Improving Node Localization and Energy Efficiency for Wireless Sensor Networks using Hyper-Heuristic Optimization Algorithms

By

Name: Oluwasegun Julius Aroba
Student Number: 22064647

A thesis submitted in fulfilment of the requirement for the Doctor of Philosophy (PhD) in Information and Technology

Faculty of Accounting and Informatics, Department of Information Technology, Postgraduate Studies, Durban University of Technology

2021

Supervisor: Dr N. Naicker (PhD)
Co-Supervisor: Dr T. Adeliyi (PhD)

DECLARATION

I, *Oluwasegun Julius Aroba*, declare that:

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

(ii) This dissertation has not been submitted for any degree or examination at any other university.

(iii) This dissertation does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

(iv) This dissertation does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

- Their words have been re-written, but the general information attributed to them has been referenced.
- Where their exact words have been used, their writing has been placed inside quotation marks, and referenced.

(v) This dissertation does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the dissertation and in the Reference Section of this dissertation.

08-04-2022

Signature: *Oluwasegun Julius Aroba* Date

Approved for final submission

Supervisor: 11-04-2022

Dr N. Naicker Date
PhD

Co-Supervisor: 8/04/2022

Dr T Adeliyi Date

PhD (Information Technology)

ACKNOWLEDGEMENTS

My gratitude goes to the Almighty God for His special grace, His mercy, favour, wisdom, strength and understanding throughout the period of my research work. I am especially grateful to my supervisor, Dr Nalindren Naicker, for his assistance, support, succour and mentorship that helped me scale the hurdles of this work. It would have been a colossal task to accomplish this project without his full support, advice and continuous inspiration. He guided me through difficult times during my PhD journey, for which I am truly grateful.

Special thanks go to my co-supervisor Dr Timothy Adeliyi. His knowledge, skills and advice helped steer me on the right path. I owe him a great debt of gratitude. I would like to appreciate Vikas Upadhyay for allowing me to make use of his DEEC algorithm which he uploaded for use to the MATLAB community. DEEC is the building block for the hyper-heuristic algorithms.

I wish to dedicate this great work to my beloved late mother, Mrs Omolayo Modupe Aroba and to my father, Mr Oladiran Joshua Aroba for their daily prayer and encouragement. My never-ending love goes to my wife, my children (King Blessed Julius Aroba, King Caleb Bethel Aroba), and to my cousin Portia Mbali for giving me their total support and motivating me to complete this work at this highly reputable institution.

Thank you to the Durban University of Technology for providing me with the support and resources to complete this PhD project.

"Great faith is an element of great resilience, great testimonies are the outcomes of great trials, great victory can only be evidenced from great trials"

~Julius Oluwasegun Aroba

ABSTRACT

Within the growing Internet of Things (IoT) paradigm, a Wireless Sensor Network (WSN) is a critical component. In a WSN, sensor node localization is typically utilized to identify the target node's current location at the sink node (SN). This allows local data to be analysed, making it more meaningful. However, there exists an intrinsic problem with node localization and energy efficiency, as identified in the literature, which has led to poor performance, namely, poor estimation, transmission, and detection of the network. This intrinsic problem also directly affects energy efficiency in a WSN, resulting in energy loss and poor node distribution in the WSN. There seems to be no lasting and reliable solution to this intrinsic node localization problem in WSNs. Hence, this research study proposed hyper-heuristic optimization algorithms to improve node localization and energy efficiency in WSNs. This research adopts the Design Research (DR) methodology and the Theory of Modelling and Simulation as the theoretical frameworks of the study. The hyper-heuristic model designed, was considered the conceptual framework of the study. To validate the novel technique, different sizes of sensor networks, namely: - 100 sensor nodes; 100 to 1 500 nodes and 200 to 450 sensor nodes with 20 anchor nodes were simulated in an area measuring 100m x 100m. The novel hyper-heuristic model was implemented in a MATLAB R2020a environment. The hyper-heuristic optimization algorithm's substantial simulated experiment results were benchmarked utilizing state-of-the-art (modern) techniques to solve challenges related to node localization error, total energy consumed, average consumed packet energy, network throughput, shortest path, dead nodes, packets dispatched to the base station (BS), and the probability of error within the entire network dependent on size. The Data Energy Efficiency Clustering-Gaussian (DEEC-GAUSS) method was used to provide solutions to challenges related to energy efficiency in WSNs. In addition, this research study explored the use of the novel DEEC-GAUSS Gradient Distance Elimination Algorithm (DGGDEA) as the hyper-heuristic optimisation model for localization of nodes in WSNs. DEEC-GAUSS and DGGDEA were valuable additions to the body of knowledge. The results showed that the novel DEEC-GAUSS was the most energy efficient algorithm for 100 sensor nodes and 1000 to 1500 sensor nodes when compared to other state-of-the-art algorithms. Furthermore, the results showed that the novel DGGDEA was able to drastically minimize the node estimation error for sensor nodes. Reliability, accuracy and convergence using hyper-heuristic models to enhance the communication within WSNs has been simulated with evidence that DEEC-GAUSS and DGGDEA has outperformed other state-of-the-art approaches.

TABLE OF CONTENTS

LIST OF PUBLICATIONS

The following journal articles were published towards this PhD research project:

Aroba O. J., Naicker, N., Adeliyi, T.T. and Ogunsakin, R.E. (2020). “Meta-Analysis of Heuristic Approaches for Optimizing Node Localization and Energy Efficiency in Wireless Sensor Networks”, *International Journal of Engineering and Advanced Technology (IJEAT)*, Vol. 10, Issue 1, Pages 73-87. DOI: 10.35940/ijeat.A1717.1010120.

Aroba O.J., Naicker, N. and Adeliyi, T.T. (2021). "An Innovative Gaussian Clustering HyperHeuristic Scheme for Energy-Efficient Optimization in Wireless Sensor Networks", *Journal of Sensors,* Vol. 2021, 12 Pages. DOI: https://doi.org/10.1155/2021/6666742.

Aroba O.J., Naicker, N. and Adeliyi, T.T (2021). “A Hyper-Heuristic Heterogeneous Multi-Sensor Node Scheme for Energy Efficiency in Larger Wireless Sensor Networks using DEEC-Gaussian Algorithm”, *Mobile Information Systems*, Vol. 2021, 13 Pages. DOI: https://doi.org/10.1155/2021/6658840.

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS AND ABBREVIATIONS

The most important and most frequently used acronyms in this research study are listed below:

ABC	: Artificial Bee Colony
ACO	: Ant Colony Optimization
ACS	: Ant Colony System
ACK	: Acknowledgment
ANSI	: American National Standards Institute
AOA	: Angle of Arrival
API	: Application Programming Interface
BA	: Bat Algorithm
BPSO	: Binary Particle Swarm Optimization
BS	: Base Station
CH	: Cluster Head
CS	: Cuckoo Search
DE	: Differential Evolution
DEEC	: Data Energy Efficiency Clustering
DV	: Distance Vector
DV-Hop	: Distance Vector-Hop
EAS	: Elitist Ant System
EC	: Evolutionary Computing
EDEEC	: Enhance Developed Distributed Energy Efficient Clustering
EHO	: Elephant Herding Optimization
EMS	: Energy Management Systems
FFA	: Firefly Algorithm
FEECA	: Fuzzy based Energy Efficient Clustering Approach
FIND	: Future Internet Design
FND	: First Node Dead
FPA	: Flower Pollination Algorithm
GA	: Genetic Algorithm
GAUSS	: Gaussian
HEMS	: Home Energy Management Systems
ICT	: Information and Communication Technologies

IP	: Internet Protocols
IoE	: Internet of Energy
IoT	: Internet of Things
IT	: Information Technology
KSA	: Kestrel-based Search Algorithm
LAN	: Local Area Network
LEACH	: Low Energy Adaptive Clustering Hierarchy
LoWPAN	: Low-Power and Wireless Area Networks
M2M	: Machine-to-Machine
MIP	: Mobile Internet Protocols
OS	: Operating System
PAR	: Peak-to-Average Ratio
PEGASIS	: Power Efficient Gathering in Sensor Information System
PRISMA	: Preferred Reporting Items for Systematic Reviews Meta-Analysis
PSO	: Particle Swarm Optimization
P2P	: Peer-to-Peer
QoS	: Quality of Service
RIP	: Routing Information Protocols
RSSI	: Received Signal Strength Indicator
SI	: Swarm Intelligence
SN	: Sink Node
TCP	: Transmission Control Protocols
TDMA	: Time Division Multiple Access
TDOA	: Time Difference of Arrival
TND	: Tenth Node Dead
TOA	: Time of Arrival
ToU	: Time-of-Use
URL	: Universal Resource Locator
WLANs	: Wireless Local Area Networks
WSN	: Wireless Sensor Networks
WS	: Web Service

CHAPTER ONE: INTRODUCTION TO STUDY

1.1 Introduction

Wireless sensor networks (WSNs) are crucial components of the developing Internet of Things (IoT) paradigm. A WSN is an autonomous connection of different systems of sensors to detect data such as temperature, light, sound, pressure and humidity to monitor the state of the environment (Abella *et al.* 2019). WSNs are multiple channels of communication that are in groups that consist of battery powered sensor nodes that meaningfully manage the processing and storage unit with the goal of gathering and analysing data, while manipulating their sensor models (Ferreiro, Rabaçal and Costa 2016; Cheikhrouhou and Koubâa 2019; Arora and Singh 2017). The WSN comprises a self-configuring network system made up of micro nodes that enable low-cost data processing and communication via wireless transmission (Sun, Dong and Chen 2017). The fundamental aspect for many WSN-based applications is the positioning of anchor nodes at a base station (BS) which acts as the destination. Information in the form of packets travel from target nodes or static nodes from unknown locations using a path – through intermediate sensor nodes – to the BS or sink node (SN) where the information must be localized.

It is important to ensure that the information gathered from a specific device is meaningful and relevant to that specific location. Sensor nodes in the WSN environment are used for gathering sensory packets of information from the other connected nodes in the network and for performing processing. Sensor nodes communicate using radio signals in a WSN system. The wireless environment comprises inseparable resources that are constrained by limited processing storage capacities, time taken, and communication channel bandwidth. There are packets sent from the target node connected to the IoT device through interconnected nodes responsible for the self-organizing of appropriate information until it is passed to the SN. In multifaceted communication, these sensor nodes not only deliver information but also serve as a path along which information packets travel towards the BS. If a WSN has more than four anchors, then this is termed as localized (Abdulkarem *et al.* 2020).

Node localization complications in the WSN are a major and significant obstacle in the territory of geographical coordinates of sensor nodes. Elephant herding optimization (EHO) algorithm was the technique chosen to resolve many node localization challenges in recent times

(Strumberger *et al.* 2018b). An important goal in a wireless sensor environment is to locate opportune routing paths to curtail the aggregate energy consumption within network load balancing and to reduce ‘hot spots' that cause the death of sensor nodes. Therefore, it is necessary to reduce WSN’s energy consumption for node localization during information transfer. To address the shortcoming, a variety of approaches are available, the majority of which focus on node localization, energy efficiency, service quality and coverage. However, less attention has been paid to other identified problems such as transmission, the detection of connectivity, service quality and coverage (Huang *et al.* 2019).

