1998; Elsawah *et al*., 2020).

3.3.5.2 Longitudinal environmental monitoring systems

Longitudinal data collection is crucial as most environmental resources also experience slow change and subtle trends requiring adequate time for identification (Biber, 2013; Loftus, Ni and Szpiro, 2020).

Establishing linkages between environmental conditions changes and a regulatory and management decision requires long data collection periods, particularly since ecological conditions are subject to various crucial but occasional impacts from other natural or human resources (Biber, 2013; Loftus, Ni and Szpiro, 2020).

Longevity is also necessary as it takes extended periods to collect data. As a result of these challenges, sophisticated means of collecting data may be required.

3.3.5.3 Drones value with respect to environmental conditions

a) Drones play a enabling role in aerial photography/audiometry

Dronescapture images through mounted or inbuilt cameras enabling them to collect photographic images of the terrain, weather patterns, people, land or even ocean cycles. For example these drones already mapped an area approximately 4.32 million square kilometers. A drone can fly at heights of about 200 meters, unobstructed by cloud, for an extended period taking high resolution photographs, making drones suitable for environmental monitoring and aerial mapping (Taylor-Smith, 2018; Daley, 2020). Additionally, drones also capture sounds through mounted listening sensors. The combinatorial audio-visual capability has elevated the drone's role in modern surveillance or any other use that relies on data collection, recording or transmission and this is delimited and flagged for future work (Biber, 2013; Brown, 2015; Daley, 2020).

b) Drones have been used to inspect various wildlife species and forestry

Drones may be used to inspect wildlife species in remote areas and even pinpoint the locations frequented by poachers for remedial action (Petrov and Stancheva, 2020). This technique has been effectively used to save chimps in Tanzania, observe sea birds in Australia, save Sumatran orangutans, count green turtles in Indonesia and seals in Canada and prevent illegal logging in Brazil (Taylor-Smith, 2018). Petrov and Stancheva (2020) add that intelligent drones assist with acquiring conservation information relating to different species such as seals, sea lions, and dugongs and evaluation of ecosystem wellbeing. This suggests that drones have unrestricted aerial access, which may help to minimize this problem and track down the perpetrators.

c) Drones in agriculture

The environmental monitoring process deciphers information about the weather conditions existing within the environment of a place, providing information relating to that geolocation (Rakha and Gorodetsky, 2018). Intelligent drones are becoming popular at an accelerated pace in monitoring the environmental conditions of a place and gathering information. It also provides an overview about land erosion, wildlife risks, growth of endangered species population, and growth (Krishna, 2018; Krenz, Greenwood, and Kuhn, 2019). In this study, environmental conditions required by intelligent drones, including dry temperature, less wind, and low humidity, have been discussed.

According to Yin, He and Kaynak (2019), the usages of drone technology have become significant for keeping away birds and safeguarding the crops and hence, conditions of soil and growth of crops can be monitored by drones.

3.3.5.4 Operational challenges with current drones

The advent of new technology not only provides solutions to numerous issues, it can also creates new obstacles. These are addressed further below.

a) Drones are not weatherproof

Rakha and Gorodetsky (2018), stated that a number of drones do not possess waterproof protection , and are less likely to function in rainy conditions. The rain negatively impacts on with batteries, motors and the electronic system that contributes to its breakdown. Thus, the presence of dry weather is regarded to be suitable for flying a drone for the acquisition of effective results such as the existence of air pollutants based on knowledge about weather conditions.

Rain generally create moisture in the drone's front cameras that obstructs its view leading to collision and resulting in accidents (Athilingam, Kowshick, Jeeva and Kumar, 2019). This study uses sensors to mitigate the effects of bad weather.

b) Drones typically only capture data

The problem with frugal drones is that there is nothing they can do with the data they collect beyond transmitting it for human interpretation. This increases the time taken for the interpretation of collected data. Because of this long time, or lack of real-time analysis, environmental disasters that could have been averted still occur.

According to Tmušić, Manfreda and Aasen (2020), drones have significant challenges when it comes to the monitoring of environmental conditions, particularly in terms of harmonisation and the provision of uniform instructions for data gathering. This is supported by the findings of this study, which attempted to employ AI in conjunction with sensors to have intelligent capturing and reporting.

3.3.6 Intelligent drones for environmental monitoring

According to Manfreda, McCabe and Miller (2018), intelligent drones provide new advanced procedures for monitoring key variables like streamflow, soil moisture content, and vegetation status. They also argue that the detailed information transceived[2] by intelligent drone systems have the capacity of enhancing researchers' capabilities to describe *inter alia* the availability of water resources in ecosystem and agricultural management.

3.3.6.1 Analysis of chemical atmospheric environment through intelligent drones

The chemical instrumentation, accelerated the increase and usage of drones to sense chemicals in the environment and the swift adoption and approval of drones in a stringent environment illustrates the safety and flexibility of drones used to sense chemicals in various domains (Burgués and Marco, 2020). The drones together with platforms are used in the enforcement of environmental regulations, monitoring of industrial emissions, and atmospheric research studies.

Carrozzo, De Vito and Esposito (2018) assert that air quality has been raising a lot of questions in many cities because of the negative health implications associated with substantial pollution levels. As a result, Carrozzo *et al*. (2018) maintains that the necessity to evaluate the extent of pollutants at high chronological and three-dimensional resolution is deemed to be very pressing. Carrozzo *et al*. (2018) argue that there is an increasing interest in developing pervasive networks that integrate different technologies, including AI, to attain such capabilities.

This study has resonance with Burgués and Marco's experience and adopts this model.

3.3.6.2 Components of an intelligent drone monitoring system

Chen, Aggarwal, Choi and Jay (2017) propose a video footage drone observing system. Their system comprised a drone tracking unit and a drone detection unit. The combined monitoring system, founded on AI principles, leverages tracking and detection for high-performance monitoring of environmental conditions. Burgués and Marco (2020) note that recent size and cost developments through respective miniaturization and affordable low-cost of drones.

[2] Transceived refers to information received (acquired) and sent (transmitted) to another device for further processing.

3.3.6.3 Challenges of Intelligence Drone Systems

The major challenges of the Intelligence Drone System are shown in figure 2.7 below.

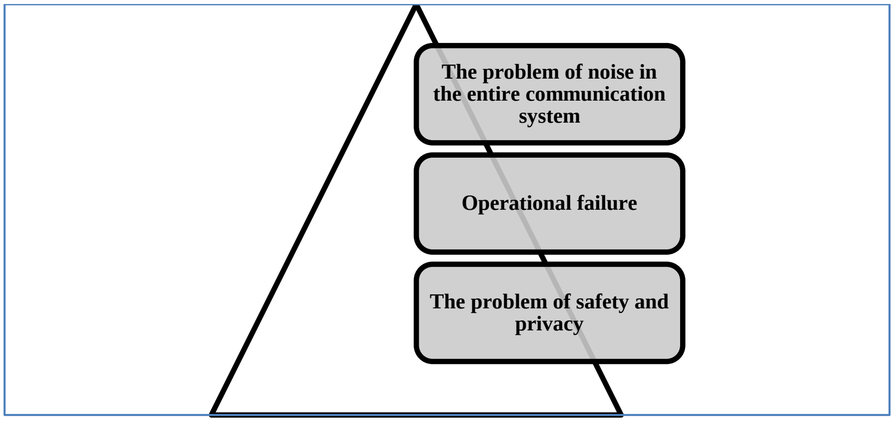

Figure 3.7: Challenges of Intelligence Drone System (Båserud *et al*., 2020)

a) The problem of noise in the entire communication system

The drone management system consists of four types of networking and communication links namely drone to drone, drone to ground location, drone to networks, and drone to satellites. Båserud, Reuder, Jonassen, Bonin, Chilson, Jiménez and Durand (2020) indicated that during passing and carrying information white and black noise is observed that deflects the coding system impacting the exchange of data. Kumar, Sharma, Singh, Naugriya, Gill and Buyya (2021) recognises this but asserts that most of these noise infringements can be rectified.

b) Operation failure

Operation failure is a challenge that leads to major problems while conducting flight management systems. Pathak, Damle and Pal (2019) assert GIS navigation often tends to face software breakups that lead to misinterpretation of codes during human-to-device interaction. Yu (2020) informed that around 42% of drones face difficulty in collecting information due to signaling or lack of device durability. Operational failure leads to problems in detecting and locating drones. A drone's power must be sufficient to return to the launch or landing base without being detected.**c) The problem of safety and privacy**

In many countries including South Africa[3] ,drone operations in some restricted areas are banned as it infringes with privacy norms of law. A constant “eye on the sky" for collecting data and information with inbuilt camera systems may violate the POPIA Act 2020 for interfering in the dimension of privacy. Drone surveillance is banned in some national keypoint sensitive areas in South Africa. The legal dimension has a major contribution in maintaining safety and privacy. Personal privacy and safety play a major role in drone operation and any kind of disorientation in the maintenance of fundamental rights can lead to problems related to safety and privacy concerns. In the case of manual aviation, both privacy law and safety are restored completely as, during any kind of faults, manual operation tends to be protective from technological dysfunction (Ferrell and Ferrell, 2020).

3.3.7 Drones and sensors

Santangeli, Chen and Kluen (2020), assert that in the context of environmental conservation, drones equipped with numerous devices and enhanced with deep learning is growing. Santangeli *et al*. (2020) piloted and demonstrated the combination of AI with drone-enabled thermal imaging techniques to discover various birds' ground-nests on farmlands with some success. The implications of their results are important to this research.

An alert reader may ponder the choice between a sensor and actuator which is now described.
Table 2.1 shows the differences between sensors and actuators.

[3] These are called National Key point Areas.

Table 3.1: Differences between sensor and actuator (Geeks For Geeks, 2020)

Sensor	Actuator
It gives output to input conditioning unit of system.	It gives output to environment.
Sensor generated electrical signals.	Actuator generates heat or motion.
It is placed at input port of the system.	It is placed at output port of the system.
It is used to measure the physical quantity.	It is used to measure the continuous and discrete process parameters.
It gives information to the system about environment.	It accepts command to perform a function.
Example: Photo-voltaic cell which converts light energy into electrical energy.	Example: Stepper motor where electrical energy drives the motor.

3.3.8 Weather conditions affecting drones

Tmušić *et al*. (2020) suggested a challenge relates to establishing protocols that can be applied across a wide range of environmental conditions.

a) Rainfall

Rainfall is also observed to be harmful to drones to fly as the front view cameras also fail to work properly in the presence of moisture. Since South Africa possesses a moderate climate with mostly warm days and cold nights with moderate rainfall, applications of intelligent drones can be beneficial for monitoring environmental conditions.

b) Wind

Cledat and Cucci (2017) determined that operating drones also becomes difficult when there are strong winds. The flying and navigation of the machine becomes significantly difficult and may lead to accidents. It can be further estimated that when an intelligent drone fails to obtain information about the air pollutants present during strong winds. It has been observed that higher drones, namely MikroKopter, possess the ability to fly at a wind speed of 49 km/hr. As highlighted by Hildmann and Kovacs (2019), the application of technologies such as AI and the IoT can be incorporated within drones to operate effectively within extreme weather conditions, including heavy rainfall.

On a similar note, the application of AI in drones offers them the chance of operating in high wind and rainfall areas where sensors of AI control the weather severity to possess a significant amount of information. This is delimited in the study.

3.3.9 Aquatic monitoring drones

Newer drones now waterproofed to operate underwater. These are called underwater drones or Remote Operated Vehicles drones (ROV drones). This allows one to obtain information about the conditions about marine life and the seabed (Fedyanin, 2021; Jovanovska and Davcev, 2020).

3.4 Environmental monitoring techniques

Environmental monitoring requires especially structured tools and techniques for the observation of the environment of a particular place (Roy, Pocock and Preston, 2012; Manfreda, McCabe, Miller, Lucas, *et* al., 2018). The most important environmental condition monitoring techniques include Air monitoring, Water Monitoring, Remote Sensing and Waste monitoring which are described in turn.

3.4.1 Air monitoring

Morales-Casa, Rebolledo, Ginocchio and Saéz-Navarrete (2019) describes air monitoring as providing a scope to evaluate a number of air pollutants such as Sulphur dioxide (SO_2), Carbon dioxide (CO_2), and Nitrogen dioxide (NO_2). Air monitoring provides scopes for exploring the degraded air quality by evaluating the amount of particulate matter existing within the climate posing threats of increase in global warming. Environmental activists are using intelligent drone systems such as Botlink which possess sensors for evaluating harmful gases and air pollutants within the climate (Campion, Ranganathan and Faruque, 2018).

Information collection about air pollution must be convenient without consuming excessive energy. Botlink enabled drones[4] are used for air condition evaluation as it incurs an insignificantly low energy consumption (Giones and Brem, 2017; Campion, Ranganathan & Faruque, 2018). Botlinks can easily operate in sub-zero conditions from -30℃ to -40℃ which extends operative areas (Vierra, 2019). The cost of Botlink however was prohibitive which is why this research undertook to develop a frugal open source model.

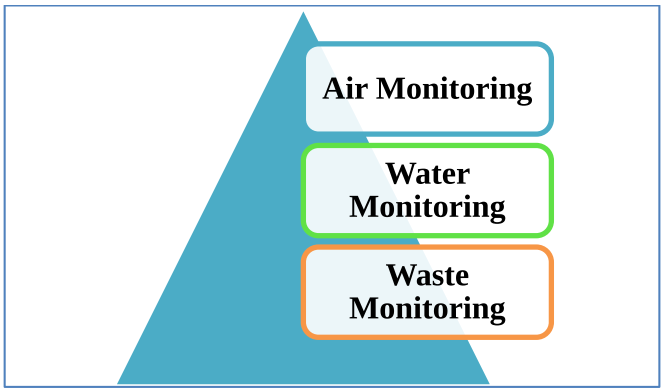

Figure 3.8: Environmental Conditions Monitoring Techniques (Giones and Brem, 2017)

Barrows, Neumann, Berger and Shaw (2017) describe grab air sampling technique which is a very convenient harvesting and storing of one pocket of air at a particular place as a sample to be examined at a later point. As this is similar to what is being done and required further laboratory work, the option was discarded.

Automated air monitoring technology such as Botlink and Weather drones are free from human interventions, and the existence of pollutants can be gathered easily Giones and Brem (2017).

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[4] www.botlink.com

3.4.2 Water monitoring

Water monitoring is generally undertaken for obtaining information about possible contaminants in the water. It provides information whether water is suitable for drinking and also for marine life to thrive (Greenwood, Mills, and Roig, 2007; Wilson, 2020).

The use of drones may appear counterintuitive when one considers that water has depth and volume. However, water has surface area which may easily be examined. Intelligent drone systems have been observed to monitor the changes of algal bloom in the surface of the water and also provide opportunities to see the changes of river beds also termed as topo bathymetry. Koparan, Koc, Privette *et al.* (2018) calls this drone technology deployment *in situ* surface water evaluation. Therefore, the application of conventional techniques of *in situ* or water quality management is being utilised by drone technology that is beneficial in water monitoring (Statista, 2021).

Remote sensing process is beneficial for the scanning of physical objects from a distance for detecting visual changes within the water bodies (Koparan *et al.*, 2018). It is accepted that drones for water is not a panacea as Angelopoulou, Tziolas and Balafoutis (2019) pointed that remote sensing fails to evaluate pollution existing within the water.

Remote sensing-based drone technologies aim at determining the amount of carbon present in the soil that affects the growth of crops significantly. This specified context of carbon existence within soils highlights that the application of remote sensing possesses the possibility of evaluating the distribution of vegetation and landfill use. As opposed by Angelopoulou *et al.* (2019) remote sensing also provides information about "airborne" particles such as plastics coming in contact with the soil decorating its quality. Poor soil quality contributes to raising the scope of unhealthy and stagnant growth of crops. Failing to contribute to agricultural growth can be determined from the satellite images for safeguarding soil erosion and promoting soil growth. Multispectral satellite sensors existing within remote sensing drones are beneficial in acquiring images from satellites about the availability of bare and healthy soils for ensuring agricultural purposes (Angelopoulou *et al.*, 2019).

3.4.3 Waste monitoring

Waste monitoring relates to strategies undertaken for the management of waste products such as plastics, radioactive wastes, and harmful chemicals for ensuring health and safety to society (Alsamhi, Ma, Ansari and Amalki, 2019). The deployment of intelligent drones has opportunities landfill waste, which are non-trivial to traverse. AI-enabled drones can identify litter bags and garbage and optimally manage the collecting of waste in public places such as beaches and parks (Alsamhi *et al.*, 2019). Drone technology contributes to surveying, evaluating and mapping landfill waste areas gaining easy access to the site in a time and labour efficient manner. As asserted by Marturano, Martellucci, Chierici, Malizia, Giovanni, d'Errico and Ciparisse (2021), drone technology possesses sensors that are able to detect harmful chemical substances existing within varied waste materials and even emissions at landfills.

As contradicted by Alsamhi *et al.* (2019) wastewater management can be easily done using drone technology as it possesses the ablity to collect water from inaccessible parts.

3.4.4 AI and monitoring

Consequently, prediction and analysis strategies can provide the necessary information required for the monitoring and capturing of environmental conditions. Scheller (2017) argues that machine learning classical algorithm is one of the effective techniques that can be used to analyse data and predict environmental conditions. In addition, Scheller (2017) asserts that machine learning is essential when dealing with AI since it entails the building of algorithms that have the capability of learning from either existing or past observations to provide a reliable output based on the new input.

The use of machine learning classical algorithms for analysis and prediction uses pre-programmed algorithms that analyse the input and predict the outcome within the accepted range. Machine learning classical algorithm relies on a number of factors ranging from the size of input data to the accuracy and interpretability of the output (Wu, Jennings, Terpenny, Gao, and Kumara, 2017). Besides, the process of predicting in classical machine learning algorithms follows a detailed procedure failure to which the prediction may fail to be reliable. The process starts by having a definition of the problem, collection of necessary data, cleaning of collected data, modelling data, evaluating the model and finally getting the solution to the problem (Wu *et al.*, 2017). Most organisations prefer machine learning classical algorithms for analysis and prediction due to the massive benefits that are tagged along with the technique. According to Kaličanin, Čolović, Njeguš and Mitić (2019), the two major benefits of machine learning classical algorithms are affordability and easier of interpretation. On the other hand, the technique is criticised as it cannot handle irrelevant features appropriately (Kaličanin *et al*., 2019).

3.5 Drone communication algorithms

Major functions incorporated by a drone can be composed of communication scheduling, smart data processing, path planning and data transfer method selection (Abdullah, Sahib, and Abu, 2019). Within a drone, the function of communication scheduling is enabled by actuators and sensors.. However, data that are collected by sensors and actuators can be used through other functions such as data processing and data transfer. “Smart data processing” has to run after the visit of “DaaG (Drone as a gateway)” in each mode of sensor. Zohdi (2020), informed that the "path planning function" can consist of two major paths such as path planning in both sensors and actuator networks. A fundamental part of the function can plan to the DaaG's flight path and it is in running mode until each sensor data is collected by DaaG. The next part of the function can be beneficial for determining the immediate visit of the actuator and its running period after finishing a collection of sensor data. "Data transfer method" can be utilised continuously within the entire operation. In this case, the "data transfer method” can be altered by using functions, therefore, all operations of DaaG can change their method of data transfer.

Backoff Based Beaconing Alogorithm is shown in Annexure B

3.5.1 Communication scheduling

Sensors and actuators can use sleep mode for minimising the consumption of power. This technique can be worked within a traditional environment where many sensors are stationary however, it cannot be appropriate in case of nodes becoming mobile. However, DaaG can be specified as a mobile therefore, the communication interface of sensors can use sleep mode by default and it has to be woken up responding to DaaG's beacon message (Thibbotuwawa, Nielsen, Zbigniew and Bocewicz. 2018). However, DaaG is focused on different communication interfaces for supporting communication through multiple sensors and actuators. Major benefits in order to reduce consumption of energy in each sensor can be observed however, DaaG has to consume much energy for supporting beaconing in each communication interface.

“Back off-based beaconing algorithm” can be used for reducing energy consumption where C denotes the entire set regarding the communication interface. $C_{i,\,bf}$ can be noted as the remaining time of back off and $c_{i,\,bmax}$ can be noted as maximum time of back off within the *i*-th stage of communication. b_{max} can be noted as maximum time of possible back off and $\propto$ can be noted as an increasing “back off factor” and t_{period} can be evaluated as an algorithm's time interval. The major idea within the algorithm in each interface of communication is used to send a "beacon message" along with the inherent time of back off. However, some interface of communication is used for increasing back off time for reducing energy in case no node is present around the same interface.

In case, no nodes can be used for a certain interface of communication within a current position, nodes can appear within DaaG’s movement towards a different position. Therefore, b_{max} is used for limiting increased back off time (Bae *et al.* 2018). However, the difference among the $c_{i,\,bmax}$ and b_{max} can be assessed for affecting back off regarding the movement of the drone through considering nodes of the drone. In case, b_{max} can be higher, DaaG is used for passing a single node among two different nodes.

3.5.2 Smart data processing

DaaG collects sensor data such as (*id, pos, st, sv, timestamp*). *Id* can be noted as a unique ID of a sensor, *pos* can be noted as sensor’s position, *st* can be noted as a type of sensor and *sv* can be noted as sensor’s value. DaaG is used for determining problems for a particular object in a particular area through using “collected sensor data” such as sv_t and “stored data” such as sv_{t-1}.