Prominent generic algorithms are the robust harmony search algorithm (R-HSA), the particle swarm optimization (PSO) algorithm, the improved meta-heuristic algorithm, the distributed algorithm, the low energy adaptive clustering hierarchy (LEACH) search algorithm, the panacea-no collision detection (Panacea-NCD) algorithm, ant colony optimization (ACO) algorithm, and the hybrid memetic framework algorithm. Localization has been extensively used in WSNs to identify the real-time location of the sensor nodes for packets to be accurately sent to their destination. Information at the SN will be unintelligible without identifying the location of the targeted node. The proposed archetype from this research foresees a more accurate node localization that will optimize connection lifetime, advance the energy efficiency of the connection, improve the total number of iterations in ensuring more packets are delivered, and increase the speed of the system overall (Arjunan and Sujatha 2018; Krishnan, Yun and Jung 2019; Prithi and Sumathi 2020).

Wireless sensor networks are a collection of nodes used for communication between the BS and the destination to which packets are dispatched, where the sensor nodes are sent into the environment via the channel to the SN. The nodes not only communicate with the anchor node, or the BS, they invariably also communicate with each other by employing their different wireless radios channels, authorizing them to send their data for processing and analysis. There are different geographical layouts that are used to erect the WSN which are not limited to ring, star, bus, cluster, and mesh networks in the hierarchy of the setup (Mosavvar and Ghaffari 2019; Fahmy 2021). The choice of network topology depends on the volume of data and their various rates of incidence of the data aggregation to be transferred, the transmission distance, whether the sensor nodes are mobile compatible, and the lifespan of the battery (Mosavvar and Ghaffari 2019; Fahmy 2021).

Information is dispatched from the anchor nodes to the BS or vice versa in WSNs. When the sensor node dispatches information to the BS, a great deal of energy is lost resulting in a gradual decline in the amount of vibrancy that is assigned to the sensor nodes' conveyance. Various researchers have been investigating the process of energy-draining without adequately managing the energy expenditure efficiency (Abella *et al*. 2019; Alarifi and Tolba 2019; Arya and Sharma 2018). Hierarchical routing was explored to investigate energy exhaustion during the transference. The sensor node nominates a channel called the cluster head (CH) that acts as the principal node within the process of clustering. The CH communicates with and dispatches information to the appropriate channel. In doing so it uses a high residual energy rate compared to other sensor nodes (Prabowo, Abdurohman and Erfianto 2015).

Different approaches are used to identify the location of nodes within the WSN. These approaches are clear in the extant literature, and they are concerned with how energy utilization and localization have influenced the operation of sensor nodes that send information to the SN. Wireless sensor networks are used in a variety of industries, including the medical field, the military, fire safety for censoring, battlefield surveillance, rescuing surveillance, environmental observation and disaster control recovery monitoring programmes. They are also used by security experts for coverage of location to identify services control and by traffic control units for target tracking systems. Similarly, the majority of IoT and filtering application features are released at random, with no knowledge of the various locales (Aroba, Naicker and Adeliyi 2021b).

The routing of a WSN is crucial for the network continuance, which strengthens and improves its functionality. The crucial route assists to select the right power speedup and the direction in which to dispatch the information of packets received from the anchor sensor through the channel of the BS. There are different methods of linking nodes for network communication during the process (Aroba, Naicker and Adeliyi 2021a). Depending on the energy amplification levels for the sensor nodes, WSNs are classed as homogenous or heterogenous. Homogenous are assumed to use the same energy throughout the sensor nodes operation while heterogenous networks has varying computational power and sensing range because it is based on irregular sensor model within the WSN (Osamy, Salim and Khedr 2020; Rawat, Chauhan and Priyadarshi 2020).

It has been recommended that a better node localization validity with energy efficiency be adopted (Messous and Liouane 2020, Mozamir *et al.* 2020). Localization is equipped to demonstrate the precise locations of both indoor and outdoor environmental spaces such as universities, fields, hospitals, industries, health care organization centres, and shopping centre locations (Messous and Liouane 2020).

The WSNs are one of the main tools that are deployed for rural non-reachable places, such as checking the condition on mountains, monitoring deep forests, surveillance of oceans, security threat detection used by space engineers and to help identify fire detection before it escalates in the forest. Moreover, the Distributed Energy Efficiency Clustering (DEEC) algorithm is an alternative energy-optimization protocol that is employed for correlative performances, serving as an alternative for contrasting WSN's operations for high-intensity effectiveness. Nevertheless, an energy-saving plan is displayed for homogeneity in WSNs that are not deemed fit when it comes to deployment processes (Prakash, Mishra and Kushwaha 2020).

WSNs are intelligent networks that make use of data connectivity to communicate within the nodes in any organization, such as healthcare, environment, safety monitoring, precision control of irrigation and water usage monitoring. WSNs increase the growth of the quality practice, adding value to human life (Tiwari *et al.* 2015; Chandrakanth, Anand and Peter 2017, Strumberger *et al.* 2018a). WSNs can be used by electrical organizations for calculating multi-hops or electricity usage for appropriate distribution rather than oversupply (Al-Hayani and Ilhan 2020; Kumar, Tripathi and Agrawal 2020). The WSNs are flexible when additional sensor nodes or workstations are required for implementation with the price being minimized to save cost. The WSNs require less wiring than wired networks and can accommodate new setups for physical partitions using a centralized BS.

The motivation for this research work on WSNs is based on the research gaps that were identified from the extant literature research. These identified gaps include poor energy consumption by sensors, which is one of the most serious problems as it results in the sensors not functioning for long enough periods of time. Another challenge is access points that are less than optimally secure which allow hackers to gain easy access to the WSN. Additionally, they are complicated to set up when compared to wired networks; node localization which entails allowing for identifying an unknown node's location has been a challenge. Furthermore, they are also not considered cost-efficient in terms of their energy utilization (Tiwari *et al.*

2015; Javaid and Bansal 2021). The WSNs are valuable, flexible networks that adjust to changes within a specific time frame and easily allow new devices to communicate. A WSN is cost-effective when considering the connection of the sensors during setup. The gaussian elimination algorithm was used in calculating the shortest path and thereby helps with the reduction of energy consumption.

Wireless sensor networks have various practical values, and many scholars have published articles in academic journals on their WSN-related in-depth investigations. One of the persistent key emergent challenges is that of energy consumption for node localization during data transmission. In the quest for alternate medium to solve the issue of energy efficiency, a number of techniques have been offered related to node localization (Bhat and Santhosh 2020).

The ability to locate sensor nodes is crucial for WSN applications so that local information can be meaningfully understood (Sun, Dong and Chen 2017; Sun, Yu and Wang 2019). The flower pollination algorithm (FPA) has contributed to improving node localization, but gaps still exist in the research (Pan *et al.* 2017). Node localization in WSNs was improved with the use of the butterfly optimization algorithm when compared to other algorithms such as PSO algorithm and Firefly Algorithm (FFA) (Arora and Singh 2017). Yick, Mukherjee and Ghosal (2018) improved on the method by proposing hybridisation method to minimise location estimation error. The gaps in the body of knowledge and challenges of node localisation have led to the current research being conducted. Therefore, there exists a need for this research study.

1.2 Statement of the Research Problem

Wireless sensor networks are used by transportation services in South Africa, Nigeria, the United Kingdom and virtually on every continent for real-time traffic control information. This allows for drivers to be alerted to problems such as traffic congestion, and other risks like road users not obeying the speed limit. Wireless sensor networks are also used in the supervision of accurate assessment of energy consumption in transportation services (Adu-Manu *et al.* 2018). Environmental and earth sensing is one of the areas in which WSNs are needed to detect and manage the changes affecting nature and the environment. Therefore, WSNs are used in application areas to prevent harm to the human beings.

However, the health care sector has suffered losses of wearable or implanted medical devices when connectivity issues have prevented the means to track people appropriately. Despite the various applications of WSNs, the node localization problem persists. The identification of sensor nodes' locations in WSNs is important because BSs are required to calculate the node locations of the sensors that are not identified using the various location information transmitted and the different transmission ranges (Vojdani and Dehghan 2011).

Challenges in node localization encompass high bandwidth requirements, high energy consumption levels, localisation estimation error, inadequate data processing and compressing methods, and poor quality of service (QoS) (Yang and Wu 2015). Poor estimation error in WSNs is the multipath interference caused by inefficient signal fluctuation with low complexity for self-calibrating (Sun, Yu and Wang 2019). Furthermore, network localisation errors are caused by the challenges relating to the loss of packets of data, environmental factors, unauthorised attacks, power depletion, and being out of network range. Identified limitations in previous research studies in WSNs were poor management, poor data clustering, time coordination challenges, poor communication arrangement, and data congestion (Han, Zhang and Sun 2018; Khalaf and Abdulsahib 2019).

The high level of energy decomposition in WSNs is a serious aspect of the node localization problem. Redundant data at the SN provides more accuracy, reliability, and security problems and leads to depletion of the energy at the SN. There is a need to provide more accurate data in an energy-efficient manner. Concerns have been raised over the need for data redundancy to ensure reliable data for decision-making. Methods like data gathering and data fusion can help to reduce the effects of information redundancy and reduce congestion of data for localization packets that are dispensed from the origination (target) to the landing (SN) in a WSN (Verma and Singh 2018).

The transmission between sensor nodes is usually carried out using wireless communication protocols. Most studies have focused on the lack of sensor networks with competent energy resources during wireless communication. One of the main issues is the dimension of nodes' capacity and the size of the energy in WSNs which has made recent research papers aim to work with 50–100 target nodes and hundreds of iterations. Energy consumption in node localization is the most important issue as the lifespan of WSN is determined by the battery life located in sensors. To increase the lifespan of WSNs, there is a need for energy efficiency.

The problem with the methods of node localization has led to poor estimation, transmission, and detection of the network. Localization techniques using nature-inspired approaches such as the salp swarm approach (SSA) and the PSO method make the deployment of WSNs economical for solving node localization and energy efficiency challenges. However, these state-of-the-art algorithms are fraught with issues and there seems to be no solution to these intrinsic WSN challenges of node localization and energy optimization (Gharghan *et al.* 2018; Strumberger *et al.* 2019; Singh, Sharma and Singh 2021). Hence this research work was conducted using experimental simulation to show that the proposed hyper-heuristic scheme will outclass any hybrid heuristic, meta-heuristic, and state-of-the-art perspective in node localization and energy efficiency in WSNs. The accurate localization of these sensor nodes makes monitoring data more meaningful as the sensor can be tracked and located for local information feedback.

The exactness or precision is contrived by integrating their shortfalls and multipaths for measuring the localization algorithm performance (Paul and Sato 2017). In this research project, hyper-heuristic algorithm approaches of Gaussian Elimination Algorithm, Distributed Energy Efficiency Clustering (DEEC), and Gradient Distance Algorithms (GDA) were employed to scale up the poor performance of unknown nodes' coordinates.

Node localization solutions assist the organization of sensors to minimize the overall energy consumption distribution by each network of nodes, utilize data gathering to minimize the number of information messages, reduce the 'hot-spotting' problem and to improve load balancing in the network environment by extending the lifetime of the connection. The overall proposed hyper-heuristic optimization solution will offer solutions to industry-based problems.

1.3 Aim and Objectives

The aim of this research study was to develop effective hyper-heuristic optimization algorithms to efficiently optimize energy efficiency and node localization in WSNs.

Aligned to the aim the following research objectives [ROs] were set:

- **[RO 1]:** Develop novel hyper-heuristic optimisation algorithms for energy efficiency and maximization of node localization for WSNs.

- **[RO 2]**: Implement the novel hyper-heuristic optimization algorithm for energy efficiency in smaller and larger WSNs in a simulation environment.
- **[RO 3]:** Simulate the novel hyper-heuristic optimization algorithm for node localisation in WSNs.
- **[RO 4]:** Analyse the performance of the hyper-heuristic optimisation algorithms with other state-of-the art algorithms using simulations.

1.4 Significance of the Study

The study attempted ground-breaking work in the field of WSNs to contribute to the body of knowledge. The significance of this study was to:

1. **Improve energy efficiency in WSNs**: Energy efficiency optimisation with the hyper-heuristic optimisation algorithm to minimize and optimize the energy efficiency stability within the WSN (up to 100 sensor nodes).
2. **Improve energy efficiency for larger WSNs**: Energy efficiency stability for larger networks (1000-1500 sensor nodes) within the WSN using the hyper-heuristic optimization algorithm to compare the efficiency with the ultra-modern algorithms.
3. **Minimize node localization errors in WSNs:** Node localization effectiveness for probability of error and localization of sensor nodes using 20 anchor nodes and 200 to 450 sensor nodes in WSNs before and after the implementation of the proposed hyper-heuristic optimization scheme.

1.5 Scope and Delimitations of Study

The research work mainly focussed on energy efficiency optimization and the amount of information dispatched to the BS within a time frame using 100 sensor nodes, 1000 sensor nodes to 1500 sensor nodes for energy optimisation efficiency, and we further examined 100 sensor nodes to 450 sensor nodes and 20 anchor nodes for localization error including probability of error (PoE) in comparison to other modernized algorithms. This research work is not associated with routing delimitations, bandwidth demand, QoS, compressing techniques, layering of the sensor nodes, monitoring of different sensor nodes' temperature, monitoring peak performances, and data usage in WSNs.

1.6 Research Output

This research project has produced three publications in approved peer reviewed journals. The details of the publications are specified at the beginning of this thesis. All the publications have detailed reports by peer-reviewers and are available on request. The revised manuscripts after the reviewer's comments are available online.

1.7 Structure of the Thesis

There are seven chapters in this thesis. Each of the individual sections is structured to enable the easy flow of acquired information. A description of the chapters are presented below:

- **Chapter One: Introduction to Study:** This chapter introduces WSNs, explains what they consist of, how they work and various problems identified. The chapter provides the aim, objectives, and node localization as an aspect of deficiencies in WSNs. The purpose of the hyper-heuristic optimisation algorithm approaches and the need to improve node localization for WSNs using a hyper-heuristic optimization algorithm are amplified.

- **Chapter Two: Literature Review:** The critical review covers the relevant works on WSNs, node localization, energy efficiency, nature bio-inspired algorithms, non-nature bio-inspired algorithms, meta-heuristic approach, hybrid-heuristic, and hyper-heuristic approaches. The current problems, and meta-analysis review of heuristic approaches is used to present the established facts and identifies the gaps.

- **Chapter Three: Theoretical Framework and Conceptual Models:** The theoretical framework and the conceptual approach are discussed in this chapter. Design Research, comprising six phases, was the theoretical framework selected for this study. Two conceptual models were derived for this study, namely a hyper-heuristic framework and an emergent model for the development of the proposed hyper-heuristic algorithms.

- **Chapter Four: Research Methodology-A Scientific Approach Using Hyper-Heuristic Models:** The introduction of the Design Research with in-depth knowledge of the hyper-heuristic optimisation approaches are presented as follows:

- **Distributed Energy Efficiency Clustering, Gaussian Elimination-Energy Efficiency – Small Networks:** The proposed model for the energy optimization of smaller networks using mathematical equations, algorithms and pseudocode are presented.
- **Distributed Energy Efficiency Clustering, Gaussian Elimination-Energy Efficiency – Larger Networks:** The proposed model for the energy optimization of larger networks is presented.
- **Distributed Energy Efficiency Clustering, Gaussian Gradient Distance Elimination Algorithm:** The proposed model for node localisation estimation error of 200 to 450 sensor nodes using mathematical equations, algorithms and pseudocode are presented.

■ **Chapter Five: Analysis of Results and Discussion of Novel DEEC-GAUSS Algorithm for Energy Efficiency** The analysis and discussion of the hyper-heuristic approach, and representation with related issues with the analysis of tables of the hyper-heuristic optimization algorithm presented. The table of the analysis, and graphic explanations for the hyper-heuristic optimisation approach are also presented.

■ **Chapter Six: Analysis of Results and Discussion of Novel DEEC GRADIENT DISTANCE ELIMINATION ALGORITHM (DGGDEA) for Node Localization**: Analysis is provided in the form of tables and graphs for the hyper-heuristic optimisation approach.

■ **Chapter Seven: Summary, Conclusions and Significant Contributions:** According to the analysis of the results from Chapter Five and Chapter Six, conclusions are reached, significant contributions are outlined, the areas for further research work are presented for WSNs.

1.8 Chapter Summary

Chapter One of this thesis presented the overview of WSNs, the problems of WSNs, scope, aim, objectives and significance of the research study. The last section of this chapter discusses the research work structure. The next chapter will provide the literature contributions from various scholarly works that have been carried out both locally and internationally.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

In recent times, researchers and experts have demonstrated that wireless sensor networks (WSNs) are becoming more popular in power production and node localization. This chapter presents a broad review of the extant literature available in accredited libraries, namely, IEEE database, Web of Science, Inderscience, Norwegian accredited database, Scopus, IBSS, and a host of other journal papers from scholars' recent studies on node localization and energy efficiency problems in WSNs.

The current chapter is subdivided into 10 sections. The first section presents the introduction and the overview of WSNs, while the second section presents node localization and energy efficiency. Furthermore, the third section presents nature bio-inspired algorithms that have been used by various researchers while the fourth reviews non-nature bio-inspired algorithms. Thereafter, the fifth section reviews power management in WSNs. Sections six, seven, eight and nine review power management in WSNs, cluster head selection, data aggregation and performance metrics, respectively. The final section in this chapter presents the heuristic approaches and Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA). This analysis is important for the selection of the best heuristic approach for the study. This chapter concludes with a chapter summary to sum up the chapter. The major problems associated with WSN are shown below in Figure 2-1.

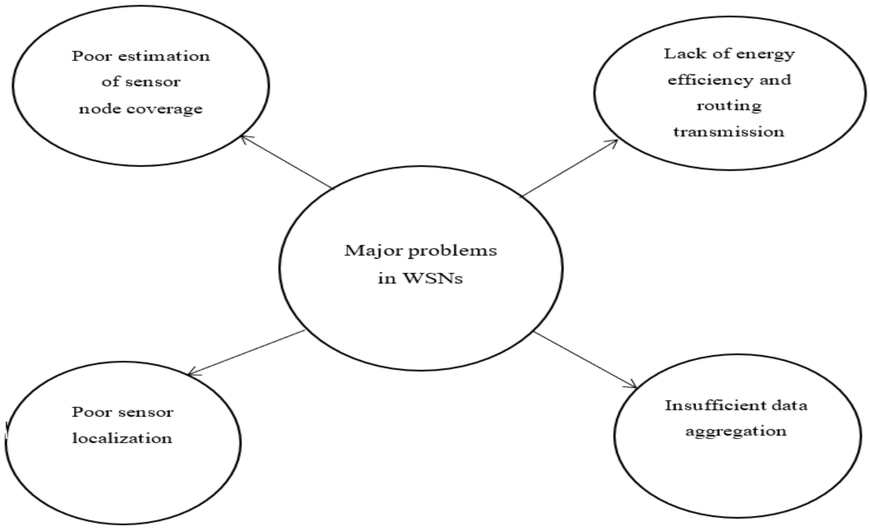

Figure 2-1: Major problems in WSNs
Source: Researcher's own construction

Major problems associated with WSNs as revealed in the extant literature has led to the following, as shown in Figure 2-1:

- Poor estimation of sensor nodes coverage in WSNs (Gouda *et al.* 2021),
- Lack of energy-efficient clustering and transmission of energy routing usage within the network (Farooq 2019),
- A low level of detection of the network operation signals led to poor sensor localization (Kanwar and Kumar 2021), and
- Insufficient calibration of data aggregation for energy accountability due to lack of node localization with unknown accountability (Barcelo-Ordinas *et al.* 2019).

2.2 Wireless Sensor Networks

The burgeoning Internet of Things (IoT) relies heavily on wireless sensor networks (WSNs). Wireless sensor networks have grown in popularity over the last decade, with a number of new applications based on the sensors (Arora and Singh 2017). Wireless sensor networks are a self-configuring linking system made up of large number of small nodes capable of information processing in wireless communication (Yang, Li and Ye 2016; Yong-jun, Shen-fang, and Yuan 2012). Telecommunications, energy firms, health care organizations, data recording, threat detection, landslide supervision and educational institutions are all affected by the WSN's node localization problem (Sun, Dong and Chen 2017).

Wireless sensor networks are becoming apparent in high (advanced) technology and have seen an increase in its utilization (Puri and Bhushan 2019). These have applications in surveillance, environmental sensing, and biosphere monitoring. Recent advances in infrastructure systems have helped connect the world through the smart grid, intelligent networks, smart cities, and intelligent transportation (Shankar *et al.* 2021). According to Guimaraes *et al.* (2018) WSNs are used to monitor the surrounding environment, by sensing the physical elements, deployment topology, dynamic distribution of sensors, and the constraints in bandwidth. Temperature, sound, and pressure sensors are used by WSNs to supervise environmental conditions. Current research has proliferated in the application of WSNs in wide-ranging disciplines.

The knowledge of the smaller nodes is important for the administration of WSN aggregated local information to be meaningfully understood. To detect an optimal critical path of data transmission, the ant colony optimization (ACO) algorithm was proposed for calculating shortest path (Sun, Dong and Chen 2017). Similarly, the elephant herding optimization (EHO) algorithm was deployed in an attempt to reduce the node localization problem in WSN (Strumberger *et al.* 2018a). Also, the flower pollination algorithm (FPA) was often utilized to optimize localization issues in WSNs (Sun, Yu and Wang 2019).

Considering that WSNs have great practical value, different scholars have carried out in-depth investigations on them and one of the emergent key persistent challenges is high energy consumption by node localizations during data transmission. Various techniques have been proposed toward node localization problems. Wireless sensor networks have several weaknesses that affect its implementation such as connectivity detection, time synchronization, acknowledging of data, unknown packets, energy consumption, the nature of administration, and the system security (Alghamdi 2020; Essiet, Sun and Wang 2019; Al-Janabi and Al-Raweshidy 2017). Most of the works cited in literature have looked into proffering alternatives to solve these inefficiencies in WSN but with no concrete resolution on the matter (Hassan *et al.* 2019; Wang *et al.* 2019).