Major conditions are as follows:

- The difference among "$sv_t$and sv_{t-1}" can be greater than threshold values such as sv_{th}
- sv_t is lower than “predefined lower bound” such as sv_{lb}
- sv_t is higher than “predefined upper bound” such as sv_u

It can be illustrated that

- $| sv_t - sv_{t-1} | \geq sv_{th}$
- $sv_t \leq sv_{lb}$
- $sv_t \geq sv_{ub}$

Assuming memory capacity and performance of the sensor is low, "sv_t and sv_{t-1}" are considered. Through using this approach, energy consumption, memory usage and processing time can be reduced (Bae *et al.* 2018). Sensors can consider higher performance in complicated operations, however, the sensor can accumulate data within a fixed period to analyse accumulated value with the aim of detecting problematic sensors.

Therefore, sensor *id* can be added within PSL and for managing the problem, DaaG can calculate correlation among actuator and problematic sensor. Correlation as follows:

$$\boxed{Corr_{si,\, aj} = \lambda/(dist\ (si, aj)) + (1 - \lambda)\ (avt - avt - 1)/(svt - svt - 1)}$$

Dist (s_i, a_j) can be considered as the distance within "i-th sensor named s_i and j-th actuator named a_j and λ can be concierge as weight value whereas, *av* is noted as actuator's value. DaaG is used to find the highest amount of correlation within problematic sensors therefore, it can be explained that chosen actuators can be estimated as the best monitor for all actuators of problematic sensors.

3.5.3 Path planning

Assuming DaaG's ability for knowing actuation and positions of sensors, it can be elaborated that "$pos_i = (x_i, y_i)$ for $\forall_i \in V$", where "undirected graph" G = (*V, E*), *V* can be noted as nodes set and *E* can be noted as edge set.

Calculation of edge weight as follows:

$$W_{ij} = \sqrt{(\ 〚(xi - xj)〛\ \hat{}2 +\ 〚(yi - yj)〛\ \hat{}2)}$$

In case of "$\forall_{i,j} \in S$", "$S \in V$" can be noted as set of sensors.

Algorithm 2 shown in Annexure C can differentiate “path-planning algorithms”, however, this algorithm can result in calculating missing nodes of the sensor. DaaG marks flag value such as F_i in the sensed node and flag value has been set within nearby two visited nodes.

After the collection of each sensor data from DaaG within the sensor network, the algorithm as shown in Annexure D can be used for moving DaaG within the actuator network along with giving command messages for an appropriate actuator.

3.5.4 Case 1 for single connectivity of drone with BS

A drone can be elected as a Cluster Head (CH) for its connectivity with the Base Station (BS). In case one drone in this network has the connectivity along with BS, the drone can be eligible for forming CH (Jakubiec, Golański and Schoeneich, 2018). Therefore, the drone declares it as CH and sends a message regarding cluster formation where the rest drones can become cluster members. Major reasons for this selection can be done for the drone within direct connection with BS that can receive quick special command along with control packers in nearby drones. It is not necessary for making a connection with drones.

3.5.5 Case 2 for multiple connectivity’s of drones with BS

In order to avoid quick changes in CH and stable network, drones can be connected with BS then evaluated CH focused on luciferin value and redial energy (Aftab, Khan and Zhang, 2019). Therefore, CH can be sued for changing the level of energy and connectivity can be lost in aspects of BS. Having more fitness with all drones along with stronger connectivity with BS, CH can be selected.

3.5.6 Case 3 for no direct connectivity with BS

In case, no drone is located for maintaining direct connectivity with BS and therefore much can be focused on fitness through focusing on current position and energy level. The highest fitness holding drone can be selected as CH and the rest of the drone can be actuated as Cluster management or CM as shown in Annexure E.

3.6 Cost of drones

Senior economist Dr. Roelof Botha (Drone Con, 2017) presented an economic impact study which demonstrated that the South African drone industry could generate more than R2-billion per annum towards the country's gross domestic product and could create 30 830 employment opportunities every year. The drone industry, without obstacles, could steadily grow at 25% per annum for at least the next ten years, suggesting the transformative power of this technology for the country (Drone Con, 2017; Reitz, 2017).

The regulator, the South African Civil Aviation Authority (SACAA) and business operators have both acknowledged that drones are safer, more efficient and less costly than current equivalent methods deployed across sectors, such as engineering, mining,, agriculture, security, surveying, telecommunications and disaster response services (Reitz, 2017).

Drones however are mostly imported technology making them dollar-sensitive. The design and manufacture of local drones is an economic opportunity and scope for further research. For similar projects the average price of a drone is approximately R30 000.

The relatively low cost of high end sophisticated drones—an MQ9 Predator drone costs approximately $15 million, compared to $150 million or more for the F-35 aircraft—has made a number of governments around the world turn to them as a lower cost alternative to conventional aircraft for simple domestic tasks (such as monitoring borders, countering smuggling and environmental conservation) and a growing number of military tasks (Boyle, 2015; Frymann and Manulis, 2019).

3.7 Conclusion

This chapter introduced environmental monitoring, drone technology, why monitoring is essential, its general and current uses, and the potential of Intelligent drone systems. Drones applicability to environmental monitoring is motivated through careful literature support. Drone communication algorithms were also presented. This research considers the prospect of using technology for automated data collection. The next chapter highlights the research design and methodology of this study.

Chapter Three: Research Methodology

4.1 Introduction

This chapter introduces and discusses the experimental research organized by the aviation team and the environmental analysis to improve challenging conditions such as ozone layer depletion, the rise of CO_2 emission, and changing weather and climate change. This research used an Agile Design Science Research Methodology (ADSRM) to combine the multidisciplinary ICT (software and AI), Engineering (artefact construction and 3D printing) along with an environmental science approach. The data analysedwas quantitative. The ASRM process and rationale is presented.

4.2 The Agile Design Science Research Methodology (ADSRM) model

ICT is enabling multidisciplinary solutions to be proposed, tested and implemented.. These solutions were sometimes considered non-trivial or even impossible. There are now 3D printers printing edible food such as chocolates and meat steaks and autonomous vehicles flying to and surveying Mars (Yang, Zhang and Bhandari, 2017). For example, imagining and creating such products or services requires an agile authentication process methodology such as a Design Science Research (DSR) approach. DSR studies are effective with the *continual improvement* – providing new solution options to old problems; *exaptation* - the migrating of old problems through new solutions or *invention* - taking new solution options to new problems (Gregor and Hevner, 2013; Conboy, Gleasure and Cullina, 2015). This research comprises each of these solutions.

An agile perspective balances traditional procedural rigour with the concomitant need to consider empirically driven solution to swiftly home in on the most meaningful and even unanticipated problems. The ADSRM model, presented schematically in Figure 3.1, draws upon industry breakthroughs by adopting those 'agile' perspectives gained from ICT agile development lessons (Conboy, Gleasure and Cullina, 2015).

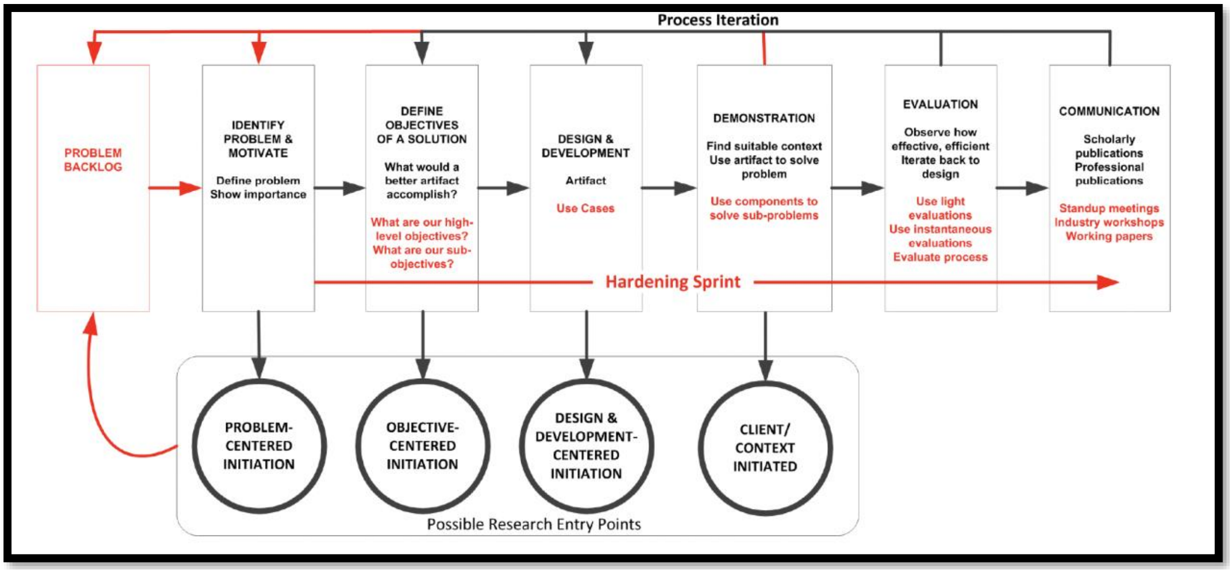

Figure 4.1: AGILE Design Science Research Model (ADSRM) (Conboy, Gleasure and Cullina, 2015)

3.2.1 The problem identification and motivation sub-process guides the development of design components. It ensures industrial relevance by linking the practitioner and academic knowledge base. This caters for scenarios where the customer is unaware of the software capabilities until an initial prototype was prepared which make concepts and other issues tangible (Conboy *et al*., 2015).

3.2.2 The problem backlog represents a new space where individual problems are identified and motivated. The feedback from other stages is also "wired" to the problem backlog, providing an ability for any stage to afford opportunities on the real-time problem space (Conboy *et al*., 2015; Conboy, 2009).

3.2.3 The objectives of a solution sub-process defines the solution characteristics that addresses the defined design problem which may as have detailed or causal. Agility breaks solution requirements into smaller 'digestible' user narratives producing decomposed identified sub-objectives that are somewhat 'stable', allowing creative space for objectives to emerge to the more uncertain, turbulent objectives (Conboy *et al*., 2015; Conboy, 2009).

3.2.4 The design and development sub-process creates the ICT artefact. The ICT artefact may undertake different forms such as instantiations, models, technological rules, and principles of implementation (Gregor, Jones, 2007). Agile methods and ADSRM add useful perspectives such as nonfunctional requirement's reliability, testability security and usability (Glinz, 2007; Conboy *et al*., 2015) which builds a quality-focused dimension into the project. Focussed user participation through all the design iterations expedites this goal accomplishment.

3.2.5 The demonstration sub-process identifies an applicable instance of the problem to solve by using inter alia, a simulation, proposed design, experimentation, case study or proof. This sub-process translates abstract elements of the problem into specific operational solution contexts (Goldkuhl, 2004; Conboy *et al*., 2015; Conboy, 2009). Agile principles demonstrate a design through an actual implementation. This strategy addresses any perceived gaps of validity and reality.

Thus, ADSRM prescribes that early and frequent implementation should be considered for all design concepts not just finished artefacts.

3.2.6 The evaluation sub-process resolves whether the proposed solution addresses the defined problem. Evaluation approximates the theory-testing component of traditional descriptive or explanatory research, although the emphasis is on the utility of the design, rather than its accuracy (March and Smith, 1995). Evaluation can take place in a contrived *artificial setting*, where variables are controlled or risks lowered, or a *real-world environment*, where socio-technical aspects and stakeholders' responses may be observed (Venable, Pries-Heje and Baskerville, 2012; (Conboy *et al*., 2015). Some agile methods use automated testing to gauge component-level changes (Hummel, Rosenkranz and Holten, 2013) while others advocate evaluation of the artefact and its agility (Conboy, 2009).

3.2.7 The communication sub-process is the final stage of a DSR project. Here findings are shared with relevant audiences including professional, and scholarly which is vital to properly integrate into the knowledge ecosystem. The ecosystem in turn harnesses valuable feedback from audiences during this communication. Agile communication emphasizes the diversity of communication methods and interactions (Hummel, Rosenkranz and Holten, 2013). This research publication is part of the communication.

3.2.8 The flight path may cross urban areas which require permission or added security to be considered.

4.3 The research process

This section uses the ADSRM methodology explained in section 3.2. For ease of reference the sub-headings conform with Figure 3.1

4.3.1 The problem identification and motivation

For this research the problem identification was to identify, design and modify a drone. It had to be equiped with a microcontroller and sensors which introduced the need for a power source. Each of these are independently non-trivial tasks.

4.3.2 The problem backlog

Here challenges encountered are documented and addressed utilizing agile and DSR methodologies. In order to minimize future research and development initiatives, other researchers will be informed of potential problems and how they have been solved throughout this phase.

4.3.3 Objectives of a solution

Given that the drone flew in a highly populated urban campus harvesting real-time atmospheric data through the sensors, there was a requirement for human, environment, building and equipment safety. In order to conduct the experiment, it was necessary to use appropriate controlling technologies, such as a microcontroller supplied by an external power source that was attached to the experiment, as well as required sensors and a storage module with an SD card.

4.3.4 The design and development

The ADSRM model was followed for the design and development of the experiment.

4.3.4.1 Selection of components

This section highlights and identify the components used for the experiment using the ADSRM model.

The following steps are described.

a) Identify the drone: this is a non-trivial decision given the range, scope and cost of drones. Appropriate selection criteria will be researched and implemented. A safe drone flight path was created to ensure safety and security for the drone, humans and surroundings.
b) Identify the sensors: the correct sensors were chosen to ensure a wide range and extent of different types of data that could be harvested.
c) Identify the Microcontroller: an economically viable device was identified with both digital input and output.
d) Identify Data Storage and a Real Time Clock: data harvested had to be dated and timed, and was stored in order to be downloaded to a computer when the drone landed, for analysis.
e) Identify the Power Source: a reliable external power source was needed to power the microcontroller and sensors.
f) Embedding the sensor subsystem and the container onto the drone: a 3D part was designed and printed to hold the carriage unit in flight and mount seamlessly onto the drone without interfering with any of the functionalities of the drone.
g) Identify the Carriage Unit: a safe secure method had to be found to attach the microcontroller, sensors, SD card module and battery pack.

4.3.5 Demonstration

If 3.3.4 was successful, the next requirement was to fly the drone. This required the planning of the flight path, the creation of way points and the actual flying of the drone with the experiment. For safety reasons, the drone had to be flown and programmed on its own. Once successful, the experiment attached must be flown on this path.

4.3.6 Evaluation

The drone experiment was flown at least thirty times over a compressed four-day period. The data was transferred after each flight and subjected to a clustering algorithm for proof-of-concept. It calculated the humidity, pressure, and gases such as carbon dioxide, nitrogen dioxide, oxygen, and sulphur dioxide.

4.3.7 Communication

The researcher used the attention that the two disasters listed in 2.2.2.1 and 2.2.2.2. This attention was within local and national media an opinion editorial (Op-Ed) was published (Asmal and Thakur, 2021; Asmal, Thakur and Adeliyi, 2021; Asmal, Adeliyi and Thakur, 2021). An abstract was submitted to an accredited conference.

4.4 Conceptual framework

This study adopted a spiral model approach as the conceptual framework for the drone processes as shown in Figure 3.2, due to the iterative nature of the model. This allowed the researcher to combine the clustering algorithm with that of the drone and AI. However, such an approach required conducting experiments in order to identify and apply the best clustering algorithm.

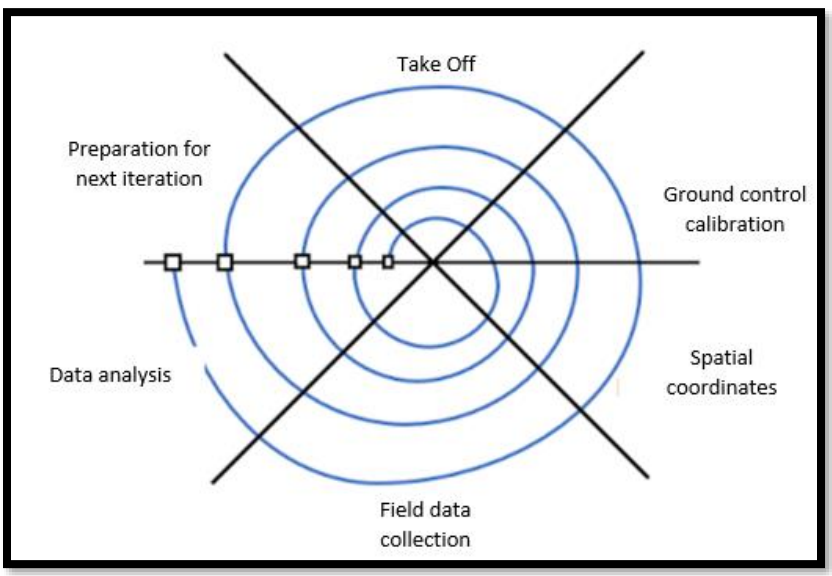

Figure 4.2: Conceptual Framework for Drone Environmental Monitoring

4.4.1 Take-off

This is the time (T_0) the drone takes off from the base station. The take-off could be manual where a drone pilot will have to navigate the drone through the locations for data collection or automatic where the drone will use global position system (GPS) to automatically navigate through the locations with little to no human interference.

4.4.2 Ground control calibration

This is the step where there is a synchronization of the drone to the base station and to perform a classical aerial triangulation of any image block. Hence, at this stage the flight height was selected for precautionary reasons.

4.4.3 Spatial coordinate

The spatial coordinate phase will follow in order to locate the geographical entities for environmental monitoring. For the purpose of this study, the spatial coordinates was between the take-off site at Durban University of Technology Ritson Campus (-29.851081,31.007511) to Steve Biko Campus (-29.853195,31.007283) and ML Sultan Campus (-29.850092,31.008647), situated in Durban, South African.

4.4.4 Field data collection

The method of collection of data while conducting research can be significantly crucial as first-hand experiences and valid facts can be acquired for the successful completion of a research study. In this study, it has been demonstrated that the data collecting process was regarded to take several days, which was substantially advantageous in the determination of more reliable data in the end. For a better understanding of data analysis, the time deemed to have been invested in field data collecting may be represented by an equation, and the equation can be shown as follows.

$$
\begin{aligned}
D_0 &= T_1, T_2, T_3, T_4 \ldots\ldots T_n \\
. & \quad\quad\quad . \\
. & \quad\quad\quad . \\
. & \quad\quad\quad . \\
D_n &= T_1, T_2, T_3, T_4 \ldots\ldots T_n
\end{aligned}
\tag{3.1}
$$

From the above-stated equation, it can be highlighted; here "D_0" denotes a single day and T has been represented for the period which has been associated with to be Tn denoting a significant period leading to infinity. Therefore, it can be highlighted that Tn denotes the time limit for an intelligent drone system to be conducted during a day. As opined by Levitt et al (2018) gathering credible data can be acquired when an experiment has been conducted for analysing the effectiveness of specified attributes.

4.4.5 Data analysis

The data collected was imported and analysed in MATLAB R2020b where a clustering algorithm was used to understand the pattern of different weather monitoring data collected. Cluster analysis is a technique for determining the underlying structure of a dataset by dividing it into groups and assigning related components to the same group while dissimilar components are allotted to other ones (Vo-Van, Nguyen-Hai and Tat-Hong, 2020).

4.4.5.1 K-Means

The major objective of the "K-means" in clustering algorithms is important as the specified algorithm is useful in evaluating the signals processed from different central sensors. According to Levitt *et al*. (2018), clustering algorithms have been beneficial in bridging the gap of different signals from that of the centre points. In this study also, K-means algorithms were considered to be crucial in the processing of different signals from centroid points and thus, intelligent drone construction can be effectively done.

4.4.5.2 Performance evaluation metrics

There are quite a lot of general internal measures that can be applied in the evaluation of the validity of a set of clustering algorithms Silhouette combines two clustering criteria, compactness and separation, which imply that spherical cluster shapes are preferred over others—a property that can be seen as a disadvantage in the presence of complex, non-spherical clusters, which is common in real situations. This study suggested a generalization of the silhouette width using the generalized mean. The Davies-Bouldin (DB) index evaluates the dispersion of data based on the distances between cluster centroid. Furthermore, Dunn index was incorporated which is significant in providing information about the ratio of distances between clusters (Zhang *et al.* 2017).

4.5 The selection of the components for experiment

This section describes and discusses the factors that were considered in choosing the appropriate drone, sensors, housing unit, SD card module, real time clock and 3D printed part in line with the ADSRM model.

4.5.1 Identify the drone

The column labelled **Description** in Table 3.1 itemizes the factors that were considered in choosing a drone for the experiment to be successful. The column labelled **Requirements** were the main ADSRM requirements that were researched and identified. The column labelled **Reason** identifies why the requirement was needed.

Table 4.1: Identify the drone

Description	Requirements	Reason
Intelligent and programmable	Programmable	Autonomous
Minimum flying height	60 meters	Avoid obstacles such as tress, buildings, construction cranes
Minimum flying distance	1 km radius	Area coverage for data collection
Loss of radio frequency signal	Return to take-off point on signal loss	Drone retrieval and safety feature
Collision Avoidance feature	Accident avoidance	Preserve drone by avoiding obstacles
Autonomous flight	Flight path with waypoints	Autonomous drone operation
Operational payload capacity	Maximum 900 grams	Able to fly with experiment attached
Operational Battery life	Minimum 25 minutes	Enough time to collect data and return to take-off point
Camera	Recording through pictures and video	To record and plan an optimal convenient flight path
Launch and home point detection	Drone must have autonomous capabilities	This will assist with safe and secure drone retrievable
Hovering	Minimum 5 minutes	Collect data from a geostationary spatial point

GPS	Identify and track flight path	Tracking necessary for recording exact point of data collection
Rotors	4 rotors	For flight, balance and geostationary data collection

This evidence would be derived from a trusted source like the manufacturers OEM manual and specifications. Tests will also be conducted to verify the requirements.