Aircraft are sometimes involved in natural disasters which can be avoided by employing micro sensor node technology in WSNs. The micro sensor nodes might not be able to detect the current locations and the location of all the sensor nodes which leads to an expensive outcome (Bongale, Nirmala and Bongale 2019). Nonetheless, the geolocations which are known as main anchor nodes pinpoint bearings of unknown nodes but require a great deal of energy. The unknown micro node position is approximate to the location from the identified anchor node's locus, and the unknown microsensor node is also tagged as the unknown location (Babayo, Anisi and Ali 2017). The comprehensive achievement of the wireless network is downgraded if one of the micro node locations is delinquent. As a result, erroneous data of anchor sensor node circumference is escalated within the tasks that are performed (Engmann *et al.* 2018; Garimella, Edla and Kuppili 2018).

WSNs comprise of many tiny, randomly deployed low power sensor nodes, that have sensing, communication and processing capabilities (Elshrkawey, Elsherif and Wahed 2018; Sangaiah *et al.* 2019). The circuits of WSNs have been studied extensively, specifically, over the last two decades, and with this significant knowledge of the impact of digital technology across the globe, a few of the outputs have been implemented at a fast pace (Ilyas *et al.* 2015).

Data has been transformed to a set of the characters whose length surpasses the ability of dynamic database software applications and tools to store, manipulate and analyse in the data warehouse (McKinsey 2018). A wireless network is a passage of interconnection, the backbone of the active segmented area of data communication used for carrying out the task of developmental technology in the IoT space (Elisha 2016; Mishra *et al.* 2018). Over the years, there has been a rapid change in the space of IoT that helps to supply users with different data to allow for mobility to other areas of the networks. This wireless technology has improved communication processes in institutional buildings, companies, offices, the health sector, and schools, without having a physical presence and movement. The high-tech equipment installed to enhance the delivery of services consists of telepresence, videoconferencing, voice, and data, transferred in packets (Haseeb *et al.* 2019; Karabiyik and Akkaya 2019). In addition, WSN have key objectives that speak to the latest trends in the IoT paradigm. The evolution of WSN over the previous decade has resulted in a plethora of implementations based on sensors (Arora and Singh 2017). The self-arrangement processes of WSN consist of a multitude of nodes which meet the minimum data processing requirement for communication, as shown in Figure 2-2 (Yuan *et al.* 2017).

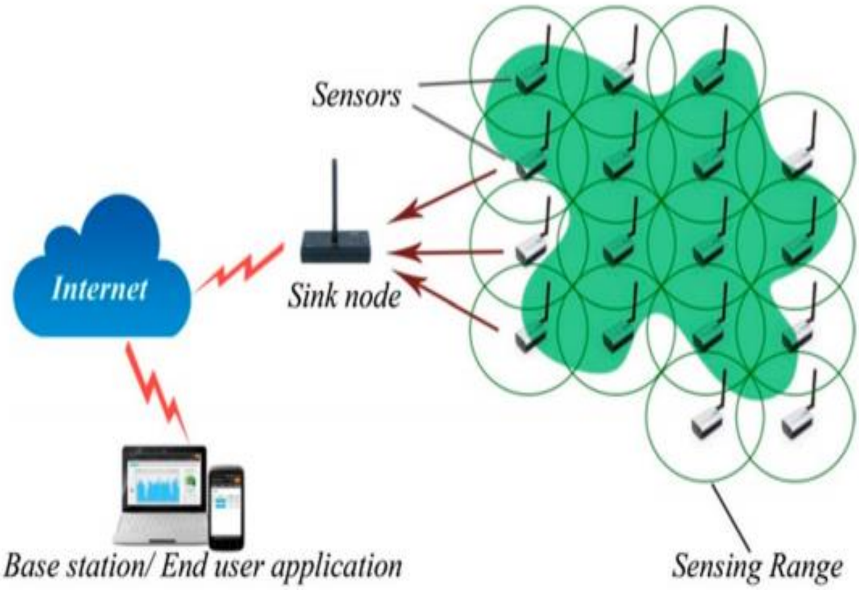

Figure 2-2: Data gathering process in wireless sensor networks
Source: Extracted from Poonguzhali and Ananthamoorthy (2020)

2.2.1 Wireless Sensor Networks Usage and Deployment

Wireless Sensor Networks have countless of usages. These affect the execution of the system including the time synchronization, sending, restriction, nature of the administration work, the cost of directing the implementation and ensuring the security of the implemented project. Different research articles and proposals have introduced some sort of solution to solve the numerous challenges of localization in WSN (Zhang *et al.* 2021). Xia *et al*. (2020) cited the example of an aircraft in an unforeseen natural disaster. Micro sensor nodes were placed throughout the aircraft in a speculative form. These microsensor nodes might identify the aircraft's location and the aircraft might be located because of the advancement of global positioning system (GPS) technology that is deployed (Xia *et al.* 2020).

Micro-sensors with GPS capabilities are called the anchor nodes. Sending out beacons of data by approximating the position of the unknown sensors might require a large quantity of energy to be efficient. These unknown sensors are placed with an estimated value of the distance from the anchor sensors that are tagged as the known (Behera *et al.* 2019). The performance of WSN on node localization becomes a concern when the location is unknown (Bhat et al 2020). Some algorithms and techniques have been developed to increase the energy efficiency by lowering the high communication costs during the test run of a WSN. However, the mathematical models calculated are not extensive during the processes when carrying out the steps involved for setting up the techniques involved in minimizing localization error (Rajakumar *et al.* 2017).

Routing protocols in WSNs are determined by ant colony optimization (ACO) and are categorized into two groups, namely, the run free endurance and extended dependant (Jayekumar and Nagarajan 2018; Patil and Kadam 2018). The typical routing protocols which are used for residual energy and localization are considered for quintessential routing in reducing energy usage when compared to large parts of its routing protocols. Furthermore, combining energy efficiency algorithm and weighting parameter approach helped in solving node localization problem (Han and Zhang 2018; Han, Zhang and Sun 2018).

2.2.2 Wireless Sensor Network Applications

Wireless Sensor Networks are used to monitor temperature, sound, pressure, and the status of the environment. A substantial amount of research has been conducted on WSNs and it is evident that knowledge of the micro sensor in node localization is important for WSN applications (Chen *et al.* 2018). However, with node localization, getting an optimal critical path of data transmission is a significant challenge, therefore, the ACO algorithm was proposed (Sun, Dong and Chen 2017; Mazumdar, Nag and Nandi 2021). FPA with six selected benchmark metrics, namely, accuracy, speed, values, iterations, initial range, and random seeds was utilised in support of energy efficiency and node localization (Pan et. al 2017; Dhanalakshmi, Sai-Ramesh and Selvakumar 2021).

Energy efficiency is a focal research point in WSN applications, as high energy consumption impedes the lifetime of the network. In order to improve the WSN application performance Panneerselvam *et al.* (2020) proposed the arsh-fati cluster head solution method. The EHO approach was designed to address the sensor node localization complication in WSN (Strumberger *et al.* 2018b). However, the FPA strategy was deployed for preventing the localization stumbling block in WSNs (Sun, Yu and Wang 2019). In the period, 2016 to 2021, a number of researchers acknowledged that WSNs experienced problems related to node localization (Alquhayz and Jemmali 2021).

Some WSN challenges are caused by the duplication of data that was transferred within the network. New security systems have been implemented to circumvent the import of data, in a bid to solve the problems of information theft and data redundancy within the WSN operations. One of the benefits of wireless networks is that the geo-location barrier is never a disadvantage with data communication (Kumaresan and Kalyani 2021; Pradeep *et al.* 2021). Information technology infrastructures refer to some form of the latest trends in technology, that is obtained from various sources of information on their applications in their focus areas. Information technology is an electronics technology that is used for collating, processing, and disseminating pieces of information. WSNs are explored for acoustic performances (Williams 2016; Barakabitze *et al.* 2019).

Areas for application of WSN are discussed below: -

Area Monitoring: Wireless Sensor Networks are used for obtaining a bird's eye view of a particular region using a security camera. The military, for example, uses sensor nodes to detect possible intrusions. Some oil and gas organizations use the sensors for geo-fencing of their oil and gas pipelines as well as for close supervision of operations, to avoid breakdowns in the system (Vera-Amaro, Rivero-Ángeles and Luviano-Juárez 2020).

Health Industry Supervision: In this modern technology age, there are various types of wireless sensors used in medical applications such as wearable devices, implanted skin devices, and environment embedded sensors. Implanted devices are those that are transplanted within the human body for tracking purposes, whereas wearable embedded devices are worn on the human skin surface (Zhu, Zou and Zheng 2017). See Figure 2-3 for an example of sensors used in health care.

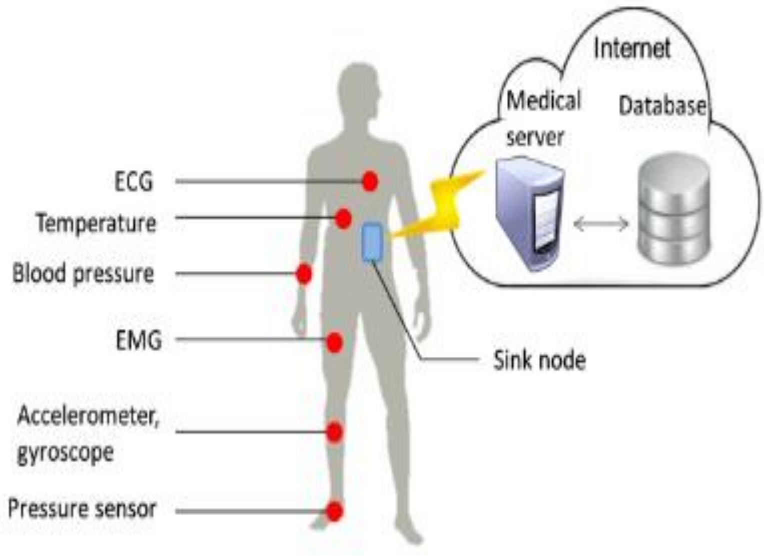

Figure 2-3: Health care body sensors

Source: Extracted from Rault, Bouabdallah and Challal (2019)

Health systems monitoring: It helps to engage the sensors within the environment for the position, location, body measurement and for tracking the location of persons. They are also used to monitor and observe ill patients in medical facilities such as hospitals and in care home environments. These devices are stored in the environment to detect and monitor progress and to compile progression reports on the health diagnostics patients, with the input of data captured from a human motion (Gao *et al*. 2019).

The human body vicinity networks help to generate data to produce a comprehensive health fitness report. The generated data builds up in terms of strength based on the applications installed and agreed to by the patient for privacy and authenticity of patient information. The linking of the sensor and their IoT with patient’s authorization makes medical care and diagnostics easier as it is possible for researchers and doctors to make use of the sensor data collated for usage in the healthcare sectors (Abdulkarem *et al.* 2020).

Earth sensing: These sensor networks help to sense and monitor changes in the environment. They are used to set up energy parameters during the geo-positioning. This reduces power usage between the control room and the use of a micro-electromechanical system (MEMS) to carry out monitoring in real-time (Zhenhua 2016; Wang and Tu 2020).

Air tainting monitoring: WSNs are tools of great importance used in several countries, cities, and towns for monitoring the channel of hazardous gases emitted into the atmosphere. The wireless sensors linking together make them more mobile for carrying out test readings in the environment within a stipulated time frame and are more beneficial than the wired category of sensors that may clutter the environment and are not aesthetically pleasing (Ng 2018; Tiwari 2019).

Forest fire detection: Wireless sensors can be configured and installed in thick forests to detect and monitor fires. These sensor nodes are coded with different mechanisms to assess the humidity, and the levels of gases emitted during a fire. Early detection of a fire outbreak allows for rapid response by firefighters (Kadir, Rosa and Yulianti 2018; O’Mahony, Harris and Murphy 2020).

Landslide detection: Landslide identification mechanism uses sensors to detect the landslide movements of soil that are likely to occur during a landslide. The aggregated information may make it possible to predict when a landslide is likely to occur in the environment (Giri, Ng and Phillips 2018).

Water quality monitoring: This sensor type is for supervision of water properties and analysis from the dams, seas and oceans. The sensor networks are used to enable the setup of the right mapping of the state of water and allow for close monitoring and supervision, especially in areas of constrained physical access (Pule, Yahya and Chuma 2017).

Wastewater monitoring: WSNs help to monitor the quantity of the underground waste water or surface dirty water for the benefit of both animal and human purposes (Poonguzhali and Ananthamoorthy 2020).

Earth disaster deterrence: This sensor networks are successful in predicting natural disasters, such as tsunami's, floods, and fires (Ahmad *et al.* 2018; Khan, Gupta and Gupta 2020).

Data register: The WSNs allow gathering of packets of information and for overseeing environmental data. Data logging and image processing are considered 'kings' in the research space of WSN (Faheem *et al.* 2019). These provide an easy way of gathering data regarding the temperature level of power plants in the register. The amount of information is utilized to display how the program works. The benefit of sensors over nominal data loggers is the real-time information feeds that are evidenced (Renu *et al.* 2017).

Grape production: The WSN sensors are used for close monitoring of wine and grape production in both field and remote areas within the coverage zone. They assist winemakers to effectively supervise and upscale their delivery in an efficient manner (Cravero, Lagos and Espinosa 2018).

Forewarning detection: The WSN aerial tracking systems (WATS) are prototype networks that are used for forewarning of natural hazards that are likely to occur in the WSN. These WATS sensors are deployed into certain positions or stationed on the vehicles for mobile protection within the exact location used by ZigBee sensor devices (Pule, Yahya and Chuma 2017). The examples of WSN applications are shown in Figure 2-4. The synthesized usage of WSN application is classified into different deployment categories. The healthcare system does use WSN for determining the temperature and patient record tracker within the vicinity to save time. The environment and air tainting use WSNs for light detection, fire detection and real time land sliding reading from the remote office. Furthermore, WSNs are used for area monitoring and military transport layer system. The transportation industries use WSNs for collation of data and data logging to ascertain the register update of vehicles. The water and grape systems are deployed for carrying out water right mapping, and level monitoring system. Figure 2-4 below shows the different applications of WSN usage as synthesized from the extant literature.

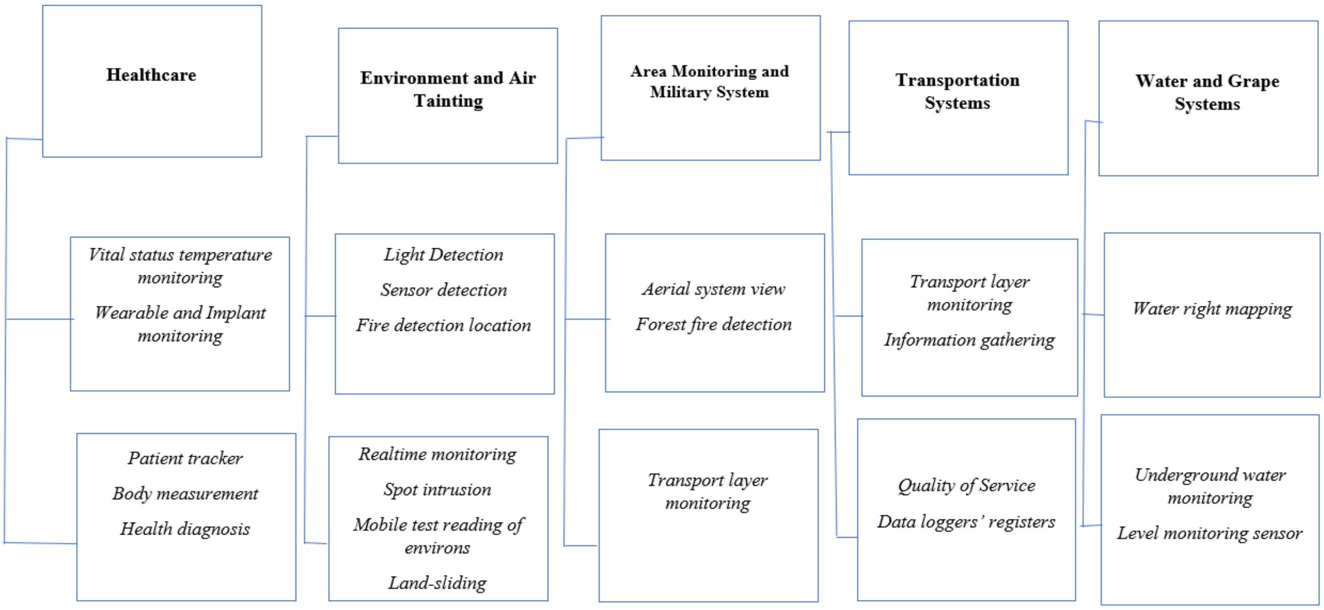

Figure 2-4: The Synthesized Usage of WSN Applications
Source: Researcher's own construction

2.3 Localization

Localization is broadly and extensively used in WSNs to associate the connected locations of the sensor nodes (Sun, Dong and Chen 2017). The WSN node localization is used in industries such as energy corporations, telecommunications, and care homes. The pathway of the wireless caged sensors has been signalling routes over the last few years, and some results have enabled the continuous growth of the devices in WSNs (Ilyas *et al.* 2015). Information whose capacity is far beyond the preparedness of the archetype database software applications for capturing, storing, managing large volumes of data for accuracy when localization is involved (McKinsey 2018).

Different approaches are used to effectively manage costs, while maximizing power. While these are mathematically applied in the 21st century, most of these procedures are not commonly used in the established form of WSNs (Rajakumar *et al.* 2017). In the literature the swarm intelligence approach was developed to feature new shift such as scalability, speed, adaptation, parallelism, autonomy, and fault tolerance in WSNs (Kassabalidis et al. 2019). There are two categories of localization techniques. The first being the range free localization approach which is used for identifying distance between two sensor nodes and the second technique is application-based which is applied to identify vital localization information in WSNs (Nemer et al. 2021).

Notably, the essence of localization is to direct and establish the location of sensor nodes which is an area that research work has focused on in recent times and it is desirable for the low-cost, scalable, and efficient mechanisms used in WSN. Localization techniques using non-nature-inspired algorithms such as ACO algorithm, PSO algorithm, and gradient distance algorithm make the deployment of WSNs economical. This is one of the major reasons why optimization is necessary, because the node localization problem affects the performance of WSNs (Shen *et al.* 2018; Tuba, Tuba and Beko 2018; Kulkarni, Desai and Kulkarni 2019; Lee and Lee 2021; Lu *et al.* 2021).

Localization within the WSN is the focal point within virtually every sector that makes use of its deployment. Localization is key in the IoT space for gradient distance approach measurements. There has been a recent trend in WSN techniques that are used for location gathering of information that comprises of different anchor nodes for evaluation of error estimation, probability of error as suggested by researchers by using gradient distance approach. The gradient distance approach were also explored by researchers for multi-dimensional scaling and weighting scaling. Some of the major functionalities are, decomposition of distance measure algorithms, Receive Signal Strength Indicator (RSSI), individual-DEEC, and PSO localization (Lan and Wei 2017; Nehra, Sharma and Tripathi 2020;

Xia *et al.* 2020; Zhang *et al.* 2021).

2.3.1 Node Localization in WSNs

In general, localization is mainly codified into two separate classes which are range-free and range-based techniques to estimate an unknown location of sensor nodes by figuring out how far two or more sensor nodes are apart through self-arrangement. The nodes create a network that includes time similarity of arrival, the angle of arrival, the signal strength, and the time of entry (Sharma and Kumar 2018). A WSN can retrieve, aggregate data before sending it to the supervised packet stages in the synergizing the location of sensors (Najeh, Sassi and Liouane 2018; Prashar *et al.* 2021).

The WSN's sensor nodes are fuelled by an energy source that is unsuitable for this application. The lifespan of the sensor nodes relies on the time span of the charged power bank. Unrestricted power usage will make the network operation depreciate preterm and minimize the connection lifetime (Roselin, Latha and Benitta 2017). The power utilization of sensor nodes is unknown, making node localization a complex WSN problem. Node localization problems in detecting changes in sea conditions were experienced in WSNs (Rajakumar *et al.* 2017). In 2004, 228 000 people lost their lives in the Indian Ocean tsunami. This possibly could have been preventable.

Node localization is important to many applications of WSNs that are usually set up by organizing different types of sensors in an ad-hoc form. These nodes are intellective regarding the physical features of the world. The sensors used have different properties, depending on their application and are used to detect sound, light, temperature, and pollution. Base stations are responsible for guiding queries, for the collection of data from various nodes and for forwarding them to the server (Kennedy and Eberhart 2019). Node localization algorithms are generally used for combining the location of nodes in WSNs and a typical display of how node localization error and identification of unknown location accuracy works is displayed in Figure 2-5.

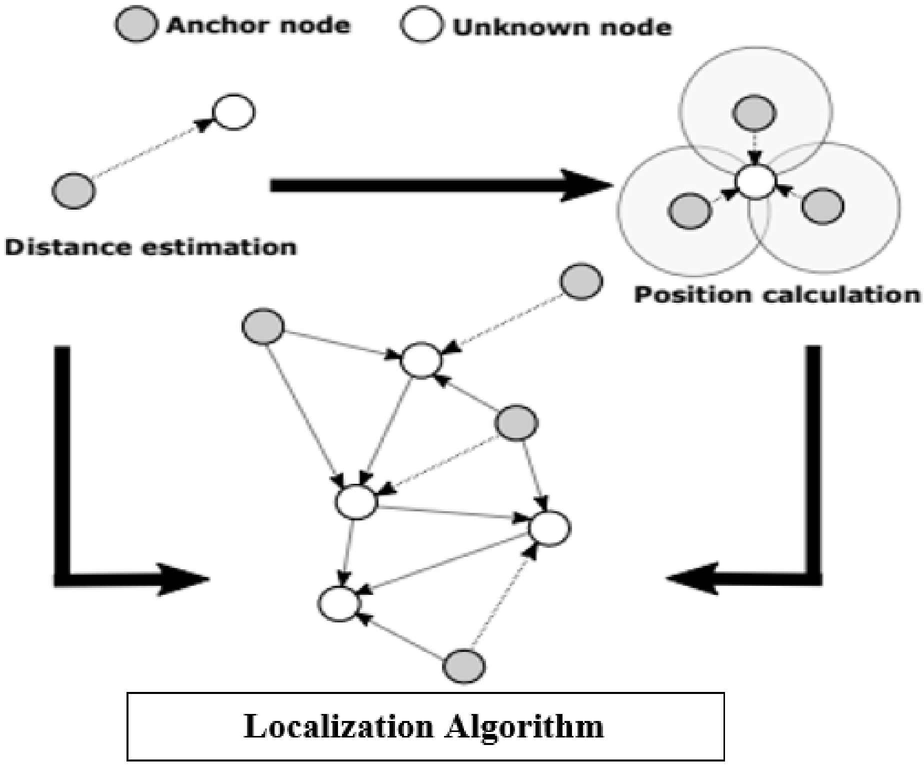

Figure 2-5: Node Localization Algorithm
Source: Extracted from Singh, Sharma and Singh (2021)

As shown in Figure 2-6 below, there have been various problems surrounding node localization. It is of great importance for the security of the data to detect the location of sensor nodes which are unknown. Malicious sensor nodes have been sent to attack or threaten the network which has brought setbacks in the form of link failures, resulting in a lack of smooth back-and-forth communication. The grey wolf ant lion re-occurrence (GWALR) model was developed to enable easy identification of the unknown locations and the mean error to scale up the location accuracy (Sruthi and Sahadevaiah 2021). The malicious node helped to spot the difference between the known and unknown nodes operation in WSNs.