4.5.2 Identify the sensors

The research goal was to demonstrate the range and extent of different type of data that could be harvested by a single drone with appropriate sensor payloads.

The column labelled **Description** in Table 3.2 itemizes the sensors that were considered for data collection. The column labelled **Symbol** is for scientific rigour. The **unit of measure** column reminds researchers of the nature of the quantum of data for each line item.

Table 4.2: Identify the Sensors

Description	Symbol	Unit of measure
Oxygen	O_2	percentage of oxygen
Temperature	T	Degree Celsius
Humidity	H	Kg^{-1}
Pressure	P	Pa
Carbon Dioxide	CO_2	ppm
Ammonia	NH_3	µg/dL
Nitrogen Oxide	NO_2	grams

4.5.3 Identify the microcontroller

The column labelled **Description** in Table 3.3 itemizes the factors that need to be considered in choosing a microcontroller for the experiment to be successful. The column labelled **Requirements** were the main ADSRM requirements that were researched and identified.

The requirements for the microcontroller needed to be affordable, lightweight, small in size, must be able to interface with the sensors seamlessly, be programmable, expandable and must be able to input and output both digital and analog signals. In line with the research methodology the information in Table 3.3 was derived from OEM specifications and websites.

Table 4.3: Identify the Microcontroller

Description	Requirements
Size	Small as possible
Weight	Light as possible
Interface	Able to attach a minimum of 7 sensors, SD card module and external power source
Programmable	Able to programmed in C language
Signals	Input and output digital and analog signals

4.5.4 Identify data storage and a real time clock

In order to analyse the data a means of storing the data was necessary. The requirements for the unit were to interface to a microcontroller, hold a micro SD Card with at least 16 GB storage capacity and a Real Time Clock(RTC) in order to record date and time of the data captured.

The column labelled **Description** in Table 3.4 itemizes the factors that needed to be considered. The column labelled **Requirements** were the main ADSRM requirements that were researched and identified.

Table 4.4: Identify the data storage and real time clock

Description	Requirements
Storage	16gigs SD card
Date and time logging	Real time clock
Interface	Must be able to connect to the microcontroller

4.5.5 Identify the power source

A separate power source was needed to power the sensors and microcontroller. It required a minimum of 9 Volts, a battery holder, a connector to the microcontroller and an on/off switch.

The column labelled **Description** in Table 3.5 itemizes the factors that needed to be considered. The column labelled **Requirements** were the main ADSRM requirements that were researched and identified.

Table 4.5: Identify the power source

Description	Requirements
Voltage	9 volts required to power the sensors and microcontroller
Battery holder	To hold 6 x 1.5v AA batteries
Switch	To power on and off

4.5.6 Embedding the sensor subsystem and the container onto the drone

A design requirement of the sensor, microcontroller and drone subsystems is that they operate and perform their functionalities without interfering with each other in any form whatsoever. This affirmed the ADRSM research method as the appropriate choice as this problem fitted into the realms of problem backlog which is explained in Section 3.2.2 and shown in Figure 3.1.

The device had to be able to fit onto the drone and be both robust and lightweight, which were the specifications for the unit. However, a suitable container could not be found by the researcher. This led to the idea of creating a 3D printed part. Once again the ADRSM method of problem backlog assisted because of a new set of requirements for the 3D printed component. These requirements after much research, were the 3D printed part. The 3D printed part was required to attach to the experiment and be of high quality print using PLA; and the software to design the part required. This 3D component was an important contribution to the body of knowledge.

The column labelled **Description** in Table 3.6 describes the description criteria, along with its **Requirements.** This was also a mission critical component as any failure would have terminated this research at this point.

Table 4.6: Embedding the sensor subsystem and the container onto the drone

Description	Requirements
Size	Fit onto drone without any interference to the functionalities
Design	CAD software – Dassault Systems
Printer	Flashforge IIs
Printer Material	PLA

4.5.7 Identify the carriage unit

The carriage unit is a container which will house the experiment that the drone would carry. It must therefore be light in weight, large enough to contain the experiment and able to fit onto the drone seamlessly.

The column labelled **Description** in Table 3.7 describes the description criteria, along with its **Requirements.** This is an example of a problem backlog in the ADRSM model.

Table 4.7: Identify the Carriage Unit

Description	Requirements
Weight	Less than 900 grams
Size	large enough to contain the experiment
Fit	Able to mount onto 3D printed part

4.6 Relevance of research methodology to reaseach objectives

3.6.1 To comprehensively review relevant publications based on the use of UAVs in general and in monitoring environmental conditions in particular order to compare well known systems to our proposed system

3.6.2 To design and implement the proposed frugal intelligent drone system that helps monitor environmental conditions

3.6.3 To analyse and evaluate environmental condition data using clustering algorithms

4.7 Conclusion

This chapter discussed and motivated the Agile Design Science Research Method (ADSRM) choice which is a combination of the ICT Agile method along with Design Science Research (DSR) method. Various aspects of this quantitative study pertaining to data collection, validity and reliability were detailed in this chapter.

Chapter Four: Results and Discussion

5.1 Introduction

This chapter summarizes the outcomes of the data collection procedure, provides the findings, and examines the experiment's conclusions. The information gathered was analyzed in light of the objectives mentioned in chapter one. There were a range of safety, security, environmental, operational and legislative factors to identified through research, appropriate choices through research, benchmarking and evaluation. The experiment comprised the drone, the three sensors and SD card connected to a microcontroller which was housed in a secure container attached to a 3D printed part together were mounted onto drone.

5.2 Review of research objectives

This section describes the process to satisfy the research objectives. The research objectives were:

- To comprehensively review relevant publications based on the use of UAVs in general and in monitoring environmental conditions in particular order to compare well known systems to our proposed system
- To design and implement a frugal intelligent drone system that helps monitor environmental conditions
- To analyse and evaluate environmental condition data using clustering algorithms

5.2.1 Research objective 1

To comprehensively review relevant publications based on the use of UAVs in

general and in monitoring environmental conditions in particular order to compare

well known systems to our proposed system

The literature review undertaken in Chapter 2, comprehensively reviewed drone technology and its evolutionally-use in a diverse set of circumstances. It also described how drones were used in a variety of interesting and useful leverage of exponential technologies such as AI to create new solutions and methodologies to arrive at our goal. Its use cases, opportunities, and challenges. It then described drones and environmental cases by discussing two crucial Durban disasters where drones could have risen to the challenges. It further reviewed the value of AI when used along with drone technology. Environmental monitoring appears to be a fit-for-purpose branch of science that can benefit from the use of drones. The literature infers that more industries should neutrally examine drones for the value and even the potential risk that drones introduce to them. For example, drones flying in urban areas introduce a physical threat to buildings and humans.

Lovett, Burns and Driscoll (2007) informed that environmental monitoring is often criticised as being unscientific, expensive, and wasteful, a complaint that drones easily overcome. This is where the researcher contends that drone-based monitoring may have value.

5.2.2 Research objective 2

To design and implement the proposed frugal intelligent drone system that helps monitor environmental conditions

The combination of technologies to solve new problems is an opportunity that must be harnessed. However, this union-combination often introduces new, sometimes unanticipated challenges which must be addressed and mediated.

This proved to be the case with environmental monitoring through sensors with drones. This research objective is discussed in Section 4.3 to Section 4.9.

5.2.3 Research objective 3

To analyse and evaluate environmental condition data using clustering algorithms

One deploys drones to acquire data, which must be analysed with some consequence in mind. A reason environmentalists used drones less frequently was because of a lack of drone skills, lack of awareness or perception that the cost may be prohibitive.

The research objectives are further addressed in Section 4.10.

5.3 The selection of the components for the experiment

This section describes and discusses how the appropriate drone, sensors, housing unit, SD card module, real time clock and 3D printed part were selected using ADSRM.

5.3.1 Identify the drone

The column labelled **Description** in Table 4.1 itemizes the factors that need to be considered in choosing a drone for the experiment to be successful. The column labelled **Requirements** were the main ADSRM requirements that were researched and identified. The researcher identified three possible drones, Column labelled DJI Mavic Pro, PowerEgg and Voyager Typhoon. The tick and cross represents compliance with the Description and Requirements.

It may appear that Voyager Typhoon fails on most requirements. Note, this is not an indictment on this drone but merely a binary assertion of whether it fulfills this research project requirement. PowerEgg was eliminated due to the non-negotiable payload requirement. This led to Dji Mavic 2 Pro being chosen.

In line with the research methodology, the information in Chapter 3, Table 3.1 was derived from OEM specifications and websites. Each of the drones were evaluated by the researcher.

Discussion

The technological role played by the UAVs was evaluated using live experiment-based collecting environmental data which reduced the overutilization of expensive human resources (Khan, Gupta and Gupta, 2020).

AI-based quadcopter drone systems are capable of taking off in a vertical direction and can fly smoothly in any direction (Zhang *et al.*, 2017; Li, Sun and Cai, 2019; Fadhil, Moeckel & Rothfeld, 2019). This literature justifies the choice of quadcopter.

Table 5.1: Identify the Drone

Description	Requirements	Dji Mavic 2 Pro	PowerEgg	Voyager Typhoon
Intelligent and programmable	Programmable	✓	✓	×
Minimum flying height	60 meters	✓	✓	×
Minimum flying distance	1 km radius	✓	✓	×
Loss of radio frequency signal	Return to take-off point on signal loss	✓	✓	×
Collision Avoidance feature	Accident avoidance	✓	✓	×
Autonomous flight	Flight path with waypoints	✓	✓	×
Operational payload capacity	Maximum 900 grams	✓	×	×
Operational Battery life	Minimum 25 minutes	✓	✓	×
Camera	Recording through pictures and video	✓	✓	✓
Launch and home point detection	Drone must have autonomous capabilities	✓	✓	×
Hovering	Minimum 5 minutes	✓	✓	✓
GPS	Identify and track flight path	✓	✓	×
Rotors	4 rotors	✓	✓	✓

5.3.2 Identify the sensors

The aim of the study was was to demonstrate range and extent of data that could be collected by a single drone with appropriate sensor payloads. The sensors were chosen with the following design requirements. The sensors had to be small in size, programmable, able to interface with a microcontroller, lightweight, able to be calibrated either manually or through software.

The column labelled **Description** in Table 4.2 itemizes the sensors to be considered in for data collection. The column labelled **Symbol** is for scientific rigour. The **Unit of measure** column reminds researchers of the nature of the quantum of data for each line item. Finally, the column marked **Sensor** informs of the sensor model number part number. These were chosen on availability and costs; given that this is a frugal model. Other models are available.

Table 5.2: Identify the Sensors

Description	Symbol	Unit of measure	Sensor
Oxygen	O_2	percentage of oxygen	MQ135
Temperature	T	Degree Celsius	DHT11
Humidity	H	Kg^{-1}	DHT11
Pressure	P	Pa	BMP180
Carbon Dioxide	CO_2	Ppm	MQ135
Ammonia	NH_3	µg/dL	MQ135
Nitrogen Oxide	NO_2	Grams	MQ135

5.3.3 Identify the microcontroller

The column labelled **Description** in Table 4.3 itemizes the factors that need to be considered in choosing a microcontroller for the experiment to be successful. The column labelled **Requirements** were the main ADSRM requirements that were researched and identified. The researcher identified two possible microcontrollers, Column labelled **Arduino Uno** and **Raspberry Pi.** The tick and cross represents compliance with the Description and Requirements.

The requirements for the microcontroller needed to be affordable, lightweight, small in size, must be able to interface with the sensors seamlessly, be programmable, expandable and must be able to input and output both digital and analog signals.

The Raspberry Pi does not have analog inputs and is much more expensive than an Arduino Uno. Arduino Uno was chosen as a microcontroller for the experiment as it met all the criteria and it is economically feasible.

In line with the research methodology the information in Table 3.3 was derived from OEM specifications and websites. Each of the microcontrollers were evaluated by the researcher.

Table 5.3: Identify the Microcontroller

Description	Requirements	Arduino Uno	Raspberry Pi
Size	Small as possible	✓	✓
Weight	Light as possible	✓	✓
Interface	Able to attach a minimum of 7 sensors, SD card module and external power source	✓	✓
Programmable	Able to be programmed in C language	✓	✓
Signals	Input and output digital and analog signals	✓	✗
Expandability	Able to add more sensors	✓	✓
Cost	Affordable	R 420	**R1550**

Discussion

Given that this was a frugal design. the economic cost choice of Arduino Uno was made. A further reason was the need for both analog and digital signal processing capabilities. the literature supports this approach (McGriffy, 2016).

5.3.4 Identify data storage and a real time clock

The requirements for the unit was to interface to a microcontroller, hold a micro SD Card with at least 16 GB storage capacity and a Real Time Clock(RTC) in order to record date and time of the data captured.

The column labelled **Description** in Table 4.4 itemizes the factors that need to be considered. The column labelled **Requirements** were the main ADSRM requirements that were researched and identified. The tick and cross represents compliance with the Description and Requirements.

Table 5.4: Identify data storage and a real time clock

Description	Requirements	Achieved
Storage	16 GB SD card	✓
Date and time logging	Real time clock	✓
Interface	Must be able to connect to the microcontroller	✓

Discussion

A Scandisk 16 GB SD card was chosen. This is a reputable popular brand.

5.3.5 Identify the power source

A separate power source was required to power the sensors and microcontroller. It needed a minimum of 9 Volts, a battery holder to cater for the 6 by 1.5 Volt AA batteries, a connector to the microcontroller and an on/off switch.

The column labelled **Description** in Table 4.5 itemizes the factors that need to be considered. The column labelled **Requirements** were the main ADSRM requirements that were researched and identified. The tick and cross represents compliance with the Description and Requirements.

Table 5.5: Identify the power source

Description	Requirements	Achieved
Voltage	9 volts required to power the sensors and microcontroller	✓
Battery holder	To hold 6 x 1.5v AA batteries	✓
Switch	To power on and off	✓

5.3.6 Embedding the sensor subsystem and the container onto the drone

A design requirement of the sensor, microcontroller and drone subsystems is that they operate and perform their functionalities without interfering with each other in any form whatsoever. This affirmed the ADRSM research method choice as this problem fitted into the realms of problem backlog which is explained in Section 3.2.2 and shown in Figure 3.1. This challenge turned out to be non-trivial and the requirements and solution are described.

The requirements were for the unit required to fit onto the drone which had to strong but lightweight. A suitable container could not be found by the researcher. This led to the idea of creating a 3D printed part. Once again the ADRSM method of problem backlog assisted because a new set of requirements for the 3D printed component. These requirements after much research were the 3D printed part must not interfere with any of the functionalities of the drone, 3D printed part must be able to attach to the experiment, high quality 3D printer required to print PLA and software to design the part required. This 3D component is an important contribution to the body of knowledge.

The column labelled **Description** in Table 4.6 describes the description criteria, along with its **Requirements** and whether it was achieved. This was also a mission critical component as any failure would have terminated this research at this point.

The printing of the part was a success and the **Technology Deployed** is named.

Table 5.6: Identify the 3D printed part

Description	Requirements	Technology Deployed
Size	Fit onto drone without any interference to the functionalities	✓
Design	CAD software	Dassault Systems
Printer	3D Printer	Flashforge IIs
Printer Material	Durable plastic	PLA

Discussion

This experience demonstrates 3D printing has evolved beyond toy and vanity products. Replication study researchers should consider 3D technology when confronted by similar challenges.

5.3.7 Identify the carriage unit

The carriage unit is a container which housed the experiment that the drone carried. It was therefore light in weight, large enough to contain the experiment and able to fit onto the drone seamlessly.

The column labelled **Description** in Table 4.7 describes the description criteria, along with its **Requirements** and whether it was achieved. This is an example of a problem backlog in the ADRSM model.

Table 5.7: Identify the carriage unit

Description	Requirements	Achieved
Weight	Less than 900 grams	426 grams
Size	large enough to contain the experiment	✓
Fit	Able to mount onto 3D printed part	✓

Discussion

This was a mission critical component and failure would have terminated the research at this point.

5.4 Systems specifications

The system was designed to collect data from the atmosphere, store the data on a SD card and be downloaded to a computer to be analyzed once the drone has landed. The project was subsequently divided into two system components, namely a hardware development component of a drone and a method to interface with the sensors and a software development component which collects and stores the data.

5.4.1 Hardware Developmental component

That following steps were followed to ensure the smooth autonomous flight of the drone with the experiment unit attached.

5.4.1.1 Drone parameters establishment

The drone project design consideration required the sourcing of a quad-rotor UAV capable of carrying a load comprising consisting a battery pack, sensors, SD card and the microcontroller which has an approximate mass load of 700g. This number was chosen as it is which is far greater than the required mass of approximately 426g.

After several attempts a DJI Mavic 2 Pro drone was finally chosen to attach the experiment to. The drone has the capability of carrying a mass load of 907g, which is far exceeds the required design requirement. It also had a flight distance of 31km with a maximum altitude of 500m (Mavic 2, 2021) Figure 4.1 Shows the DJI Mavic 2 Pro Drone used in the experiment.

Figure 5.1: DJI Mavic 2 Pro Drone (Source: Researcher)

5.4.1.2 Drone familiarization

The drone was test flown to familiarize the controller with the device. A drone practitioner and airline pilot, though not required, was enlisted in the training of the researcher to safely operate the drone**.** The Drone Council was approached to provide advice on the purchase, assembly, and deployment of the drones. The advice proved useful as the drone flew without any operational issues. The ADRSM model recommends communication with experts throughout the development cycle to support other similar research.

Further, the pandemic-related semi-lockdown of the university (where the drone was flown) mitigated safety because of the much reduced on campus population. The experiment, which weighed 426g, was attached to the drone and flown. The drone was able to fly comfortably, without any perceived issues, with the additional load.

5.4.1.3 Create a flight path map

The researcher was comforted that the drone with the payload will fly which then necessitated a need for a flight path. The experiment was temporarily removed purely as precautionary measure and the drone was then flown manually to create an optimal flight path to record data. The drone was programmed to fly at an altitude of 55m to avoid collision with obstacles, particularly given that there were two consruction cranes on Steve Biko Campus. Four-waypoints were set creating an automated path for the drone to follow. A waypoint is a point of reference that can be used for location and navigation (Perazzo, Sorbelli, Conti *et al*, 2016). This is now discussed.

A flight path using waypoints was programmed into the drone to enhance autonomous flying capabilities. Table 4.8 shows the flight path created.

Table 5.8: Flight Path

Description	Location
Take off point	Car Park Ritson Campus
Waypoint 1	Fred Crookes Sports Centre, Steve Biko Campus
Waypoint 2	Winterton Walk, Sastri College
Waypoint 3	M L Sultan Library, M L Sultan Campus
Waypoint 4	Curries Fountain
Landing point	Car Park Ritson Campus

Figure 4.2 shows the flight path created to autonomously fly the drone while Figure 4.3 shows the flight path with waypoints.

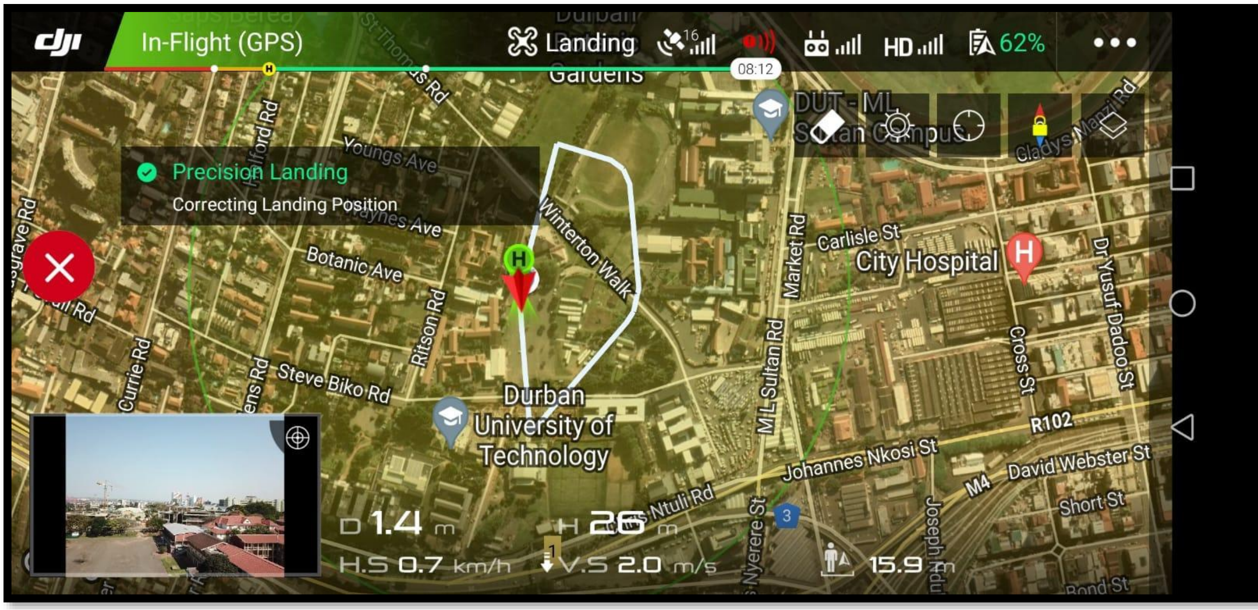

Figure 5.2: Drone Flight Path (Source Researcher)

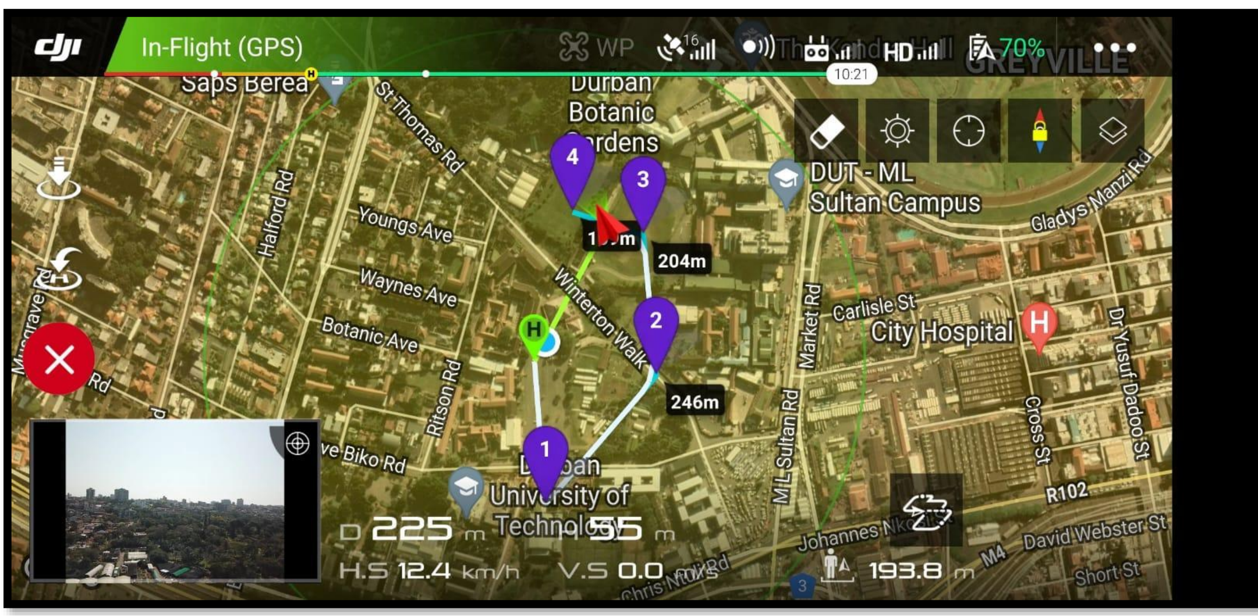

Figure 5.3: Flight path with way points (Source Researcher)

Discussion

In typical drone operations the launch point and home is the same i.e. The drone will take off and land in the same geo location. It may well be that a drone can take off at point A and land at a different Point B with a payload such as blood.