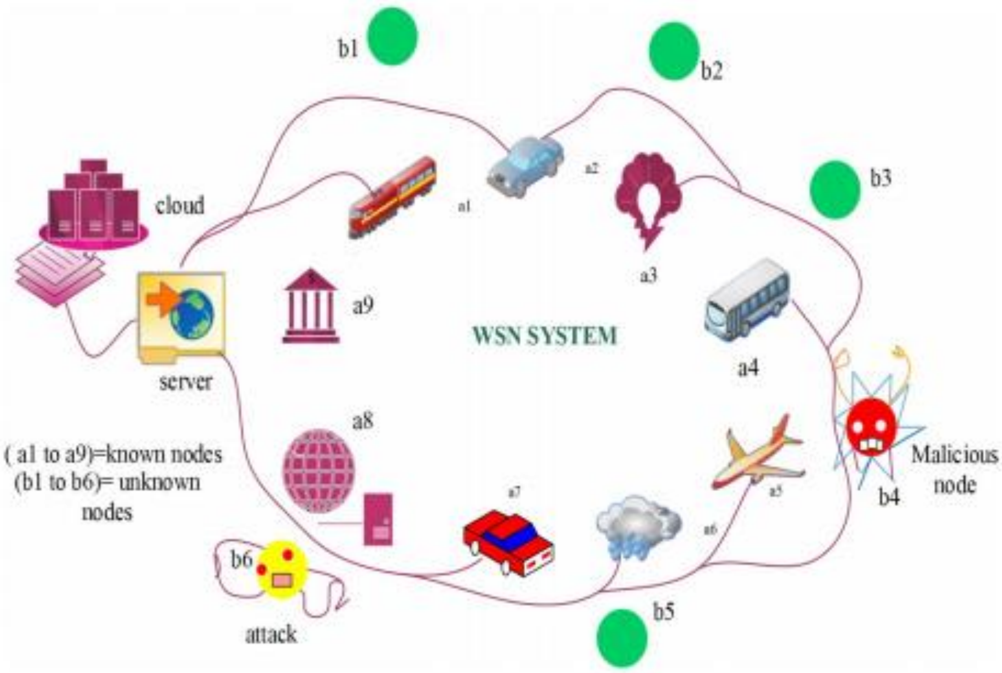

Figure 2-6: Node Localization WSN System Problem
Source: Extracted from Sruthi and Sahadevaiah (2021)

2.3.2 Energy Efficiency

Energy optimization is one critical deficiency along with poor quality of service and security in WSN. The use of an optimizer was suggested to improve the power maintenance (Singh, Sharma and Singh 2021). Energy is critical for the socio-economic growth of many countries across the globe and energy efficiency is central in this regard for optimization of the cost of hybrid renewable power generation, using spider prey techniques (Frimpong *et al.* 2020). The energy efficiency relies on the node estimation cooperation that is employed for transmission of its power utilization and reliability efficiency, relating to the provision of reliable implementation strategies for WSNs (Tan 2020).

Clustering in WSNs results in energy efficiency, which helps to minimize the usage and extend the network lifespan (Hassan *et al.* 2019; Manikandan and Chinnadurai 2021). According to Singh *et al.* (2016) energy efficiency helped to extend the life cycle of WSN. There are various energy efficiency approaches in WSNs, such as T-LEACH, TEEN, APTEEN, HEED and PEGASIS (Naz *et al.* 2018; Srikanth and Prasad 2018).

The purpose of hyper-heuristic focus is to automate the adaptation and construction of heuristic medium, to tackle the challenges of computational search issues (Aroba, Naicker and Adeliyi

2021b). According to Meng *et al.* (2020), unmanned aerial vehicles (UAV) use a 3D localization method to locate these GPS-equipped UAVs. The UAV's static position was on a non-line of sight (NLOS), and the results enhanced positioning accuracy and coverage. There are two types of localization processes such as outdoor and indoor instruments (Mozamir *et al.* 2020). In WSN, the exterior bound allotted in node distribution (EBAN) and DEEC method, as well as computational and power heterogeneity were investigated, and link were used with energy m=0.15, which was 50% more than similar sensor nodes and improved the various transmission from the cluster head (CH) and sink node (Prakash, Mishra and Kushwaha 2020).

The low energy adaptive clustering hierarchy (LEACH) is supposed to give a hierarchical gathering set of rules for WSNs, with DEEC being assumed to become a clustering-based protocol that is rotated when their positions have been slightly distributed after the energy capacity of the sensor nodes that are within the various networks have been utilized (Elbhiri *et al.* 2010). PEGASIS is a collection of techniques aimed for avoiding clustering and instead uses a simple node to transmit data via a BS as opposed to a series of sensor nodes performance stable election protocols, which rely on the stochastic degree of detection to extend the communal lifetimes (Sharma 2020).

Poluru *et al.* (2020) investigated energy adaptive distributed energy-efficiency clustering (EADEEC) for connection scalability and sensor node lifespan in WSN, and recommended an extensive operational performance period. Nehra, Sharma and Tripathi (2020) proposed a method that improves the distance between BSs and distribution network nodes to account for the use of energy efficiency clustering between two-fold schema of normal and advanced hexagons and its environmental radius. Invariably, the addition of the distance to node lifetime and energy residual was calculated, with the probability of nodes that are being nominated as the cluster heads for DEEC revamps rate, and percentage covered by the area within the network lifetime-model.

There have been different energy efficiency mechanisms that speak to the localization of sensor nodes. The hyper-heuristic category comprises of high value approaches that are combined with optimization solutions in WSNs (Cowling, Kendall and Soubeiga 2002; Burke *et al.* 2010; Hudson *et al.* 2011; Burke and Qu 2019; Qu and Burke 2019). Hyper heuristics are used for information processing amalgamation approaches that are grouped as probabilistic, reasoning, and knowledge-based methods for data gathering and its statistical model was utilized a fairly recently for performance preservation of data outlier identifications (Babayo, Anisi and Ali 2017; Krishnamurthi *et al.* 2020).

Hyper-heuristics are deployed to resolve mathematical search deficiencies, hence systematic reviews on meta-analysis depict the hyper-heuristic method as the most suitable for optimizing the localization of nodes and energy maximization challenges, resulting in an increase in the WSN's performance (Burke and Qu 2019). However, the use of meta-heuristic and hybrid heuristics does not imply that they are efficient. There is evidence to the notion that the hyper-heuristic methods outperform the meta-heuristic with hybrid heuristic methods in maximizing their localization of nodes and energy utilization situations in WSNs (Aroba *et al.* 2020).

2.3.2.1 Energy Lifetime Coverage

To maximise the coverage and prolong the network lifetime the particle swarm optimization (PSO) with differential evolution (DE) algorithms were investigated to solve the clustering obstacles in a WSN (Sujatha and Siddappa 2017; Sujatha and Siddappa 2018). The DE algorithm was presented in Xu *et al.* (2018) and Cespedes-Mota et al. (2018) for scenarios in which the amount of data exchanged was unknown. The multi-objective DE perspective was used to optimize the distribution of sensors across different zones within the locations while also increasing coverage to reduce network energy (Cespedes-Mota *et al.* 2018). The PSO is one of the nature-inspired methods that is universally applicable to focus on ambiguous optimization challenges ***(***Cui *et al.* 2018***).***

A hybrid approach based on the combination of PSO with any other algorithm for transition movement was suggested to generate the greatest quantity of unmatched sets for energy maximization in WSN lifespan (Panag and Dhillon 2018). In other words, the DE algorithm was used as an alternative to look into path optimization inefficiencies of energy lifetime coverage in WSNs to obtain the optimal routing path protocols while consuming the least amount of energy (Wan, Weng and Liu 2019).

Prior studies from the works of literature, show that the modified Genetic Algorithm (GA) based on low energy adaptive clustering hierarchy (LEACH) reduce power usage and extend the connected lifespan of the energy harvesting wireless sensor networks (EH-WSNs) (Darji and Shah 2016). A GA algorithm built on self-organizing network of clustering medium was introduced to optimize energy efficiency by reducing the network life between sensor node in WSN (Yuan *et al.* 2017).

Wang, Zhan and Zhang (2018) used the distributed genetic algorithm to emphasize that a disbursed GA solves energy-optimized coverage issues in WSN, while Hamidouche, Aliouat and Gueroui (2018) suggested the distributed GA provides an alternative to energy effectiveness coverage problems in WSNs. On the other hand, a bio-inspired algorithm, used swarm behaviour, such as, the approach based on birds and fish, for adaptation to make decisions based on particle position over time (Raychaudhuri and De 2020).

Hamidouche, Aliouat and Gueroui (2018) proposed a GA-based strategy for clustering and routing to improve service speed and quality while also extending node connection lifespan (Panag and Dhillon 2018). Simple GA was proposed for improving network lifetime and reducing energy depletion in WSNs. The application of a simple PSOs further helped in optimizing energy efficiency, hence maximizing the data transmission rate in WSN (Singh and Sharma 2021). There is a probability increment in the lifespan of the connection. Singh and Sharma (2019) used the PSO approach to test a new energy-efficient clustering strategy for WSN that extends the network's life cycle.

Singh and Sharma (2019) presented an approach to high-energy usage for nodes that serves as the CH. Sensor nodes are formed to generate clusters by putting them in a uniform pattern. They endeavoured to optimize and improve the situation of node energy consumption by simultaneously maximizing data transmission. The primary similarity between these approaches and previous works is the use of PSO to select the optimal nodes as CHs. Thus, Singh and Sharma (2019) demonstrated the goal of increasing the network's lifetime. Similarly, despite decades of research, load balancing is a medium for coordinating energy utilization and the rate of energy consumption.

According to Shivapur, Kanakaraddi and Chikaraddi (2015), energy consumption should be reduced to increase the network's lifetime. Cluster heads or gateways in cluster based WSNs execute tasks such data collecting from member nodes, data aggregation, and data exchange with the base station. As a result, load balancing of gateways in WSNs is one of the most important and difficult tasks for maximizing network longevity. A shuffling frog leaping algorithm (SFLA) was enhanced to handle this problem by appropriately adjusting the frog's population generation and offspring generation phases in SFLA, as well as incorporating a transfer phase (Garimella, Edla and Kuppili 2018).