5.4.1.4 Analysis of the flight in terms of ADSRM

The drone flew in a highly populated urban campus atmosphere. The sensors harvested real-time data. 3-D printing technology had to be leveraged to design, engineer and manufacture a fit-for-purpose container to safely and securely house sensors. It further used AI Clustering techniques to show what could be done with the data. The method and rationale used to construct these using ADSRM is described in the following section.

5.4.1.5 Attaching sensors to drone

The experimental sensors were attached to the drone and the drone was autonomously flown following the pre-determined flight path in order to collect the data, which is described in Section 4.2. Figure 4.4. Shows the experimental sensors attached to the drone.

Figure 5.4: Experiment attached to the drone (Source Researcher)

5.4.1.6 The microcontroller and battery were sealed

The microcontroller and battery pack were placed in a plastic housing unit and sealed with four screws. The unit had a form factor of 50 mm x 140mm x 90mm. The sensors were attached to the top of the unit and the SD card holder unit on the side of the unit. The plastic housing unit was purchased at a hardware store. Figure 4.5. Shows the plastic unit the items were housed in.

Figure 5.5: Experiment Holding Unit (Source Researcher)

5.4.1.7 A 3D drone component was designed and printed to hold the experimental unit

A design challenge was encountered as the experiment holding unit could not be mounted directly onto the drone, given the design consideration was a flying drone with a payload. Therefore, a 3D part was designed and printed to hold the experiment unit and be able to mount the device onto the drone. This is a new contribution to drone architecture and shows that 4IR technologies may be combined to create innovation. Figure 4.6. shows the 3D printed part.

Figure 5.6: Shows the 3D printed part (Source Researcher)

The 3D component was designed using Dassault 3D Experience Computer Aided Design (CAD) software. The component was then printed on a Flashforge IIs 3D printer and took 5.5 hours to complete. This 3D printer requirement suggests that deploying a drone is not as simplistic as one assumes.

The holding unit was mounted onto the 3D printed part and secured. The entire unit was then mounted onto the top of drone and secured to the drone with Velcro straps as the unit had to be removed and replaced each time the battery had to be changed. By mounting the unit to the top of the drone, the balance of the drone was maintained and none of the drone sensors were blocked or compromised in anyway. Figure 4.7. shows the unit mounted onto the drone.

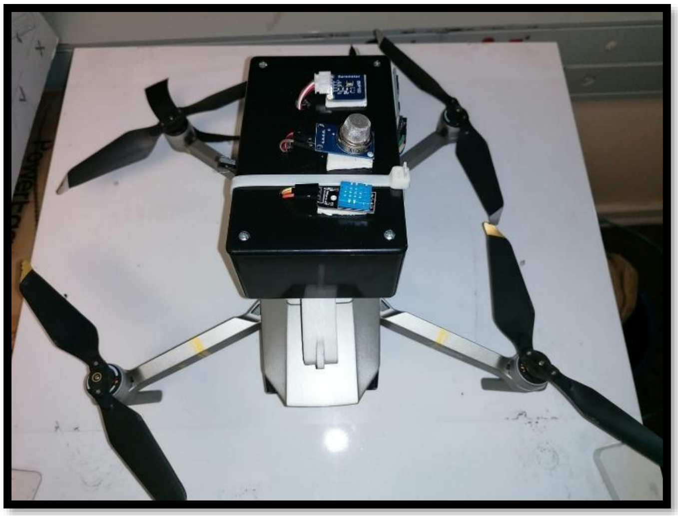

Figure 5.7: Unit mounted onto the drone System Architecture (Experiment) (Source Researcher)

5.4.1.8 Relevance to ADSRM

Development of the systems architecture consists of three sensing units, a date and time module, a battery pack containing six 1.5V batteries and a SD card unit to store the data, attached to an Arduino Uno microcontroller and housed in a case. Figure 4.8 shows the three connected devices.

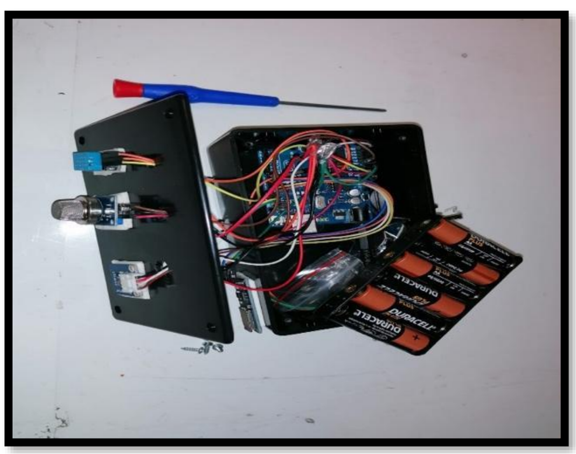

Figure 5.8: Experiment Unit (Source Researcher)

5.5 The Arduino Uno microcontroller had to be identified

Arduino Uno is a microcontroller which can be programmed with a number of programming languages. It uses a very low amount of electrical current depending on the components attached to it. Any shield module or sensors may be connected to the Arduino Uno thereby reducing weight and space required. These features made the Arduino Uno ideal for this experiment (Hughes, 2016). Figure 4.9. shows the Arduino Uno microcontroller.

Figure 5.9: Arduino Uno Microcontroller (Source Researcher)

5.6 The Sensors

A sensor is a device that detects and responds to some type of input from the physical environment. The input could be light, heat, motion, moisture, pressure or any one of the great number of other environmental phenomena. The output is generally a signal that is converted to human readable display at the sensor location or transmitted electronically for further processing (Perales, Valero and García, 2018; Teja, 2021).

This section introduces the sensors that were deployed. The choice of the sensors was mindful of the two recent environmental disasters.

5.6.1 BMP180

BMP180 is a high-pressure digital sensor. It’s an ultra-low power device which is ideal for outdoor use. It can measure the atmospheric pressure in the range of 300 hPa to 1100 hPa (Teja, 2021). Figure 4.10 shows a BMP180 sensor.

Figure 5.10: BMP 180 sensor (Source Researcher)

5.6.2 MQ135

MQ135 is an air quality sensor was used for measuring Oxygen (O_2), Ammonia (NH_3), Nitrogen Dioxide (NO_2) and Carbon Dioxide (CO_2) (Teja, 2021). Figure 4.11 shows a MQ135 sensor.

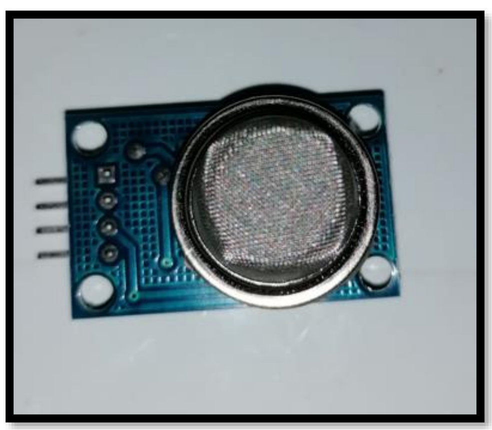

Figure 5.11: MQ135 sensor (Source Researcher)

5.6.3 DHT11

DHT11 is a humidity and temperature sensor that was used for this experiment. The DHT110 sensor is highly reliable and stable component. It is sensor with a digital signal output for capturing temperature and humidity readings. Figure 4.12 shows a DHT11 sensor (Teja, 2021).

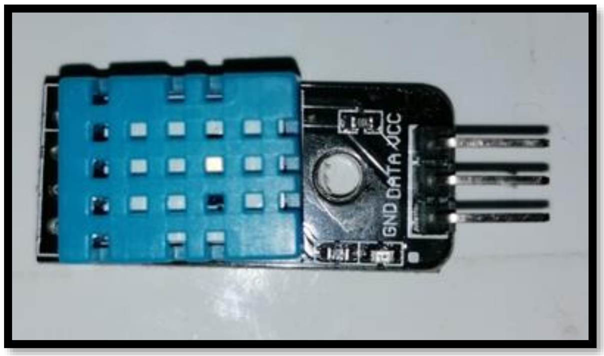

Figure 5.12: DHT11 sensor (Source Researcher)

5.7 Additional equipment

A battery pack, SD Card Module and a Real Time clock was attached to the microcontroller.

5.7.1 Battery pack

A battery pack consisting of six 1.5v batteries was used to power the microcontroller and sensors. Figure 4.13 shows the battery pack used.

Figure 5.13: Battery Pack (Source: Researcher)

5.7.2 SD card module

A SD Card module with a 16gig SD card was attached to the microcontroller to store the data collected. Figure 4.14 shows a SD Card module.

Figure 5.14: SD Card Module (Source: Researcher)

5.7.3 Real Time Clock

A real time clock (RTC) module DS2321was attached to the microcontroller to capture date and time for data logging. Figure 4.15 shows the DS2321 real time clock module.

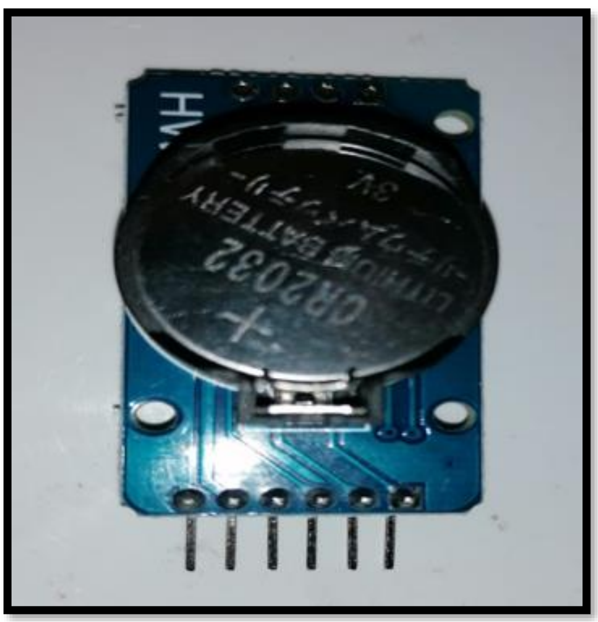

Figure 5.15: Real Time Clock Module (Source: Researcher)

5.8 Experiment set-up

Figure 4.16 shows the setup of the DHT11, MQ135, BMP180, SD card module, real time clock module and power unit attached to the Arduino Uno microcontroller. Each component is already being recognized by the microcontroller.

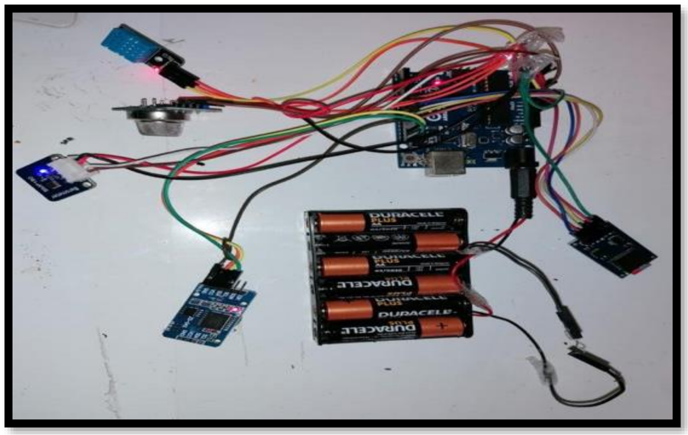

Figure 5.16: Experiment Setup (Source: Researcher)

5.9 Software

The choice of the Arduino Uno microcontroller board was influenced by the availability of a good library of software, written in the C programming language, to enable data acquisition.

Temperature and Humidity sensor DHT11, Pressure sensor BMP180 and the gas sensor MQ135 have their own libraries to work with the Arduino Uno microcontroller board. Therefore, the DHT111, BMP180 and MQ135 libraries were required to ensure that the microcontroller recognizes the components and is able to receive the data from the sensors attached. The C code for the experiment is listed in Appendix A.

The embedded hardware is logging the data onto ODBC (Open Database Connectivity) .csv file format. This file is then imported into a MySQL database onto a computer.

5.10 Data analysis and discussion

The k-means algorithm takes as input a dataset with m x n dimensions, where “m” denotes the number of records and “n” is the number of fields in the dataset. It must know how many clusters to utilize a priori in order to minimize the sum of squared errors (SSE) within each cluster using an appropriate distance function. In this study, clustering was done using the Matlab platform, with m = 2293 and n = 6. Experiments were carried out using three clustering evaluation indexes namely: Silhouette index and Davies-Bouldin across five distance measures such as Euclidean, city-block, cosine, hamming and correlation.

Silhouette is one of the most popular and effective internal measures for the evaluation of clustering validity. Silhouette analysis, which is used to investigate the separation distance between the generated clusters will be used to determine the appropriate number of clusters to use for the dataset across the selected variants of distance measures (Ogbuabor and Ugwoke, 2018). As presented in Figure 4.17-4.20, the Silhouette index was adopted experimentally to determine the best possible number of clusters using the k-means. The results as shown in Figure 4.17-4.20 shows that the Silhouette index for k-means across the four-distance measure used suggested 4 clusters.

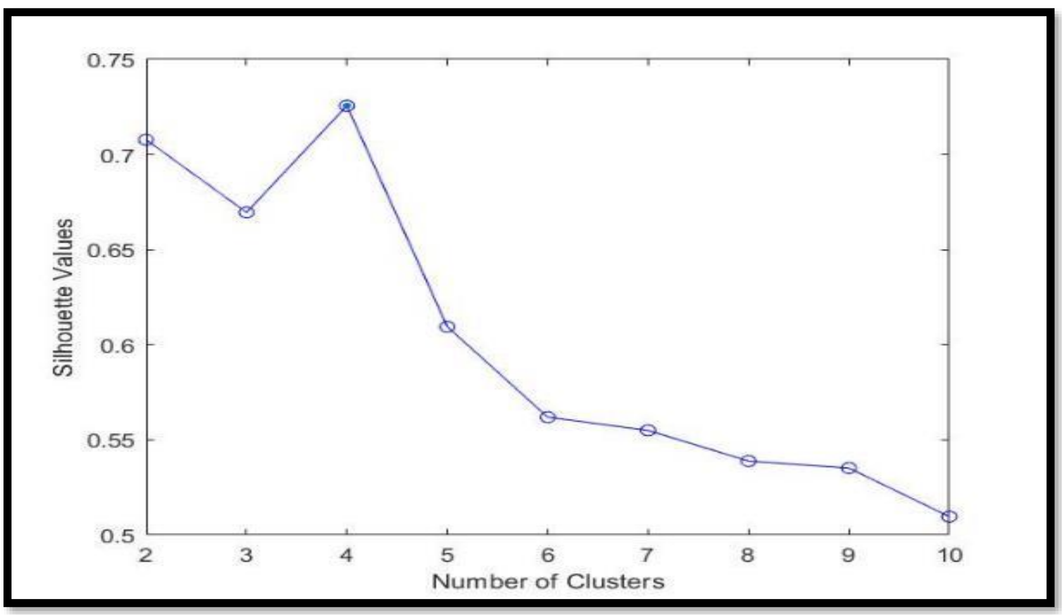

Figure 5.17: The average silhouette width for k-means with Euclidean distance measure

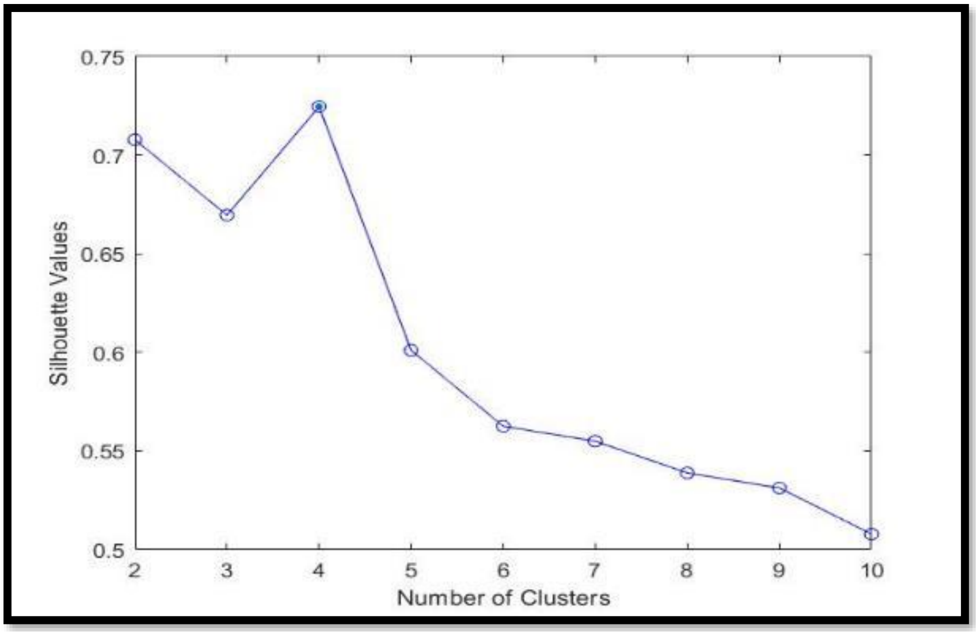

Figure 5.18: The average silhouette width for k-means with Cosine distance measure

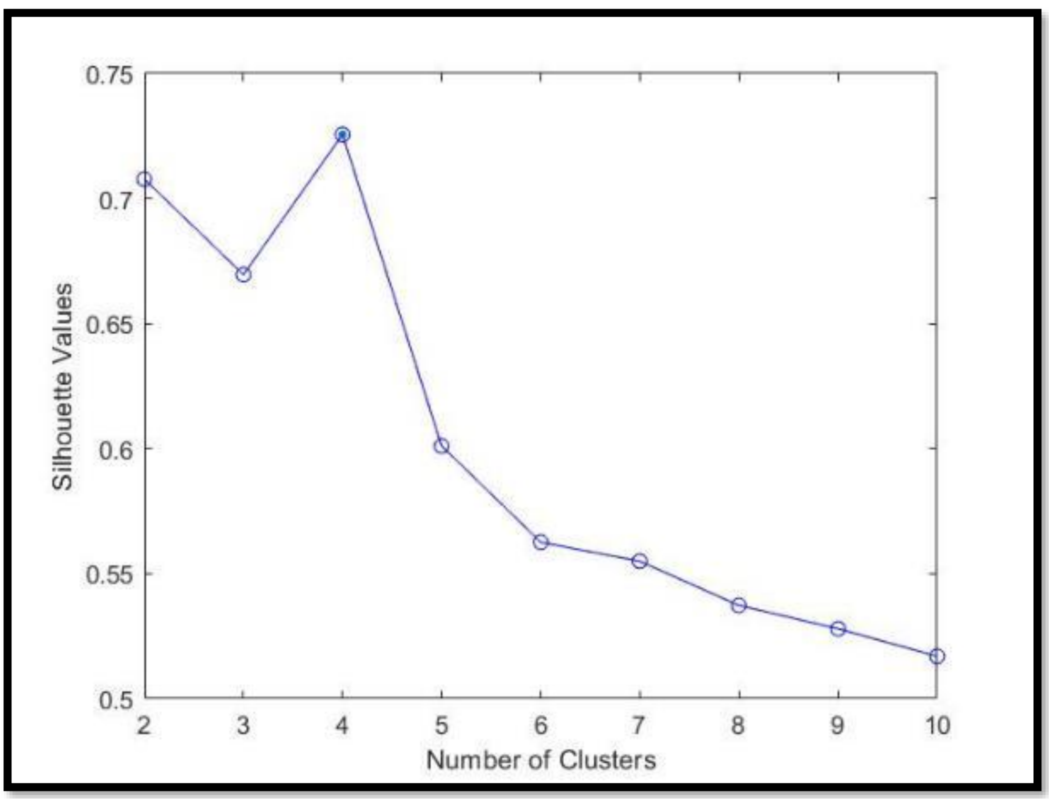

Figure 5.19: The average silhouette width for k-means with City-block distance measure

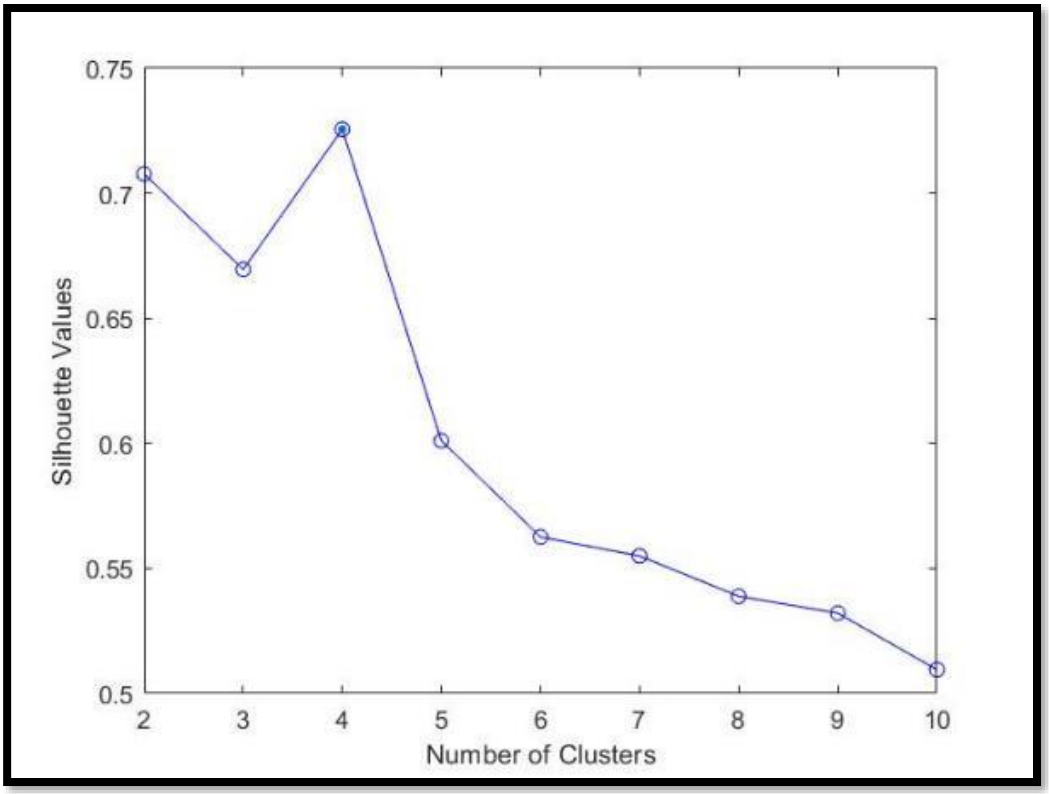

Figure 5.20: The average silhouette width for k-means with Correlation distance measure

Another alternative way for determining cluster validity in a clustering method is the Davies-Bouldin Index (DBI) (Karo *et al*., 2017). The Davies-Bouldin index is calculated by estimating the distances between clusters and their dispersion to arrive at a final value that measures the partition's quality. DBI employs clusters with a minimum value and a DBI value close to 0 when evaluating the optimal cluster to select (Sitompul et al., 2019). Although the silhouette index is the most often used clustering validity metric, Petrovic (2006) claims that the Davies-Bouldin index is considerably easier to calculate than the Silhouette index. Figure 4.21-4.24 presented the Davies-Bouldin Index cluster validity was implemented experimentally to determine the best possible number of clusters using the k-means. The results shown in Figure 4.21-4.24 shows that the Davies-Bouldin index for k-means across the four-distance measure used suggested 4 clusters because it is the index value closest to zero.

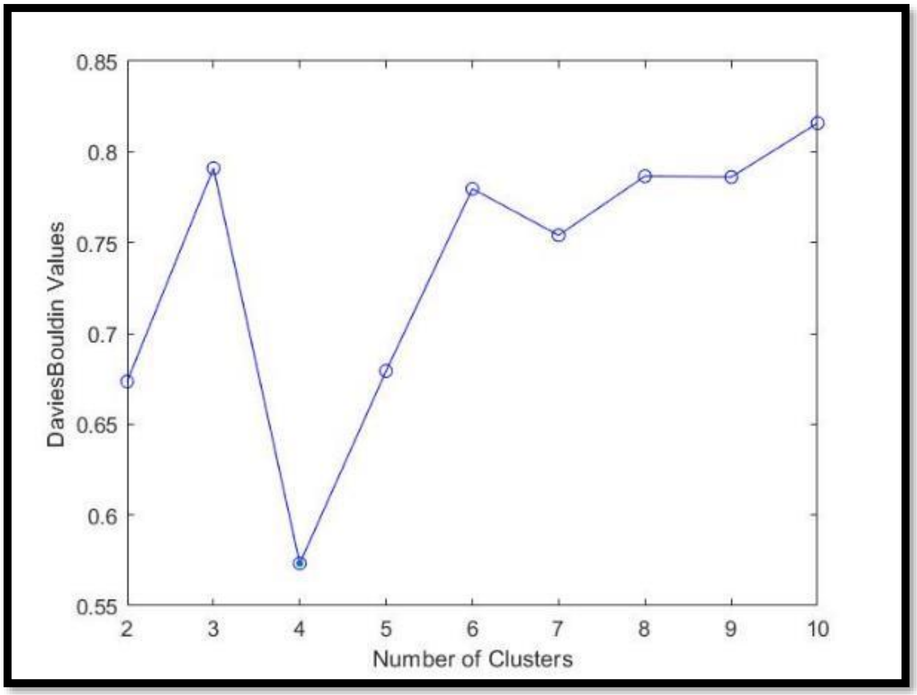

Figure 5.21: The average Davies-Bouldin index for k-means with Euclidean distance measure

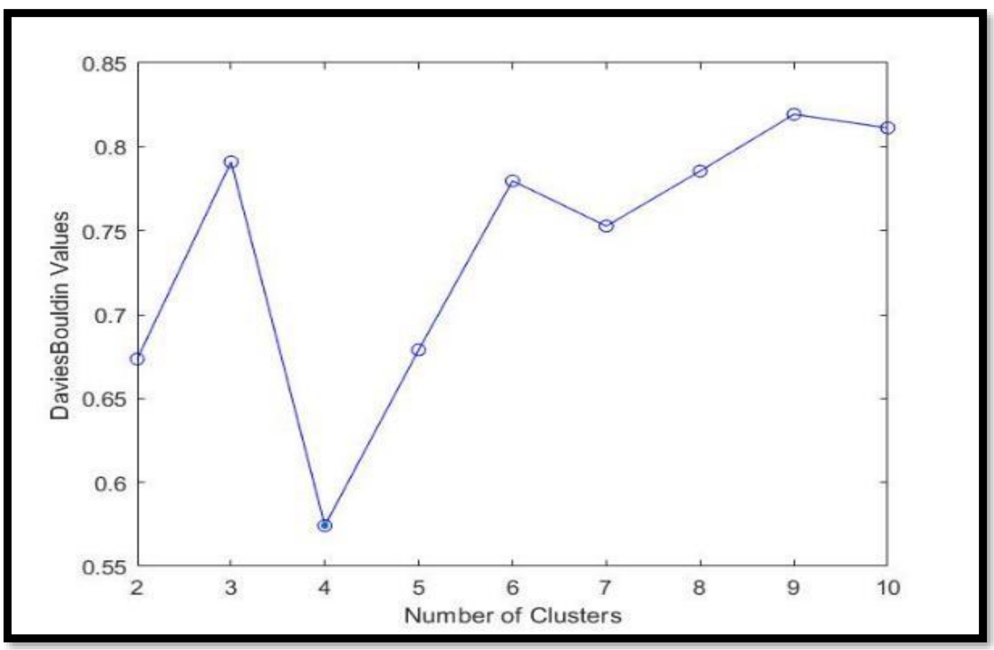

Figure 5.22: The average Davies-Bouldin index for k-means with Cosine distance measure

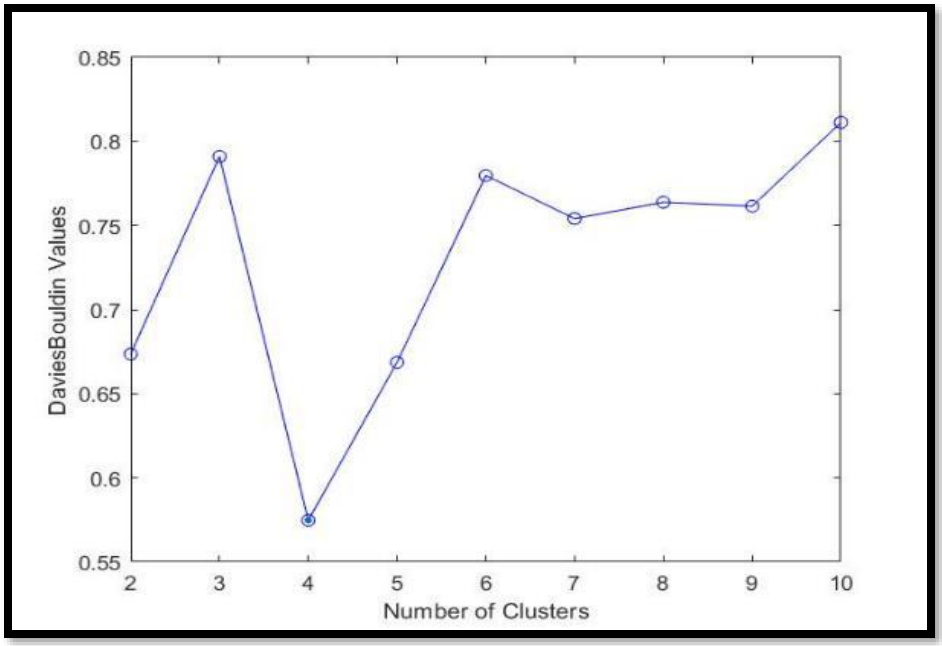

Figure 5.23: The average Davies-Bouldin index for k-means with City-block distance measure

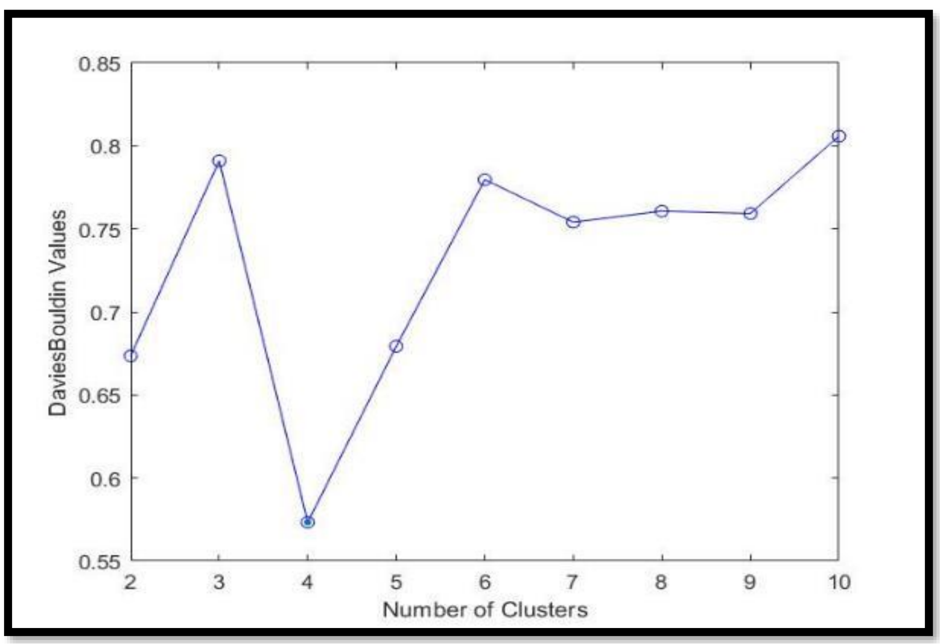

Figure 5.24: The average Davies-Bouldin index for k-means with Euclidean distance measure

Figures 4.25-4.28 presented the cluster regions by using a scattered plot to determine how effectively the clusters are divided, as well as to calculate the centroid for each cluster using the Silhouette evaluation metric for Euclidean distance, cosine, city-block, and correlation. The clusters appear to be divided into two categories: lower variance and larger variance. This could indicate that the four clusters are intertwined.

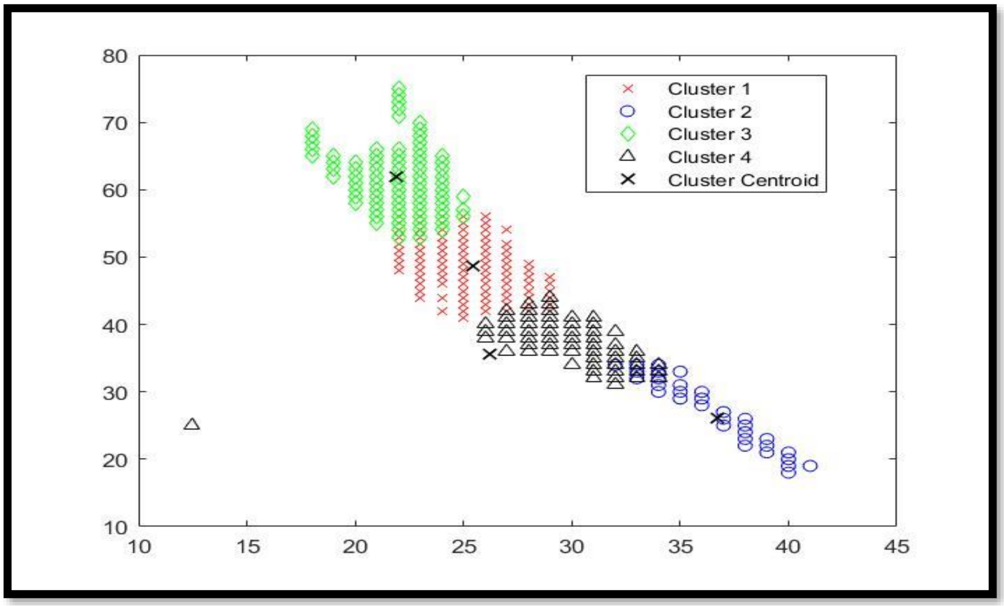

Figure 5.25: Cluster regions for the Euclidean distance with Silhouette evaluation

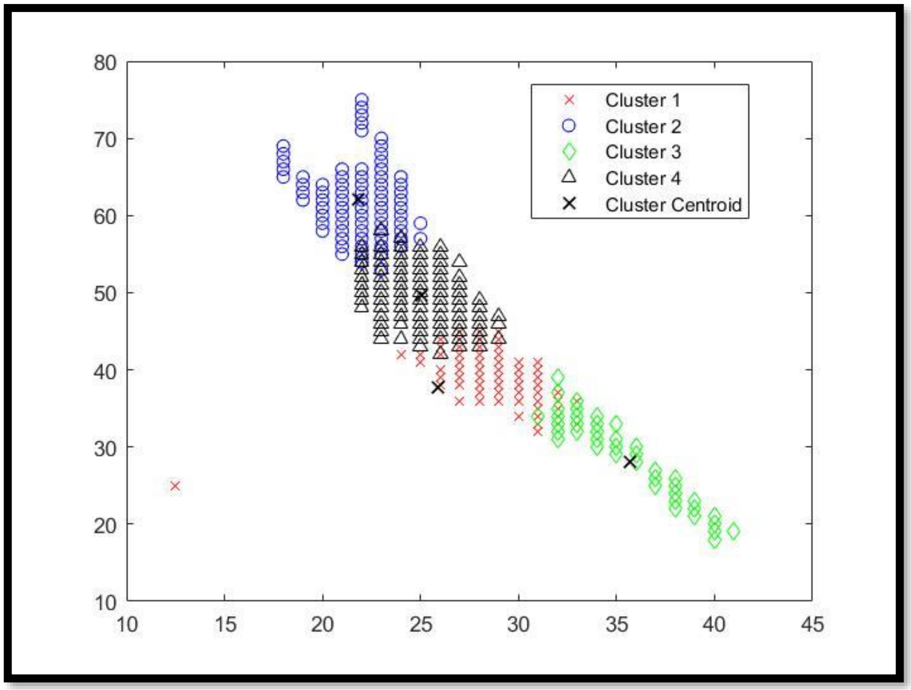

Figure 5.26: Cluster regions for the Cosine distance with Silhouette evaluation

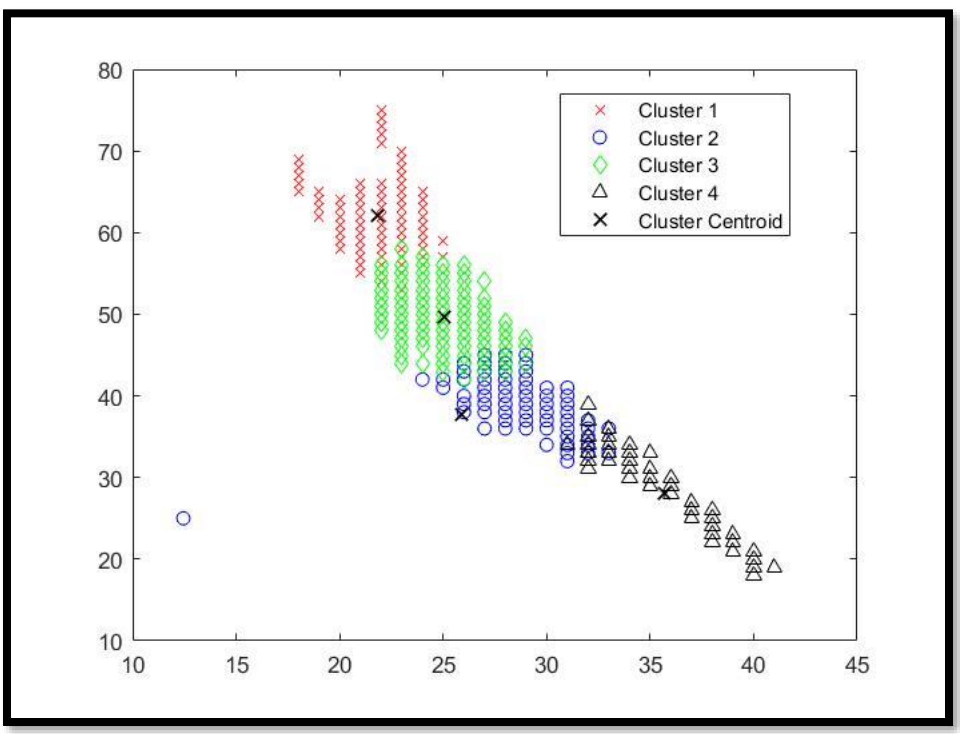

Figure 5.27: Cluster regions for the City-block distance with Silhouette evaluation

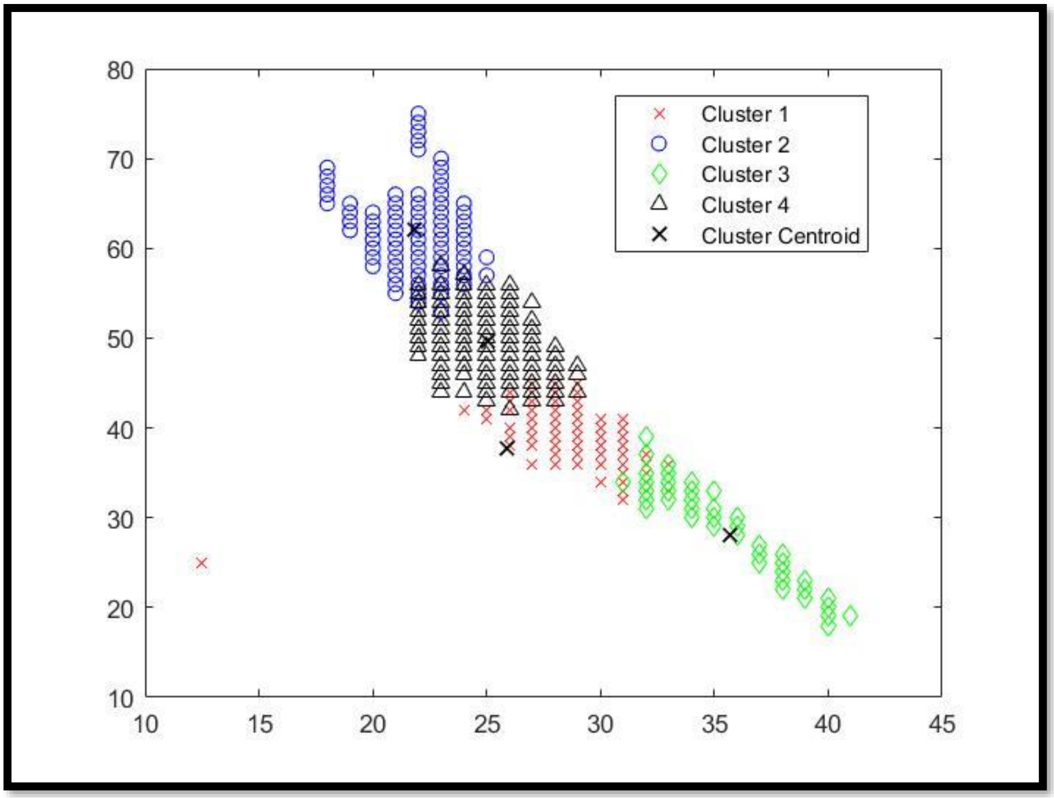

Figure 5.28: Cluster regions for the Correlation distance with Silhouette evaluation

Figures 4.29–4.32 presented the cluster regions by using a scattered plot to determine how effectively the clusters are divided, as well as to calculate the centroid for each cluster using the Davies-Bouldin evaluation metric for Euclidean distance, cosine, city-block, and correlation. The clusters appear to be divided into two categories: lower variance and larger variance. This could indicate that the four clusters are intertwined.