The dispersed approach entailed clustering the LEACH and leaving the sensor nodes on their own, with no central point to control them. Amongst the algorithms included in LEACH, schema routing is regarded as preferred, and these chips are clustering routers that are linked to the pivoted node and allow signal strength to be deduced (Moorthi and Thiagarajan 2020). However, there was a need for a change in CHs at a scattered level which was possible to break down the dissipation of energy nodes. The CHs accomplishes this balancing by selecting a node with any choice of number from 0 and 1. For the current round, each node is given a CH, which performs the task of determining whether the number of nodes is less than the threshold (Moorthi and Thiagarajan 2020).

Subsequently, LEACH entails partitioning the nodes into several clusters, with each node utilizing a CH as well as certain common nodes as its members. The CHs perform rotation-based functions for a set period, contacting other nodes at each round and this ensures an equal distribution of rounds and, as a result, an equally distributed energy usage within the network connection (Khalid *et al.* 2017). One significant disadvantage of LEACH is that it cannot be used in larger-scale networks as the network's lifetime is reduced. This is because the LEACH CHs impair communication with the distant BS, requiring greater power for data transmission (Yadav and Mishra 2021).

LEACH has the capability of implementing a randomized cluster head rotation across the network. As a result, less energy is used during transmission when LEACH selects a specific CH. Furthermore, the CHs may have various initial energy requirements, could form a single network that comprises of basic energy criteria (Kiani and Seyyedabbasi 2018). Li *et al.* (2015) discussed the design of the distributed protocols' routing that aid in the reduction of energy use, the routing, scheduling, formed assignment, and power management concerns in multi-power level for WSN. To improve the scheduling approach, the modified time division multiple access (TDMA) method was used for clustering aggregation on behalf of the sensor nodes with usual power diminishing and consumption to minimize the dissipation of energy usage (Elshrkawey, Elsherif and Wahed 2018). A seminal study employed by Roselin, Latha and Benitta (2017), explored the use of energy-efficient approach to communicate across the coverage scheduling lifespan of WSN operations execution time**.**

Swarm intelligence has the advantage of ensuring the stability and adaptability of the environment, which is beneficial when applied to the energy optimization of WSN (Kennedy and Eberhart 2019). Furthermore, PSO – which was bio-inspired by other social behaviours of birds – has become one of the most extensively used optimization approaches, having been used to investigate variety of optimization issues. Pang *et al.* (2018) and Wang *et al.* (2019) proposed the PSO approach to minimize the error of locations and perform better on the accuracy of the environment to avoid energy loop-holes that are closer to the cluster. This is usually affected by the load balancing stress when forwarding in the networks. WSNs have different concentration from the focal points of operation. Zhang *et al.* (2018a) introduced a novel hidden confusion-based data-gathering technique that reduces information traffic and energy usage in WSNs while maintaining privacy. In today's technology-driven society, it was unavoidable. It was used to address the rising issue of energy efficiency to provide effective services (Sahoo *et al.* 2019).

According to Priyadarshini and Sivakumar (2019), delivering a proportion of load balancing in sensor nodes to various territories such as high-density environments, timber, and undersea, the sensor field of energy consumption maximization is allocated to the network lifespan and sensing coverage area. Considering an alternative solution by Zhao *et al.* (2019), load balancing strategies based on immune cloned power control selection of sensor energy consumption were utilized to display a variety of suitable energy frequencies to aid the apex nodes in combining a relay step to eliminate the power hole difficulties.

A number of researchers attempted to incorporate main and on a multi-heterogeneous network parameter in order to extend the network's life even further (Anuradha and Srivatsa 2019). Several WSN limitations and solutions for minimizing data redundancy among the communicating criteria were used to obtain the intended outcome for energy effectiveness (Bhola, Soni and Cheema 2019; Srivastava, Tripathi and Singh 2019).

Clustering has been influenced by several factors, including cluster count, cluster head density, size selection and the various evaluations of existing techniques on non-probabilistic and probabilistic qualities. Clustering approaches help the communication between CHs to BS through both indirect and direct routes. The number of sensor nodes, the intended use of application and energy usage sequence scenarios were able to determine the clustering approach (Mohapatra *et al.* 2020b, Mehrani *et al.* 2010; Kumar *et al.* 2019; Gayen *et al.* 2020;

Kumar, Edalatpanah and Mohapatra 2020; Kumar, Jha and Singh 2020; Mohapatra *et al.* 2020a; Mohapatra *et al.* 2020c). The method of innovative design approach of clustering deployment for independent heterogeneous WSNs were discovered with the help of clustering medium deployment for citing clustering modelling variations with different node characteristics. The power management was improvised, and the nodes lifespan was enhanced (Tay and Senturk 2021).

A corresponding referral was suggested for a future project to prolong the archetype design to the BS using a genetic algorithm and cuckoo filtering method for high efficiency (Rahiminasab *et al.* 2020). This is considering the clustering split processes (CSP) algorithm and their analytical hierarchical process (AHP) approach to provide a suitable medium to the clustering problem by extension of the connection agedness for better optimal gathering than the BS controlled dynamic clusters protocols algorithm. This aids in energy reduction of nearly 5% compared to the BS controlled dynamic clustering procedures algorithm. Furthermore, it is suggested that future work looks into distance management, the control system, and the subway stations mechanism (Alghamdi 2020).

According to Kaur and Sharma (2020), to increase energy efficiency in WSNs, distributed power-efficiency clustering protocols were used during data processing operations. To improve the rate at which packets are carried to the BS, the DEEC is utilized to select a multi-cluster head at one round rather than a single CH per round (Dhiman, Kumar and Sharma 2020). The analysis, design routing and procedures on energy maximization in comparison to shifting sensor nodes are optimum in power scale. Thus, the use of three varieties of sensor nodes, namely; advanced, normal and super have more opportunity than others to become the CHs at the first round of operation in WSNs (Kumar and Patle 2020).

DEEC considers the average sensor node energy and CH residual energy and their alternative routes to reduce energy expenditure between the BS and the sensor nodes. The improved enhanced distributed energy efficiency clustering (iE-DEEC) showed better performance in energy reduction when compared to DEEC (Jibreel 2019). There is data modification that changes the environment of WSNs when the network's power depletion is at its peak. This shortens the network's lifetime, which is why a gateway election protocol was proposed using iE-DEEC within the network to reduce energy utilisation (Jibreel, Daabo and Gbolagade 2020).

A PSO-based energy maximization method was introduced by Gao *et al.* (2019) and Janarthanan and Kumar (2019) to increase data flow using rechargeable batteries in the WSN. Localization-Based Evolutionary Routing (LOBER) was used by Wang *et al.* (2018) to improve energy efficiency aggregation in sensor node for data gathering systems. Different viewpoints such as optimizing distance communication, cut-off value, and mobile sink innovation for communication ranges in the WSN were explored (Janarthanan and Kumar 2019). Wang *et al.* (2020) noted that the PEGASIS approach and the Hamilton loop were used to balance and remit total network resource overheads.

The approach of optimal analysis of multi-path appropriate scheme in conjunction with surplus mobile sinks was suggested by Mostafaei and Obaidat (2018) to assist sensors in transferring and monitoring data from source to sink via multiple communication channels, while the distributed efficient algorithms in WSNs were to self-protect the distributed learning process of automation (Mostafaei *et al.* 2015).

2.4 Nature Bio-Inspired Algorithms

Over time, nature bio-inspired algorithms have proven to be an effective medium to tackle the problem of WSN deficiencies. A bio-inspired method is an approach propagated by the biological evolution in nature and are useful for large-scale connections. The nature bio-inspired algorithms are used for the maximization of solutions for locating the best possible solution among all possible alternatives. Examples of bio-inspired algorithms include the genetic algorithm (GA), nature-inspired algorithms, firefly algorithm (FFA), ant colony optimization (ACO) algorithm and particle swarm optimization (PSO) algorithm (Lv *et al.* 2020; Raychaudhuri and De 2020). The three major areas that nature bio inspired algorithms addresses are security management, energy maximization and service quality. Nature bio-mimetic techniques were proposed to augment developmental methods. Biological traits of several natural occurrences are evidenced of the latest trend in meta-heuristic approaches (Mahapatra, Payal and Chopra 2020).

There has been some essence for meta-heuristic algorithms in terms of exploring some medium of trial-and-error methods. Meta-heuristics has contributed positively to the success of complex scheduling problems, space allocation problems and clustering problems because it has four advantages which are flexibility, simplicity, optimisation and clustering management (Zehra *et* *al.* 2021). Furthermore, the advantages of bio-inspired algorithms are that they are adaptive, dynamic, highly scalable, and flexible in terms of decision making. The disadvantages are that they result in an increase in overheads, inefficient data that are high in the initial stage of the algorithm deployment (Nunoo-Mensah, Boateng and Gadze 2018).

Most of the meta-heuristic approaches are classified as nature-inspired methods or sometimes researchers call them intelligent optimization approaches. Nature-inspired meta-heuristic algorithms are further broken down into different categories such as evolutionary, bio-inspired-plant-based, and swarm-based mechanisms such as flies, ants, bees, and different species of fish, with a depiction provided in Figure 2-7 (Tao, Laili and Zhang 2015; Zhang and Dong 2019; Aroba, Naicker and Adeliyi 2021b).

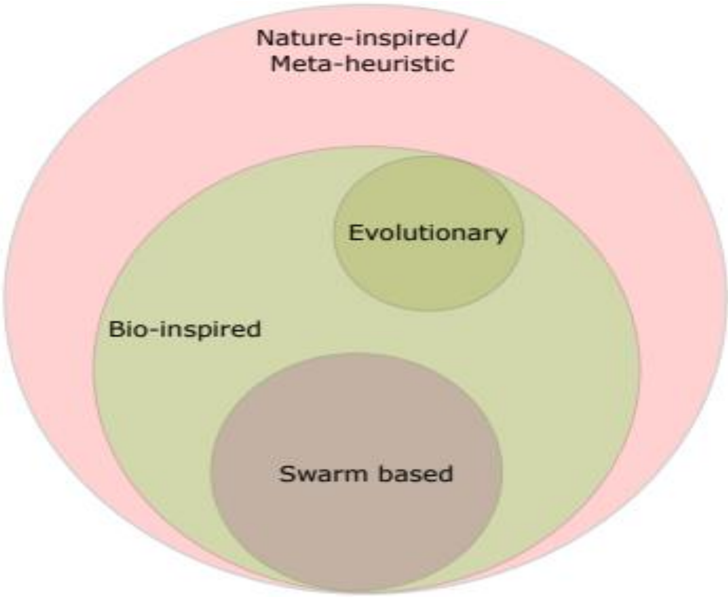

Figure 2-7: Nature Bio-Inspired Algorithms
Source: Extracted from Singh, Sharma and Singh (2021)

2.4.1 Firefly Algorithm (FFA) Application

These are nature-inspired approaches that are in the meta-heuristics category that display the behaviour of social fireflies that are found in tropical environments. The majority of them show rhythmic flashes of bioluminescence. Virtually all fireflies are thought to be unisex and they are usually attracted to each other for mating (Shahbaz, Barati and Barati 2021). Fireflies give birth to young with different combinations of patterns of flashes and light channels that are used in communicating and for carrying out their search for mating partnerships (Yogarajan and Revathi 2018).