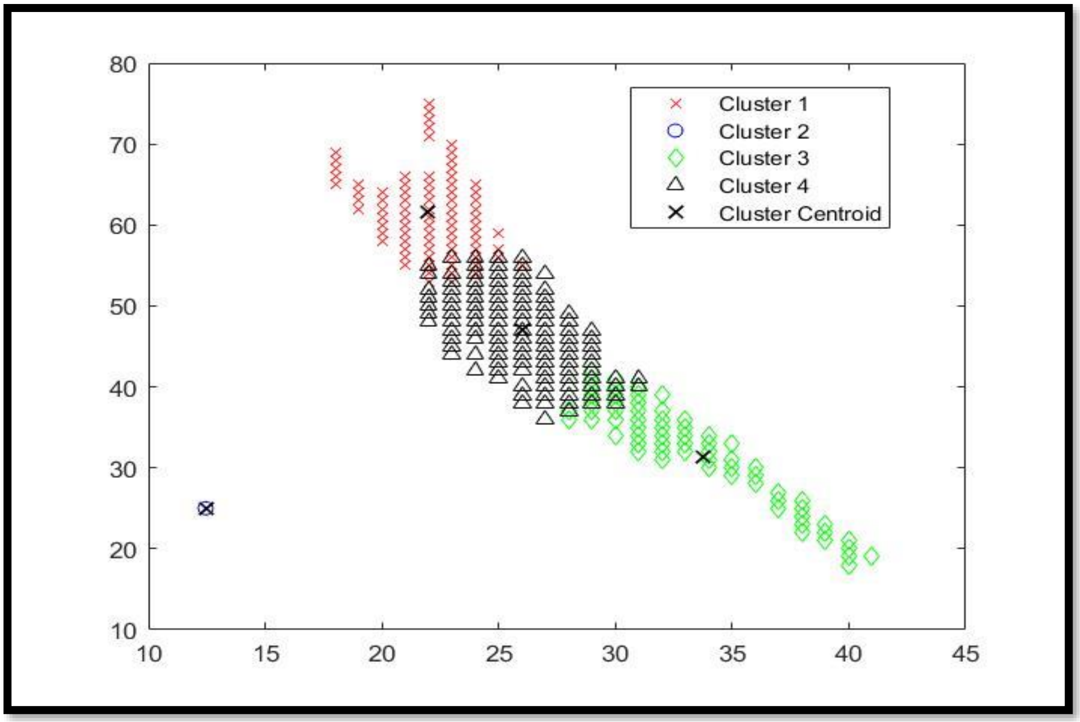

Figure 5.29: Cluster regions for the Euclidean distance with Davies-Bouldin evaluation

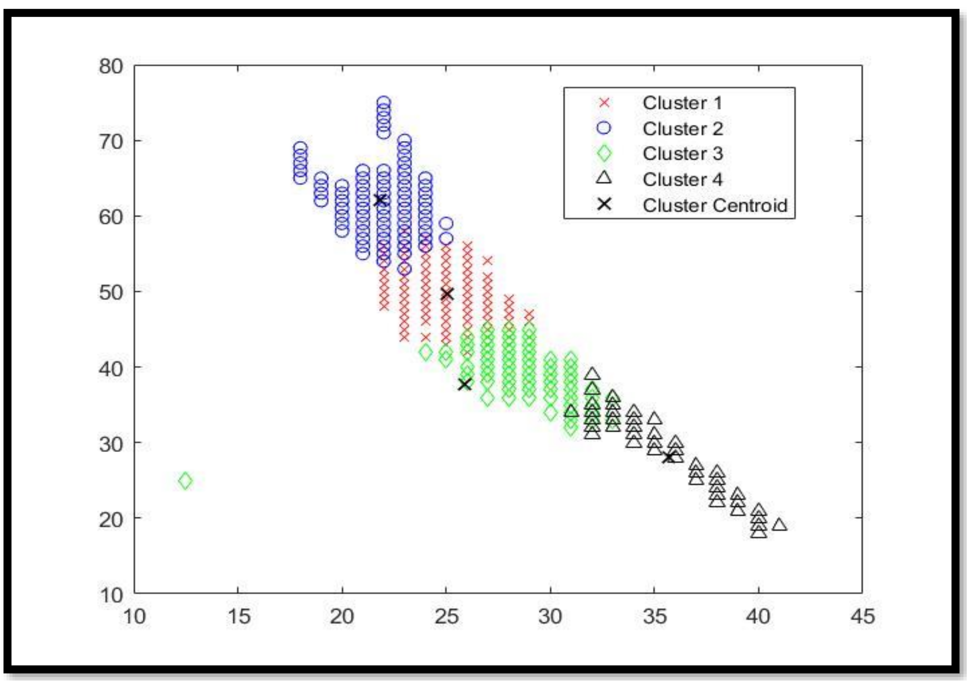

Figure 5.30: Cluster regions for the Cosine distance with Davies-Bouldin evaluation

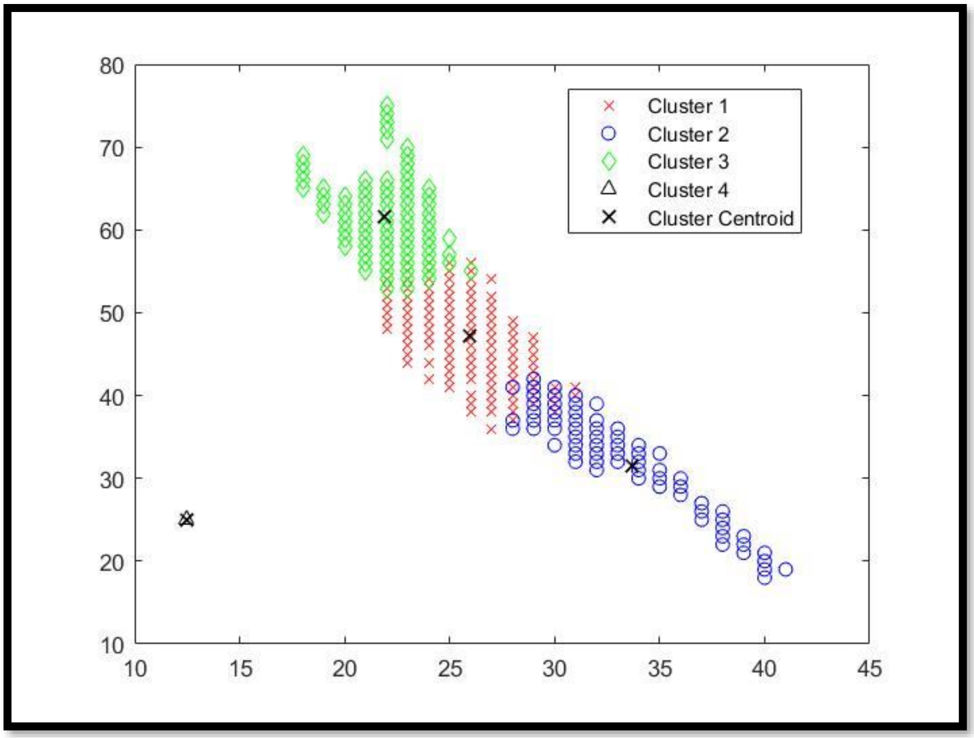

Figure 5.31: Cluster regions for the City-block distance with Davies-Bouldin evaluation

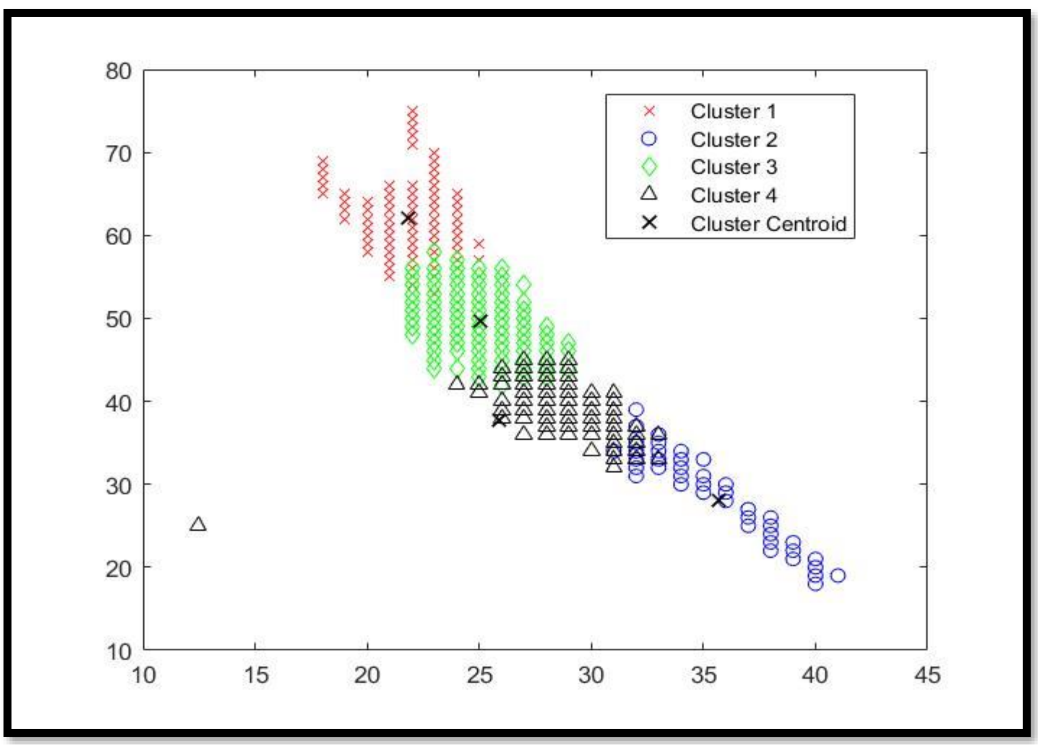

Figure 5.32: Cluster regions for the Correlation distance with Davies-Bouldin evaluation

A silhouette plot shows the distance between each point in one cluster and points in neighbouring clusters. This value ranges from 1 (showing points that are very far apart from neighbouring clusters) to 0 (representing locations that are not clearly in one cluster or another) and -1 (points that are probably assigned to the wrong cluster). In its first output, the silhouette returns these values. The Euclidean distance silhouette value per cluster is shown in Figure 4.33. The silhouette plot reveals that the majority of points in the first cluster have a large silhouette value of more than 0.6, indicating that the cluster is isolated from its neighbours. The second cluster, on the other hand, has low locations with silhouette values greater than 0.8. A few points in the third cluster have negative values, indicating that the cluster is not well separated. The fourth cluster has a large point, with a silhouette value also greater than 0.6.

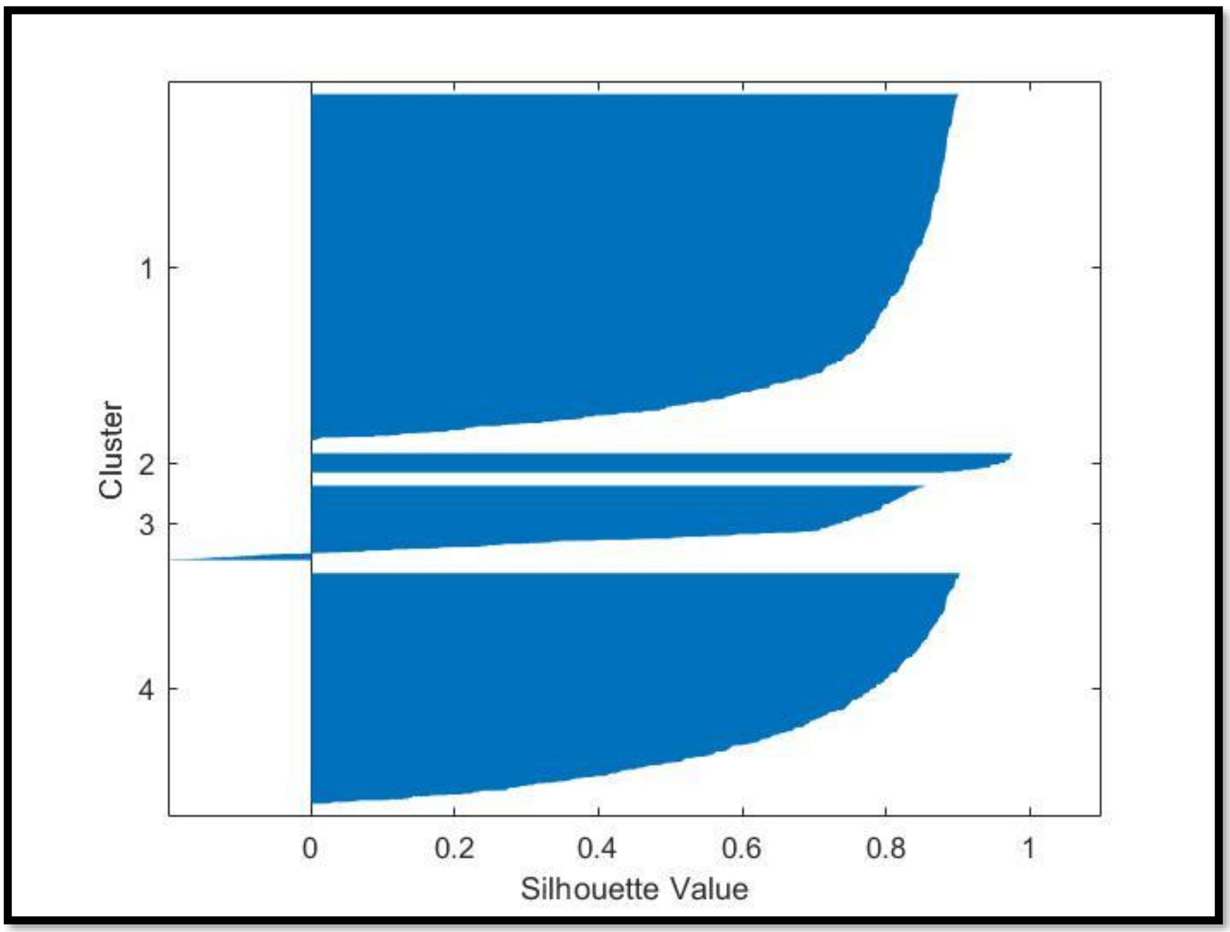

Figure 5.33: Euclidean distance silhouette value per cluster

Figure 4.34 presents the cosine distance silhouette value per cluster. The silhouette plot shows that most points in the first cluster have a large silhouette value which is greater than 0.6, indicating that the cluster is somewhat separated from neighbouring clusters although some clusters in cluster 1 contain a few points of negative value. Consequently, the second cluster contains low points with a silhouette value less than 0.6 and a high point of negative values. The third clusters contain an insignificant point with negative values, indicating that the cluster is not well separated and a low point with a silhouette value less than 0.8. The fourth cluster has a large point with a silhouette value greater than 0.6, the fourth cluster also includes few points with negative values.

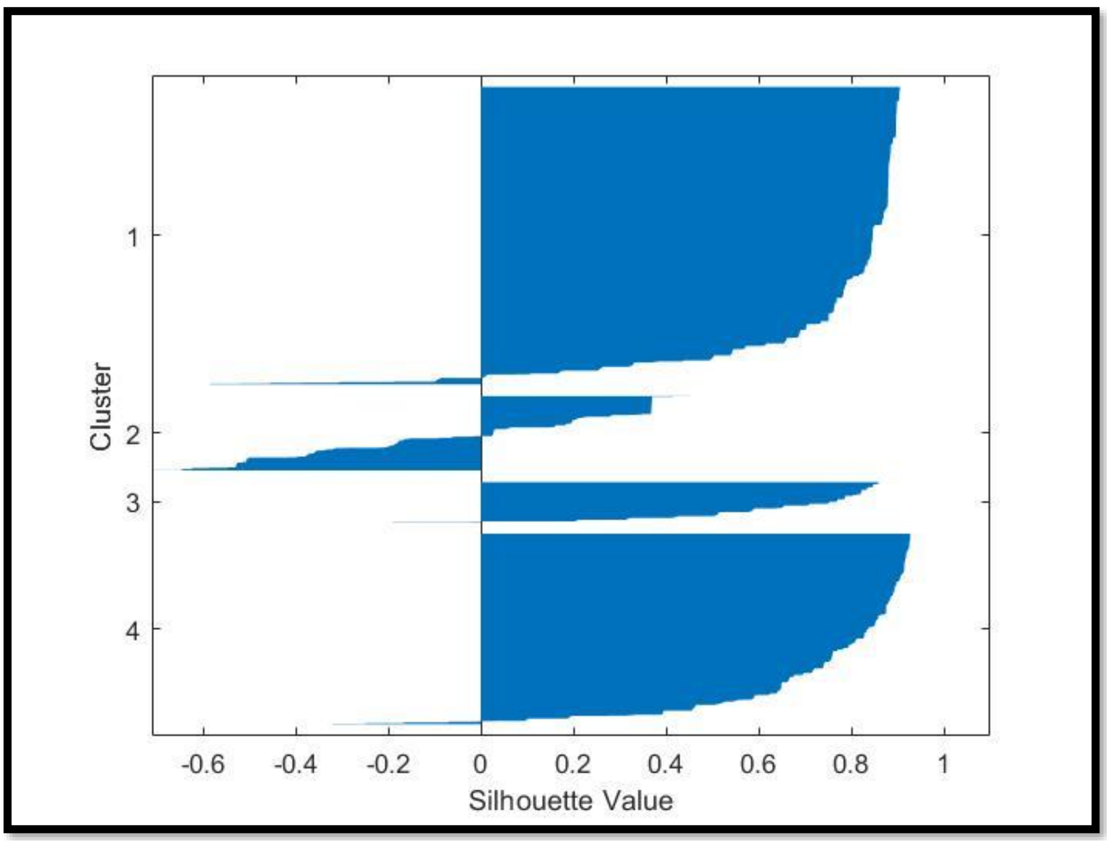

Figure 5.34: Cosine distance silhouette value per cluster

Figure 4.35 presents the City-block distance silhouette value per cluster. The silhouette plot shows that most points in the first cluster have a large silhouette value which is greater than 0.4, although some clusters in cluster 1 contain an insignificant point of negative value. Consequently, the second cluster contains low points with a silhouette value less than 0.4 and a high point of negative values. The third clusters contain an insignificant point with negative values, indicating that the cluster is not well separated and a low point with a silhouette value less than 0.8. The fourth cluster has a large point with a silhouette value greater than 0.4 the fourth cluster also include an insignificant point with negative values.

Furthermore, Figure 4.36 presents the correlation distance silhouette value per cluster. The silhouette plot shows that most points in the first cluster have a small silhouette value which is less than 0.6, although some clusters in cluster 1 contain a few points of negative value. Consequently, the second cluster contains a larger point with a silhouette value greater than 0.6 and some point of negative values. The third clusters contain an insignificant point with negative values, indicating that the cluster is not well separated and a low point with a silhouette value greater than 0.8. The fourth cluster has a large point with a silhouette value greater than 0.8, the fourth cluster also includes few points with negative values.

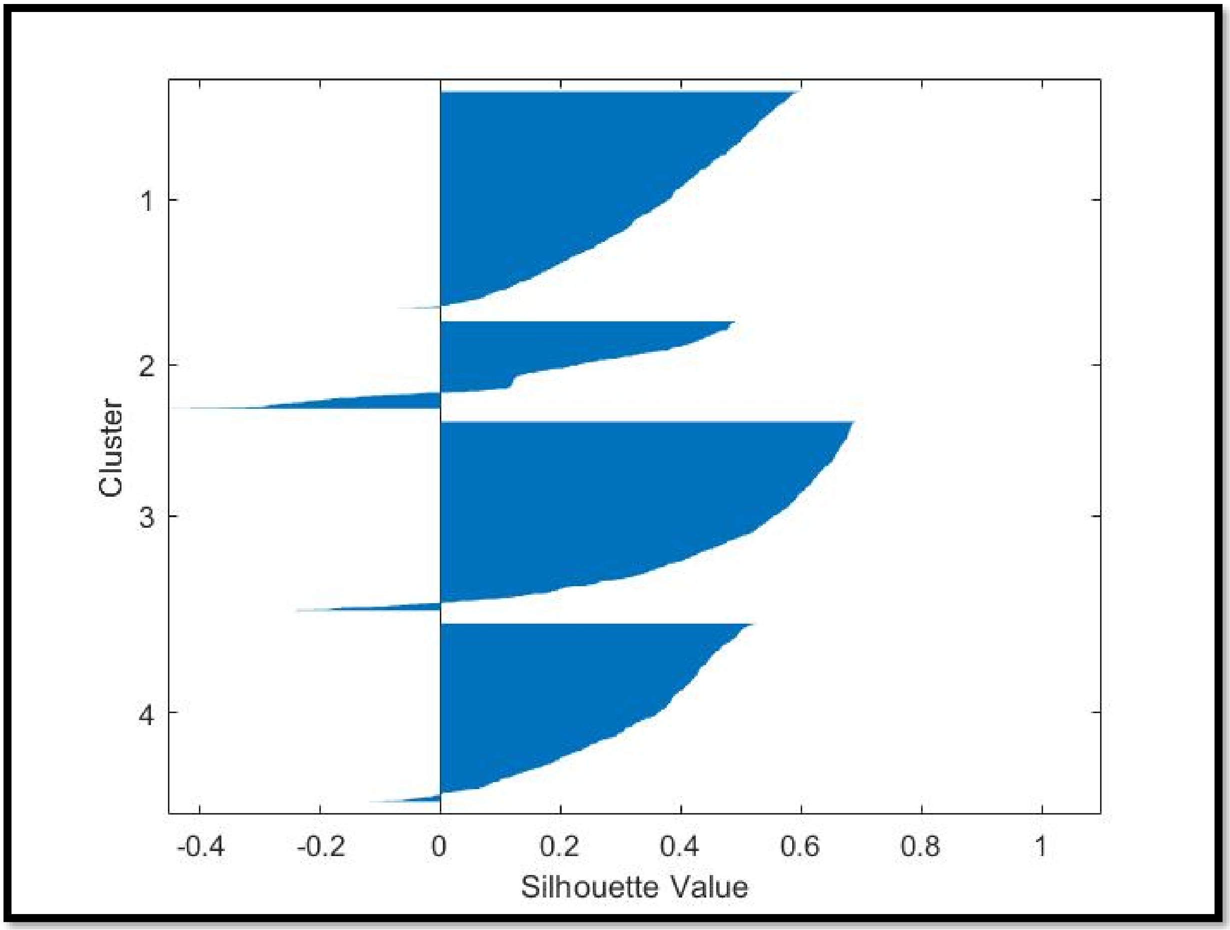

Figure 5.35: City-block distance silhouette value per cluster

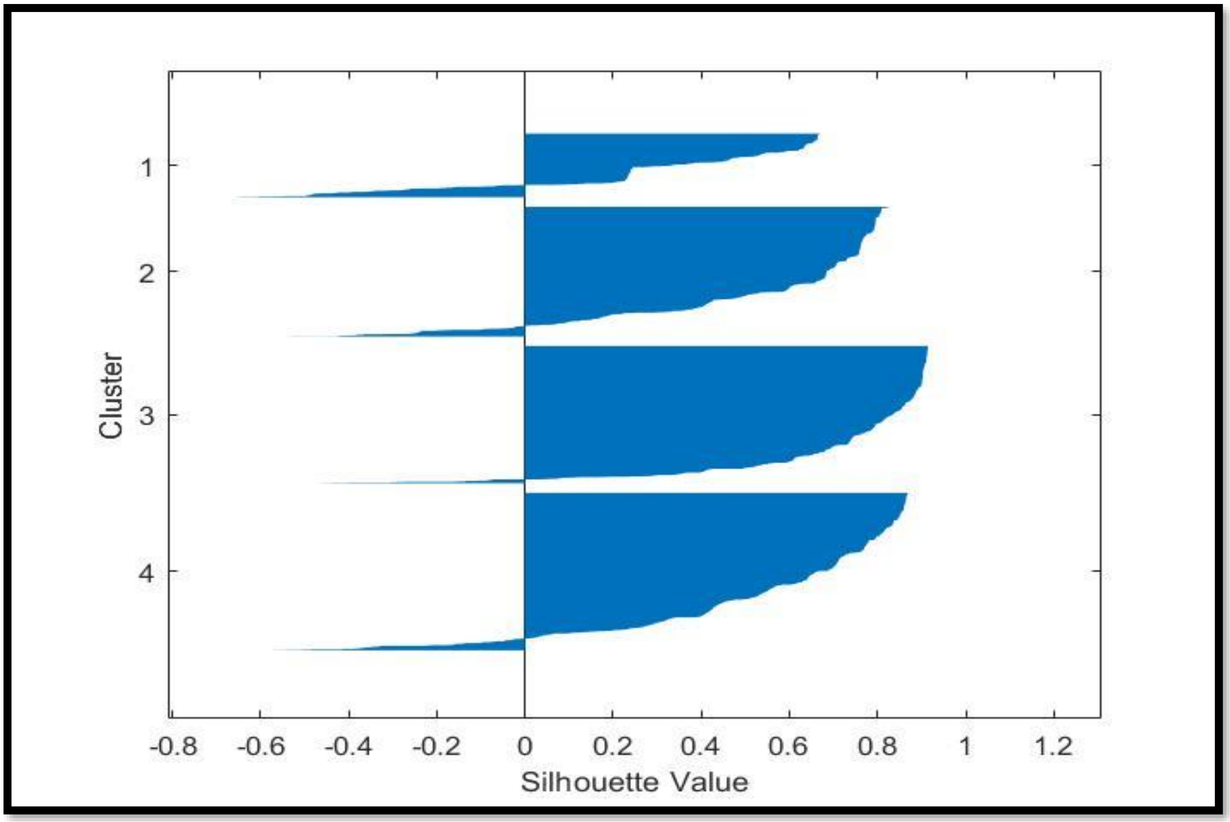

Figure 5.36: Correlation distance silhouette value per cluster

Figure 4.37 presents the Euclidean distance Davies-Bouldin index plot per cluster which reveals that the majority of points in the first cluster have a large silhouette value of more than 0.8, indicating that the cluster is isolated from its neighbours. The second cluster, on the other hand, has low location points with silhouette values greater than 0.8 although some of its clusters contain a few points of negative value indicating that the cluster is not well separated. The third cluster has a low location point with silhouette values greater than 0.8. Consequently, the fourth cluster has the largest point, with a silhouette value also greater than 0.8 indicating that the cluster is well isolated from its neighbours.

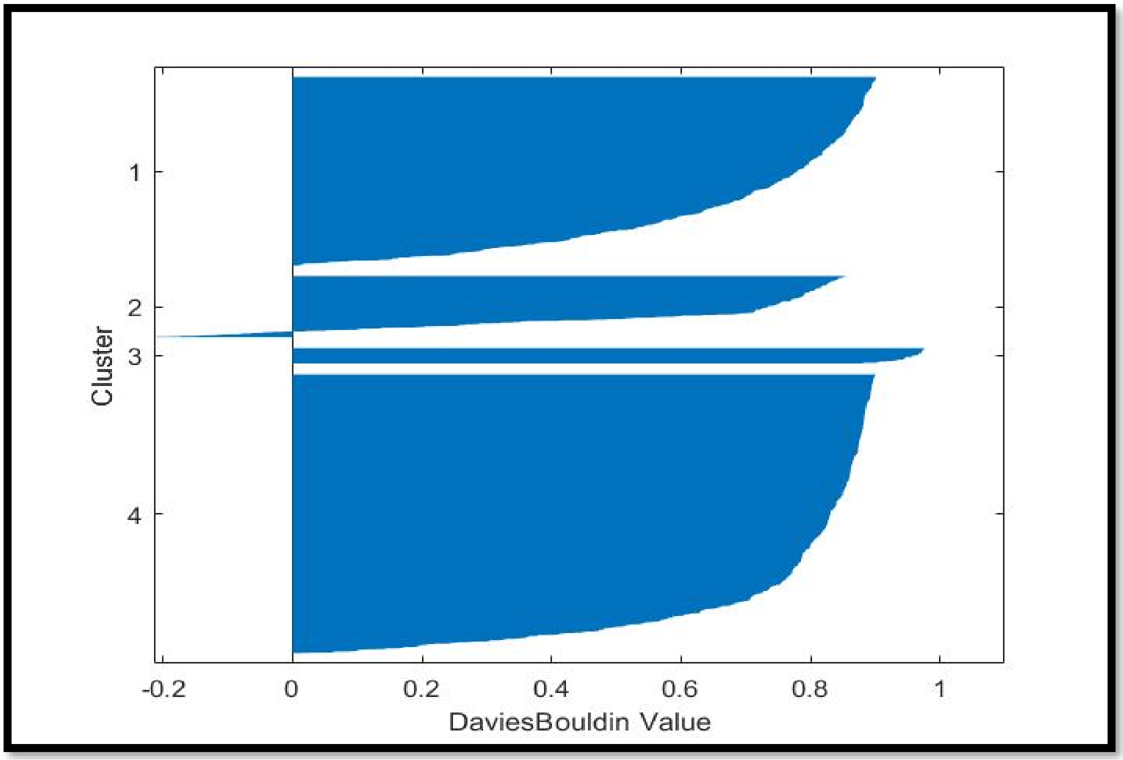

Figure 5.37: Euclidean distance Davies-Bouldin index value per cluster

Meanwhile, Figure 4.38 presents the Cosine distance Davies-Bouldin index plot per cluster which reveals that the majority of points in the first cluster have a large silhouette value of more than 0.8, indicating that the cluster is isolated from its neighbours although some of its clusters contain a few points of negative value indicating that the cluster is not well separated. The second cluster, on the other hand, also have a large location point with silhouette values greater than 0.8 although some of its clusters contain a few points of negative value. The third cluster has a low location point with silhouette values greater than 0.8. Consequently, the fourth cluster has a low point, with a silhouette value also greater than 0.6 with some clusters containing a few points of negative value.

Furthermore, Figure 4.39 presents the City-block distance Davies-Bouldin index plot per cluster which reveals that the majority of points in the first cluster have a large silhouette value of more than 0.4, indicating that the cluster is isolated from its neighbours however some clusters contains a few points of negative value. The second cluster, on the other hand, has low location points with silhouette values greater than 0.4 although some of its clusters contain a few points of negative value indicating that the cluster is not well separated. The third cluster has a low location point with silhouette values greater than 0.6, also some clusters containing a few points of negative value. Consequently, the fourth cluster has the largest point, with a silhouette value also greater than 0.4 with a minute cluster containing a few points of negative value.

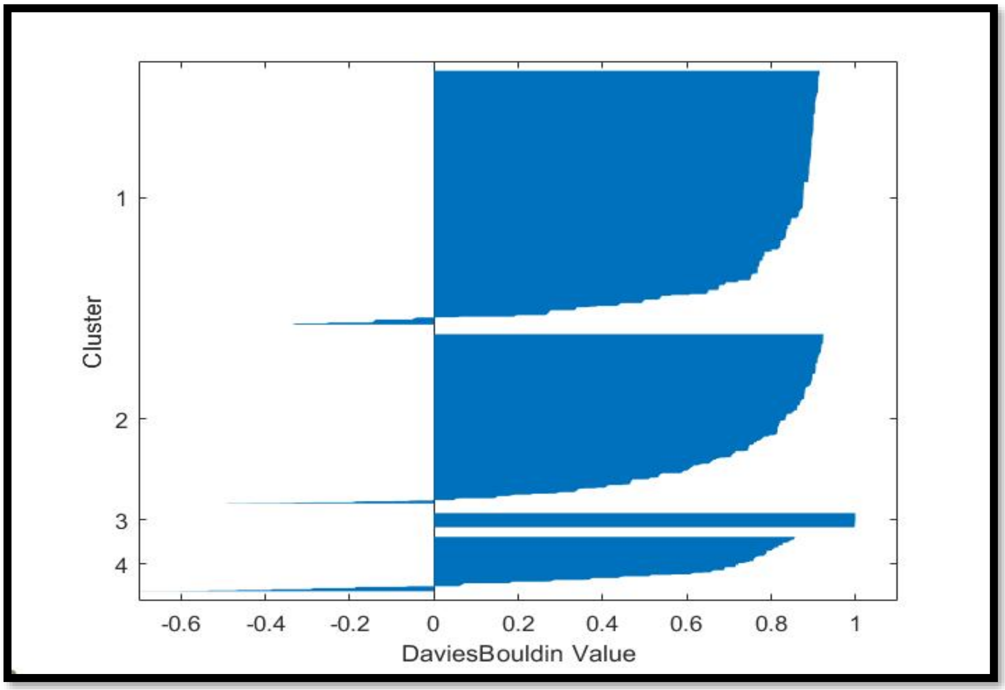

Figure 5.38: Cosine distance Davies-Bouldin index value per cluster

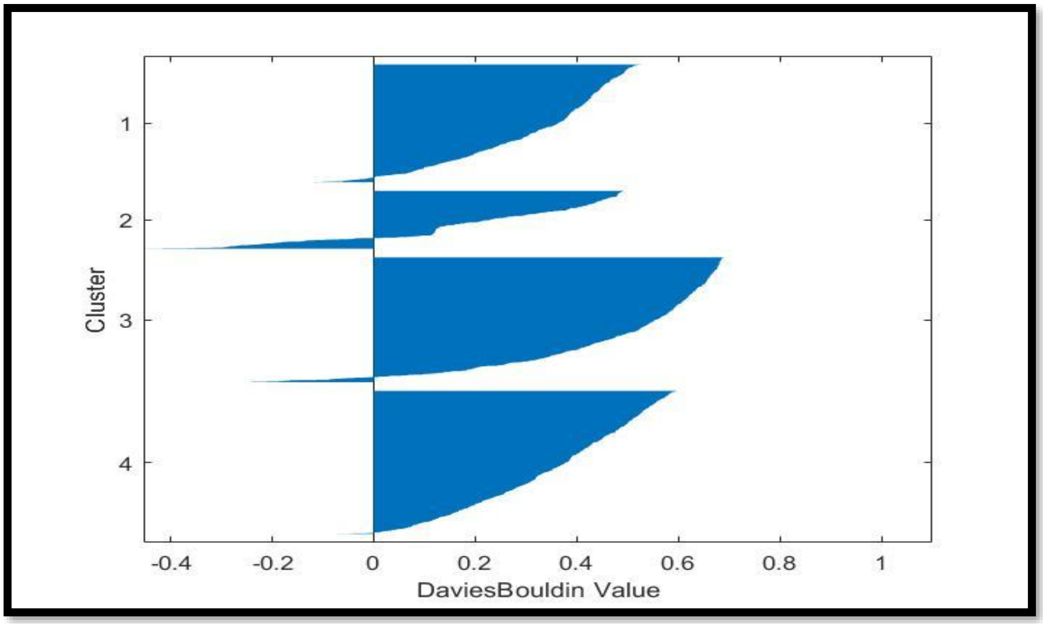

Figure 5.39: City-block distance Davies-Bouldin index value per cluster

Finally, Figure 4.40 presents the Correlation distance Davies-Bouldin index plot per cluster which reveals that the majority of points in the first cluster have a large silhouette value of more than 0.8, indicating that the cluster is isolated from its neighbours although some of its clusters contain a few points of negative value indicating that the cluster is not well separated. The second cluster, on the other hand, also has a location point with silhouette values greater than 0.8 although some of its clusters contain a few points of negative value. The third cluster has a low location point with silhouette values greater than 0.8. Consequently, the fourth cluster has a large point, with a silhouette value also greater than 0.8 with some clusters containing a few points of negative value.

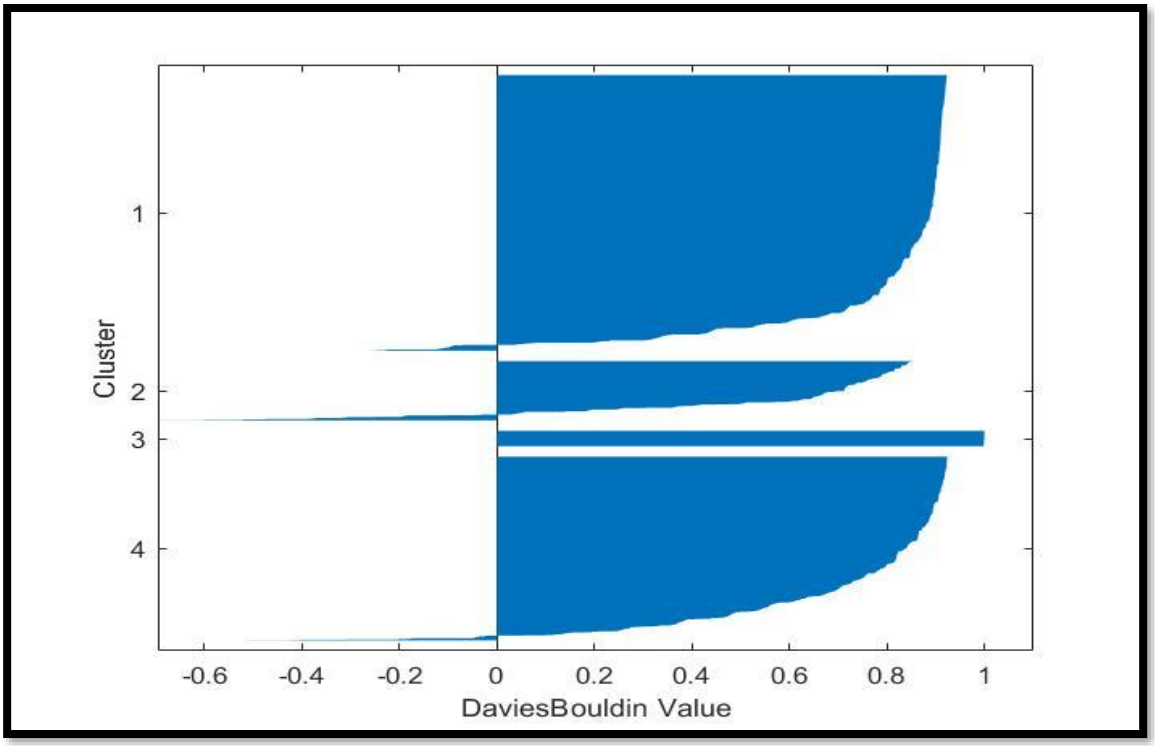

Figure 5.40: Correlation distance Davies-Bouldin index value per cluster

The final experimental result as presented in Table 4.9 can be seen that the Euclidean distance recorded the lowest average execution time for both Silhouette and Davies-Bouldin cluster validity however, it has the highest average number of iterations. The Pearson correlation recorded the highest average execution time for both Silhouette and Davies-Bouldin cluster validity however, it has 21 and 9 average number of iterations for Silhouette and Davies-Bouldin cluster validity respectively.

The Dunn index identifies the clusters that are well separated and compact to maximize the inter-cluster distance while minimizing the intra-cluster distance concomitantly. A large Dunn index implies that a compact and well-separated cluster exists (Dunn 1974; Ansari et al., 2015). The Dunn index was used to evaluate the potentiality of each distance function concerning the k-means method. As shown, Euclidean, City-block, and Cosine have equal Dunn indexes, whereas Correlation has the lowest Dunn index for silhouette evaluation. Furthermore, for the Davies-Bouldin evaluation, City-block has the greatest Dun index value, whereas Cosine distance has the lowest Dunn index. Furthermore, the Euclidean distance gave the highest sum of distance for both

Silhouette and Davies-Bouldin evaluation. However, Correlation distance gave the lowest sum of distance for the Silhouette evaluation while Euclidean and Cosine distance appeared to be the lowest sum of distance for the Davies-Bouldin evaluation.

Table 5.9: K-means performance evaluation with four distance functions

Evaluation	Distance Measure	Computing Time (s)	Numbers of Iteration	Sum of Distances	Dunn index	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Silhouette	Correlation	11.08	21	2.7e-06	2.4e-02	890	262	582	558
	City-block	5.13	17	18444.1	2.9e-02	645	609	740	297
	Euclidean	3.75	24	92777.6	2.9e-02	285	627	736	645
	Cosine	3.76	4	2.4e-06	2.9e-02	299	609	645	740
Davies-Bouldin	Correlation	3.25	9	2.7e-06	2.9e-02	1175	65	257	795
	City-block	2.50	10	19236.3	3.5e-02	1133	724	120	314
	Euclidean	2.44	13	92800.9	2.4e-02	645	740	297	608
	Cosine	2.28	8	2.4e-06	2.4e-02	740	645	609	297

5.11 Conclusion

Indeed, experimental research on intelligent drone systems and collecting data based has an impact on environmental changes and degradation is useful in evaluating different sustainable dimensions in South Africa (Günther *et al.*, 2021). Sample data shown in Annexure F.

Chapter Five: Conclusion and Recommendations

6.1 Introduction

This chapter reflects of the work on its entirety by summarising on the work done highlighting the research gaps while highlighting the unique contributions of the study.

6.2 Summary

The construction of a frugal drone, the addition of data aggregating sensor, was successfully achieved by the study. The study used ADSRM methodology to achieve the research objectives. Chapter One introduced the study and its objectives. Chapter Two provided a comprehensive literature review of drones and environmental monitoring, its use cases, opportunities, and challenges. It also describes two crucial Durban disasters where drones could have risen to the challenges. Chapter Three elaborated on the Research Methodology with a focus on the design and development of the drone for data collection. It also suggested how data could be analysed. The research motivates the ADSRM choice which is a combination of the ICT Agile method along with DSR method. Various aspects of this quantitative study pertaining to data collection, validity and reliability are detailed in this chapter. Chapter Four presented the data analysis and discussion. This chapter uses the ADSRM framework to describe the drone construction process and describe how the data will be analysed as a proof of concept. This describes the processes and challenges over drone identification, construction, and experiment design. This chapter presents the conclusions and implications of study.

6.2.1 Research Objective 1

> *To comprehensively review relevant publications based on the use of UAVs in general and in monitoring environmental conditions in particular order to compare well known systems to our proposed system.*

Drones have grown in range, applicability, type with a concomitant reduction in price. Monitoring technology is starting to use frugal methods for data collection. There is a greater demand to collect real-time, *in situ* environmental data. AI techniques are proving useful to analyse data.

6.2.2 Research Objective 2

To design and implement the proposed frugal intelligent drone system that helps monitor environmental conditions.

Drones can be purchased and repurposed through appropriate technology for the good of society. This process can be economical and frugal. Adding sensors and analytics created multidisciplinary opportunities with applicable relevance.

6.2.3 Research Objective 3

To analyse and evaluate environmental condition data using clustering algorithms

The findings of this study has shown that the environmental condition dataset collected at the Durban University of Technology's three campuses could be clustered into four categories and have been presented in the scattered plots in Figures 4.25-4.32. It is a likely indication that the environmental condition is normal and this may be due to low number of student present on campus due to COVID.

This demonstrates a range and extent of just one AI technique on three sensors collecting data over a period of time. The detailed mathematical analysis was undertaken to pedantically demonstrate the depth and range of techniques that could be undertaken using just one AI technique. Other techniques include machine learning and deep learning.

The fact that the data analytics show that the environment conditions are normal is what was expected and one would further expect that the air conditions in a major city would be normal. This type of analysis should be continued in other parts around the Durban Metropolitan area so that any changes could be discerned and rectified immediately. Consider if we could have done a similar anaylsis over the geographic location of UPL and the Engen Refinery. It is not possible to fly a drone over the Engen Refinery for security reasons as the refinery is regarded as a national keypoint.

6.3 Future research

6.3.1 Investigate data interrogation methods with expert environmentalist

The environmental data is not interrogated other than an AI-driven clustering method. This non-trivial analytical system was deliberately chosen to stress that sophisticated analytics that may be performed. Thus expert-level interpretation is deferred to environmentalist as this is their domain. The range of interpretation extends to regulatory and preventative monitoring as well as research projects. The research will have a frugal drone as a legacy and all it requires is joint research with environmentalist

6.3.2 Evolve the experiment with audio-visual capabilities

The combination of the audio-visual tuple leverages the capability of drones with camera and microphones and extends possibilities on data collection, recording, interpretation and transmission. The excitement here is over the ability to record events audio visually. It could be to record biodiversity and wildlife. The sound adds a new dimension to the data (Wich and Koh, 2018).

6.3.3 Evolve the experiment into networked system

In a complete system, a drone does not act in isolation; as it may be networked to a server to maintain seamless connectivity whereby the captured images, videos or sound may be transmitted and stored. The transmission process makes use of wireless technologies including ZigBee, Wi-Fi, WiMAX, and LTE (Yanmaz, Rinner, Yahyanejad and Hellwagner, 2017). In this study an on-board storage device SD card was mounted on the drone and data transferred for future processing when the drone lands. This data could be transmitted through satellite or even processed on-board for real-time analysis. These are an important areas and further study is recommended.

6.3.4 Introduce voice commands to the experiment

The intelligent drone is AI-enabled drone and its developmental progress mirrors building robots such as “Sophia” which communicate with human beings. Drones, will hold constructive command-driven conversations with humans, for example returning a useful answer to a question

(Brown, 2015). This will simply encourage engagement with drones. This is delimited for further research.

6.4 Recommendations

6.4.1 Investigate if the frugal drone can be commercialised

A frugal drone will spur research while contributing to the development of the scientific and academic community. By manufacturing drones, it may well persuade scientists to use an off-the-shelf product.

6.4.2 Engage in multidisciplinary research with environmental scientists.

ICT experts are technology enablers. Knowledge is created by leveraging the technology in an appropriate manner. As pointed Durban has had two environmental catastrophes in the 12-months preceding the effort (Engen, 2020) and (UPL, 2021) which motivated the study. By working with environmental scientists, chemical engineers and regulators the technology can become an enabling tool for community and industrial safety. This way industry and communities can safely coexist.

6.4.3 Investigate drone uses in other industries

The literature infers that more industries should neutrally examine drones for the value and even the potential risk that drones introduce to them and this is flagged as future work. These risks and opportunities should be reviewed as sector-wide or departmental-wide because of the different perspectives it brings. The risks must include drone, people and national safety as well as security.

For example, this study before it commenced anecdotally recognised that drones will help with environmental monitoring. The details grew as the level of granularity increased and the 3D printing was ultimately deployed. Drones must be evangelised. As the ADSRM method espouses communication is key to drive prudent adoption. Hildebrand (2020) is emphatic "**Drones** are not simply **toys"**.

6.4.4 Replicate the study in other areas of the country

Replication studies have a marketing and evangelical role, while also testing the robustness of the frugal drone.

6.4.5 Demonstrate the proof of concept to authorities and Civic Organisations

Environmental data acquisition is fraught with dangers to human collectors and data acquisition devices, allowing many environmental transgressions because the criminals know that monitoring is expensive, time-consuming, and non-trivial. The more frequent and closer the data acquisition to the geolocation under scrutiny, the more it allows for clustering, trending, time series and longitudinal analysis.

6.5 Conclusion

Independent drone-acquired accurate environmental data was proven to be a persuasive tool to neutrally influence change.

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Annexure A

```
#include <MQUnifiedsensor.h>

#include <Adafruit_BusIO_Register.h>

#include <Adafruit_I2CDevice.h>

#include <Adafruit_I2CRegister.h>

#include <Adafruit_SPIDevice.h>

#include <Adafruit_BMP085.h>

#include <dht.h>

/*

  SD card test

 The circuit:

  * SD card attached to SPI bus as follows:

 ** MOSI - pin 11 on Arduino Uno/Duemilanove/Diecimila

 ** MISO - pin 12 on Arduino Uno/Duemilanove/Diecimila

 ** CLK - pin 13 on Arduino Uno/Duemilanove/Diecimila

 ** CS - depends on your SD card shield or module.

Pin 4 used here for consistency with other Arduino examples

 */

#include <SPI.h>

#include <SD.h>

#include <Wire.h>

#include <DateTime.h>
```

```
#include <DS323x.h>

#include <Adafruit_BMP085.h>

#define seaLevelPressure_hPa 1013.25

Adafruit_BMP085 bmp;

dht DHT;

File myFile;

DateTime now;

int newHour = 0;

int oldHour = 0;

float temperature = 12.45;

float Humid = 25.00;

float Pressure = 0;

float Altitude = 0;

float Oxygen = 0;

float Co2 = 0;

float NH3 = 0;

float NO2 = 0;

DS323x rtc;

#define DHT11_PIN 7
```

```
int Analog_Input = A0;
int lpg, co, smoke;
// set up variables using the SD utility library functions:
Sd2Card card;
SdVolume volume;
SdFile root;
// change this to match your SD shield or module;
// Arduino Ethernet shield: pin 4
// Adafruit SD shields and modules: pin 10
// Sparkfun SD shield: pin 8
const int chipSelect = 10;
String SensorData, tmpdata;
void setup()
{
  // Open serial communications and wait for port to open:
  Serial.begin(9600);
  Wire.begin();
  rtc.attach(Wire);
 // rtc.now(DateTime(2021, 07, 01, 10, 45, 00));
  while (!Serial) {
    ; // wait for serial port to connect. Needed for Leonardo only
```

```
  }
  Serial.print("\nInitializing SD card...");
  if (!SD.begin(10)) {
    Serial.println("initialization failed!");
    while (1);
  }
  Serial.println("initialization done.");
  if (!bmp.begin()) {
    Serial.println("Could not find a valid BMP085 sensor, check wiring!");
    while (1) {}
  }
}
void logData( String logString){
  myFile = SD.open("log.txt", FILE_WRITE);
  if (myFile) {
    myFile.println(logString);
    myFile.close();
    Serial.println("done.");
   } else {
      Serial.println("error opening log file");
   }
```

```
}
String GetSensorData( char Parm){
 if (Parm == 0){
   Serial.println("TMP:"+String(temperature, 2));
   return(String(temperature, 2));
 }
 if (Parm == 1){
   Serial.println("HMD:"+String(Humid, 2));
   return(String(Humid, 2));
 }
 if (Parm == 2){
   Serial.println("PRE:"+String(Pressure, 2));
   return(String(Pressure, 2));
 }
 if (Parm == 3){
   Oxygen = GetSensor.Gas(0);
   Serial.println("O2:"+String(Oxygen, 2));
   return(String(Oxygen, 2)); // percent
 }
 if (Parm == 4){
   Co2 = GetSensor.Gas(1);
```

```
Serial.println("Co2:"+String(Co2, 2));
    return(String(Co2, 2)); // this is in ppm
  }
  if (Parm == 5){
    NH3 = GetSensor.Gas(2);
    Serial.println("NH3:"+String(NH3, 2));
    return(String(NH3, 2)); // this is in percent
  }
  if (Parm == 6){
    NO2 = GetSensor.Gas(3);
    Serial.println("NO2:"+String(NO2, 2));
    return(String(NO2, 2)); // this is in percent
  }
  return("ERROR");
}
void loop(void) {
            Pressure = bmp.readPressure();
    Altitude = bmp.readAltitude();
    int Co2 = analogRead(A0);
    DateTime now = rtc.now();
    SensorData = String(now.year());//"-"+now.month());
```

```
SensorData += "-";
   if (now.month() < 10)
      SensorData += "0"+String(now.month());
   else
      SensorData += String(now.month());
   SensorData += "-";
   if (now.day() < 10)
      SensorData += "0"+String(now.day());
   else
      SensorData += String(now.day());
   SensorData += " ";
   if (now.hour() < 10)
      SensorData += "0"+String(now.hour());
   else
      SensorData += String(now.hour());
   SensorData += ":";
   if (now.minute() < 10)
      SensorData += "0"+String(now.minute());
   else
      SensorData += String(now.minute());
   SensorData += ":";
```

```
  if (now.second() < 10)
      SensorData += "0"+String(now.second());
  else
      SensorData += String(now.second());
  SensorData += "|";
 for (char p=0; p<7; p++){
  SensorData += GetSensorData( p)+"|";
 }
  logData( SensorData);
  delay(10000);
  int chk = DHT.read11(DHT11_PIN);
  temperature = DHT.temperature;
  Humid = DHT.humidity;
}
```

Annexure B

$\forall c_i \in C : c_{i,\,bf} = c_{i,\,bmax} = 1$ **while** isDaaGWorking() **do**

for each c_i in C do

$c_{i,\,bf} = c_{i,\,bf} - 1$

if $c_{i,bf} \leq 0$ **then**

$c_{i,\,flag}$ = runBeaconing(c_i)

if $c_{i,\,flag} > 0$ **then**

$c_{i,\,bf} = c_{i,\,bmax} = 1$

D = runCommunication(c_i)

else

$c_{i,\,bf} = c_{i,\,bmax} = \min(b_{max}, \propto \text{x } c_{i,\,bmax})$

end if

end if

end for

if DaaG moves more than reset boundary length then

$\forall c_i \in C : c_{i,\,bf} = 1$

end if

sleep(t_{period})

end while Algorithm 1: Backoff-based beaconing algorithm (Source: Bae *et al.* 2018)

Annexure C

for i = 1 to |S| **do**

    $F_i = 0$

end for

while any $F_i = 0$ exists **do**

if DaaG visits s_i **then**

    $F_i = 2$

    s_k = getSensorToVisit(s_i)

    (pos_{sx} , pos_{sy}) = getPosition(s_k)

    moveDaaGTo (pos_{sx} , pos_{sy})

end if

T = getSensorListFromCollectedData(D)

for eachs_i in Tdo

ifF_i= 0 then

    $F_i = 1$

end if

end for

end while

Algorithm 2: Path-planning algorithm in a network of sensor

(**Source**: Bae *et al.*, 2018)

Annexure D

PSL = runSmartDataProcessing(D)

VL = List(empty)

ACL = List(empty)

for j = 1 to $|A|$ **do**

Ac$_j$= ∑_(i = 1)^($|PSL|$)corr$_{si,\ aj}$

ACL.insert(ac_j)

end for

if data ferry **then**

while$VL \neq A$ do

a_j = getActuatorToCommunicate ($A\backslash$ VL, ACL)

(pos_{ax} , pos_{ay}) = getPos(a_j)

VL.insert(a_j)

moveDaaGTo(pos_{ax} , pos_{ay})

end while

else if multi-hop then

a_j = getActuatorToCommunicate (A, ACL)

(pos_{ax} , pos_{ay}) = getPosition(a_j)

s_i= getNearestSensorFrom(a_j)

(pos_{sx} , pos_{sy}) = getPosition(s_i)

for k = 1 to n_d**do**

moveDaaGTo $((k.posax + (nd + 1 - k).possx)/(nd + 1), (k.posay + (nd + 1 - k).possy)/(nd + 1))$

end for

end if

Algorithm 3: Path-planning algorithm in network of actuator

(Source: Bae *et al.* 2018)

Energy consumed for transmission of data packet

$E_{TX} = l * (E_{elc} + \in_s * d^2)$ if $d < d_0$

$E_{TX} = l * (E_{elc} + \in_l * d^2)$ if $d \geq d_0$ …… (1)

Energy consumed in receiving data packet

$E_{RX} = l * E_{elc}$ ……….. (2)

Luciferin Value of glowworm

$L_i(t + 1) = (1 - \rho) L_i (t) + \gamma F(p_i(t))$ ………. (3)

Higher Luciferin value can be applied by

$Z \in N_i (t)$ iff $D_{iz} < rd_i (t)$ and $L_z (t) > L_i(t)$.......... (4)

Probabilities of glowworm

$Probability_{iz} = (Lz(t) - Li(t))/(\Sigma x \in Nk(t)\ Lx(t) - Li(t))$……….. (5)

Position of glowworm

$P_i (t + 1) = p_i(t) + s(Pz(t) - pi(t))/Distanceiz$……….. (6)

Decision range of glowworm

$Rd_i (t + 1) = \min\{r_s \max [0, rd_i (t) + \beta (n_t - |N_i (t)|)]\}$ …… (7)

Residential energy of drone

$E_{res}(i) = (E_I(i) - E_C(i)$ where $i = 1, 2, \ldots, N$ ………. (8) (Aftab, Khan & Zhang, 2019)

Annexure E

For every drone in a network

Calculate Fitness using equation 8 and 3;

Do (Transmit Hello message with **Fitness**);

While (Drone receives a Hello message)

Check (connectivity with BS);

Compare (**Fitness** with received **Fitness** of other drones);

Construct (Neighbour Table with drone entries);

Sort (neighbour Table according to highest value of **Fitness**);

Update (Neighbour Table with every new Hello message);

If (1 drone has connectivity with BS)

Declare (Itself a CH);

While (more than 1 drone has connectivity with BS || no drone has direct connectivity with BS in a cluster)

Check (**Fitness** information of every drone from Neighbour table);

If (drone has the highest **Fitness**)

Transmit Cluster Formation message (CH Claim);

Declare (Itself a CH);

else

Wait for (Cluster Formation message);

Consider (drone with the highest **Fitness** as a CH);

Transmit Cluster Joining message (CH recognise);

end

Algorithm 4: CH Selection and Cluster Formation Phase

(Source: Aftab, Khan and Zhang, 2019)

Annexure F

DATE	TIME	Temperature	Humd	Pressure kpa	Oxygen %	CO2 ppm	NH3%	NO2%
2021/09/09	09:13:42	12,45	25	105224	21,33	319,36	0,01	0,72
2021/09/09	09:13:43	12,45	25	105223	21,24	319,76	0,01	0,72
2021/09/09	09:13:54	21	60	105224	21,33	319,59	0,01	0,53
2021/09/09	09:14:04	21	60	105224	21,33	319,68	0,01	0,53
2021/09/09	09:14:14	21	60	105223	21,24	319,68	0,01	0,53
2021/09/09	09:14:24	21	60	105226	21,52	319,59	0,01	0,53
2021/09/09	09:39:13	12,45	25	105225	21,43	319,44	0,01	0,72
2021/09/09	09:39:23	21	61	105224	21,33	319,84	0,01	0,53
2021/09/09	09:39:33	21	60	105222	21,14	319,68	0,01	0,53
2021/09/09	10:39:01	12,45	25	105235	22,38	320,72	0,01	0,72
2021/09/09	10:39:11	27	40	105233	22,19	320,24	0,01	0,4
2021/09/09	10:39:21	27	40	105234	22,29	320,24	0,01	0,4
2021/09/09	10:39:31	28	41	105234	22,29	320,81	0,01	0,38
2021/09/09	10:39:41	28	41	105238	22,67	320,81	0,01	0,38
2021/09/09	10:39:51	29	41	105241	22,95	320,65	0,01	0,36
2021/09/09	10:40:02	29	39	105238	22,67	320,65	0,01	0,36
2021/09/09	10:40:12	29	37	105237	22,57	320,97	0,01	0,36
2021/09/09	10:40:22	29	36	105233	22,19	320,57	0,01	0,36
2021/09/09	10:40:32	28	36	105237	22,57	320,49	0,01	0,38
2021/09/09	10:40:42	27	36	105232	22,1	320,4	0,01	0,4
2021/09/09	10:40:52	26	38	105231	22	320,24	0,01	0,42
2021/09/09	10:41:02	24	42	105228	21,71	320,08	0,01	0,47
2021/09/09	10:41:12	23	46	105228	21,71	319,92	0,01	0,49
2021/09/09	10:41:23	22	49	105229	21,81	320,08	0,01	0,51
2021/09/09	10:41:33	22	51	105227	21,62	320,24	0,01	0,51
2021/09/09	10:41:43	22	51	105229	21,81	319,68	0,01	0,51
2021/09/09	10:41:53	22	52	105227	21,62	319,92	0,01	0,51
2021/09/09	10:42:03	22	51	105230	21,9	319,84	0,01	0,51
2021/09/09	10:42:13	22	51	105231	22	319,92	0,01	0,51
2021/09/09	10:42:23	22	51	105225	21,43	320,16	0,01	0,51
2021/09/09	10:42:34	23	50	105229	21,81	320,24	0,01	0,49
2021/09/09	10:42:44	23	49	105232	22,1	320,24	0,01	0,49
2021/09/09	10:42:54	24	47	105231	22	320	0,01	0,47
2021/09/09	10:43:04	24	44	105229	21,81	320,24	0,01	0,47
2021/09/09	10:43:14	24	44	105231	22	320,08	0,01	0,47
2021/09/09	10:43:24	23	46	105225	21,43	319,76	0,01	0,49
2021/09/09	10:43:34	22	48	105225	21,43	319,84	0,01	0,51
2021/09/09	10:43:44	22	48	105225	21,43	319,59	0,01	0,51
2021/09/09	10:43:55	22	51	105224	21,33	319,76	0,01	0,51
2021/09/09	10:44:05	22	52	105226	21,52	319,84	0,01	0,51

2021/09/09	10:44:15	22	51	105230	21,9	320,24	0,01	0,51
2021/09/09	10:44:25	23	50	105227	21,62	320,24	0,01	0,49
2021/09/09	10:44:35	23	49	105227	21,62	320,32	0,01	0,49
2021/09/09	10:44:45	23	48	105231	22	320,4	0,01	0,49
2021/09/09	10:44:55	24	47	105231	22	320,08	0,01	0,47
2021/09/09	10:45:06	24	49	105237	22,57	320,32	0,01	0,47
2021/09/09	10:45:18	12,45	25	105232	22,1	320,4	0,01	0,72
2021/09/09	10:45:28	26	47	105232	22,1	320,32	0,01	0,42
2021/09/09	10:45:38	27	44	105232	22,1	320,57	0,01	0,4
2021/09/09	10:45:48	27	41	105237	22,57	320,49	0,01	0,4
2021/09/09	10:45:58	27	39	105232	22,1	320,65	0,01	0,4
2021/09/09	10:46:09	27	38	105235	22,38	320,08	0,01	0,4
2021/09/09	10:46:19	26	38	105234	22,29	320,49	0,01	0,42
2021/09/09	10:46:29	25	41	105229	21,81	320,24	0,01	0,44
2021/09/09	10:46:39	23	45	105231	22	319,84	0,01	0,49
2021/09/09	10:46:49	23	49	105228	21,71	320,08	0,01	0,49
2021/09/09	10:46:59	22	51	105228	21,71	320	0,01	0,51
2021/09/09	10:47:09	22	52	105230	21,9	320	0,01	0,51
2021/09/09	10:47:20	22	52	105226	21,52	319,92	0,01	0,51
2021/09/09	10:47:30	23	51	105228	21,71	320,08	0,01	0,49
2021/09/09	10:47:40	23	49	105226	21,52	320	0,01	0,49
2021/09/09	10:47:50	22	50	105227	21,62	320,16	0,01	0,51
2021/09/09	10:48:00	23	50	105232	22,1	319,84	0,01	0,49
2021/09/09	10:48:10	23	49	105231	22	320,08	0,01	0,49
2021/09/09	10:48:20	24	48	105228	21,71	320,16	0,01	0,47
2021/09/09	10:48:30	23	46	105226	21,52	319,76	0,01	0,49
2021/09/09	10:48:41	23	48	105224	21,33	319,84	0,01	0,49
2021/09/09	10:48:51	23	49	105226	21,52	319,84	0,01	0,49
2021/09/09	10:49:01	23	47	105226	21,52	319,84	0,01	0,49
2021/09/09	10:49:11	22	49	105221	21,05	319,84	0,01	0,51
2021/09/09	10:49:21	22	51	105224	21,33	319,84	0,01	0,51
2021/09/09	10:49:31	22	51	105229	21,81	319,84	0,01	0,51
2021/09/09	10:49:41	23	50	105227	21,62	320,16	0,01	0,49
2021/09/09	10:49:52	23	49	105228	21,71	320,24	0,01	0,49
2021/09/09	10:50:02	23	49	105228	21,71	320,08	0,01	0,49
2021/09/09	10:50:12	23	49	105230	21,9	320,32	0,01	0,49
2021/09/09	10:50:22	23	49	105228	21,71	320	0,01	0,49
2021/09/09	10:50:32	24	49	105231	22	320,4	0,01	0,47
2021/09/09	10:50:42	24	51	105234	22,29	320,32	0,01	0,47