The majority of FFAs are used to create short, rhythmic flashes with varying flashing characteristics in the application of FFA. These fireflies use these flashes to communicate to catch prey. It assists to mimic the social characteristics of fireflies that are located in tropical regions. The FFA is a simple objective-based function technique that helps to produce effective output when dealing with non-linear dynamic optimization problems, with few limitations of a nature algorithm (Pakdel and Fotohi 2021).

The FFA produces several types of flashing patterns for communication. It helps fireflies to adjust to their optional brightness when they are searching for prey. Fireflies do fly with minimal brightness that will drive towards their class of beetles to open brightness opportunities during their search for food (Wohwe Sambo *et al.* 2019). In its calculated business objective function, the attraction is formulated based on a light intensity. The FFA is a powerful approach for a local search mechanism and helps in reducing variable storing memory and running consumption time. It also helps to get an accurate convergence rate and comparison rate. The FFA provides an effective way of using limited memory. In WSNs the FFA assists in communication from node to node by memorising directional paths similar to nature-inspired processes such as self-pollination and cross-pollination (Vishal and Ramesh Babu 2019).

The FFA uses an optimization technique to check if various degrees of attraction are directly proportional to the sharpness of light and speed for optimal solution. However, FFA typically use their darkness state to reduce their speed, because cross pollination exerts more energy from them (Dey 2020). In like manner, the light intensity of the fireflies is summed up by their values of functionality relating to the problems of darkness (Yang and Zhao 2020). The disadvantage of the FFA is having more control variables, requires proper setting of dependent parameters, and having a huge number of multimodal problems (Fotohi and Firoozi 2020).

2.4.2 Particle Swarm Optimization (PSO) Algorithm

The PSO algorithm is a set optimisation technique with a combination of local and global methods. They are popular algorithms that represent the social characteristics of flocks of birds and shoals of fish when locating a place with sufficient food (Wohwe Sambo *et al.* 2019, Sujatha and Siddappa 2017). Swarms coordinate their behaviour and determine their local movement pattern without any decentralized control system (Xia *et al.* 2020).

The PSO algorithm searches for a solution that optimizes particle intelligence, which is an alternative reiterative routine called the possible best value (Jari and Avokh 2021). In the entire population swarm particles are deployed for multidimensional search for determining the behaviour of flocks (Javadpour *et al.* 2018). Particle swarm optimization is a debatable, theoretical number-based meta-heuristic inspired by nature intelligence that uses a global best method (Gbest). The local alternate method (Lbest), presents a topology pattern of behaviour associated with this alternate swarm nature intelligence pattern (Yadav, Kumar and Vijendra 2018).

The particle swarm optimization (PSO) is an originator computational intelligence medium that is deployed for population-based optimization. It is one of the major, powerful algorithms used for optimization, consisting of a set of individual search algorithm for populations that are in search of space with arbitrary locations (Edla, Kongara and Cheruku 2019). An individual in a species swarm comprises three trajectories, with a dimension that is the same as that of the identified gap. To interchange experience between the particles, based on neighbourhood topology, two different forms of PSO can be used (Kaswan, Singh and Jana 2018). The neighbourhood of the particle comprises the inhabitants in the global version of the algorithm.

The PSO algorithm was successfully put together for continual enhancement issues. The PSO algorithm was used for calculating the lowest cost, identifying node localization positioning, which helps to overcome obstacle and terrain irregularities (Jabeur *et al.* 2020). The central repository of PSO helps to minimize optimal coverage and optimal loopholes in the WSN and aids optimal deployment (Cao, Liu and Xu 2021; Lu *et al.* 2021; Umamaheswari 2021). The PSO energy-efficiency and clustering and routing were highlighted as being a better option compared to the LEACH algorithm (Aroba, Naicker and Adeliyi 2021b; Devika, Ramesh and Karegowda 2021; Jari and Avokh 2021). Data aggregation was implemented to secure the authentication and access control (Chang and Liu 2021; Dou, Chen and Long 2021; Roslin and Daniel 2021).

Sensor localization approaches are shown in Table 2-1 displayed on WSN problems (Prashar and Jha 2021; Singh and Mittal 2021).

Table 2-1: The Summary of the PSO Solution in WSNs

PSO WSN Problem Focus	Authors	PSO Solutions
• Minimizing localization error. • Solving range-based localization. • The deployment of PSO for foraging. • Search for unknown locations of sensors. • Compared performance of simple PSO.	Edla, Kongara and Cheruku (2019); Kulkarni, Desai and Kulkarni (2019); Wang and Tu (2020); Prashar and Jha (2021); Singh and Mittal (2021)	Sensor Localization
• The behaviour of ants to solve optimal challenges. • The application of maritime surveillance with the use of numbering PSO. • To minimize optimal coverage. • Ensure maximum lifespan with an alternative with the use of PSO.	Fu *et al.* (2018); Ng (2018); Guleria and Verma (2019); Cao, Liu and Xu (2021)	Optimal Coverage
• Improvement on the QoS • The use of PSO for optimization. • Optimal loopholes for energy efficiency • Shortest path to energy efficiency	Li, Keegan and Mtenzi (2018b); Aroba, Naicker and Adeliyi (2021b); Devika, Ramesh and Karegowda (2021) Jari and Avokh (2021); Umamaheswari (2021)	Energy Efficiency Clustering and Routing
• Lack of data accuracy • Constrained data probability and fusion error. • Authentication and access control.	Roselin, Latha and Benitta (2017); Daneshvar, Mohajer and Mazinani (2019); Jabeur *et al.* (2020); Chang and Liu (2021)	Data Aggregation

2.4.3 Grey Wolf Optimization (GWO) Algorithm

The GWO method uses a wide range of related problems to cover the different categories. There are numerous wolf algorithms which are encouraged by the communal behaviour of grey wolves and are based on their leader-based hunting strategy techniques (Mirjalili and Lewis 2016). However, the GWO approach has never been deployed to solve WSN localization issues.

The GWO algorithms are part of the meta-heuristic approach that is used frequently in engineering applications with the following properties: (i) smooth ideas used for implementation; (ii) they do not need gradient data; (iii) they can divert domestic optimization;

(iv) they are always used within a wide range of problems by giving them different tasks. Most algorithms are deployed with alternative combinations of optimization challenges. The GWO is amongst the newest algorithms proposed in recent times for solving scheduling cases (Mirjalili and Lewis 2016). The GWO algorithms are used to initialize particles, calculate the generation of particles, determine the position of particles and the best possible solution (Daneshvar, Mohajer and Mazinani 2019).

Specifically, this GWO algorithm is based on the social characteristics of wolves. Grey wolves are grouped into four types related to hunting techniques, namely, alpha, beta, delta and omega (Lipare, Edla and Kuppili 2019). The alpha wolves are the dominant categories of wolves considered the leaders of the four groups (Rathore *et al.* 2020). In comparison, the beta class of wolves occupies the second level of hierarchy in the pack, immediately below the uppermost category of the alpha (Kaushik, Indu and Gupta 2019). The GWO algorithms comprise of two major types of techniques which are alpha and beta wolves', where the beta wolves assist in decision-making processes and the alpha wolves play the key role. The GWO have unique rights to decide whether alpha wolves can hunt without using the hunting techniques when compared to beta wolves (Hu and Cao 2010).

The delta class wolves are next in the hierarchical structure and are also classified as supporting wolves. These delta wolves belong to the high-class categories of caretakers, hunters, sentinels, and scouts and the delta wolves do adhere to laid down instruction (Faris *et al.* 2018). The omega wolves form the lowest category, and they follow the instructions of the other three wolf classes (Faris *et al.* 2018). In summary, GWO classes are meta-heuristic in optimizing technology, where the alpha is the first batch of the GWO classes that are used in decision-making processes in the WSN, while beta assists alpha in decision making, delta, and omega provide minor contributions in the decision-making process of the WSN (Faris *et al.* 2018).

2.4.4 Differential Evolution (DE) Algorithm

The DE algorithm is a bio-inspired algorithm that contains non-deterministic polynomial individual and N dimensions available in each N-dimension vector (Mohamed and Suganthan 2018). The DE algorithm is a number based meta-heuristic optimization that is used for evolutionary procedures that have no probability basis with regards to their underlying problems (Sujatha and Siddappa 2017). According to Georgioudakis and Plevris (2020), DEs are deployed to achieve a quick solution and multimodal objectives, as they help to handle complex evolutionary problems compared to other existing algorithms. The DE algorithm is usually used for load balancing and user comfort when optimizing electricity usage criteria (Essiet, Sun and Wang 2019).

2.4.5 Flower Pollination Algorithm (FPA)

This is a new algorithm used for population-based intelligent optimization algorithms because it achieves a balance between exploring and exploiting parameter processes. (Pan *et al.* 2017). The FPA is deployed for scheduling and shifting appliances (Khalid *et al.* 2019). According to (Nguyen, Pan and Dao 2019), FPA is explored to speed up diversity for search and computational optimization processes and selecting the network layout performances in the memory running period. The FPA utilizes the pollen of the population to depict individual solutions for search space compared to other algorithms (Pan *et al.* 2017).

2.4.6 Elephant Herding Optimization (EHO) Algorithm

Elephants are the biggest mammals that move in groups; they usually raise more than one offspring in a herd, and they pass information in a well-organized form using elephants routing and different radio layers. The EHO algorithm is nature inspired by the community characteristics and behaviour of elephants in the herding family (Kumar, Kumar and Batra 2020). The EHO is a meta-heuristic swarm intelligence algorithm that is deployed for localization deficiency in WSN for getting desired results especially in the area of NP-hard problems for unknown geographical co-ordinates of the sensor nodes within the routing coverage (Strumberger *et al.* 2018b).

2.4.7 Ant Colony Optimization (ACO) Algorithm

The ACO algorithm is a meta-heuristic approach that copies the behaviour of ants to solve optimal challenges (Guleria and Verma 2019). However, some authors have suggested that there be the multi-agent structure for every individual agent which is revealed by the characteristics of a live ant (Sun *et al.* 2018). Previous studies have shown that the traditional ACO combination of challenges were achieved extensively through outcomes in deciphering various challenges such as scheduling, assignment, and routing processes in WSNs. Prior research suggests that the ant’s behaviour is simple in a way that ants use their collective behaviour to perform complex processes, such as finding and transportation of food or locating the shortest paths to the food banks (Li, Keegan and Mtenzi 2018b; Sefati, Abdi and Ghaffari 2021). Anand (2020) highlighted a better routing algorithm that focuses on Ant Colony Optimization (ACO) augmentation in WSN, considering node communication channels within the transmission distance and remnant energy.

Most of the prior research on ACO algorithms helped to display the principle using very easy communication methods to identify the shortest path between two points from the starting point to the desired destination. Elhabyan, Shi and St-Hilaire (2019) investigated arguments on the lifetime of WSN with the use of the ACO approach exploring the constraint on sensor hubs' lifetime operations by delving into security and privacy in WSNs. Most early studies showed that ants identify their mate through aromas known as pheromones. Using this concept, WSNs can use the equivalent of a pheromone trail between sensor types of equipment with various mediums and detecting their network availability and diminish the vitality utilization (Yue, Cao and Luo 2019).

Recent innovative advancements have empowered smaller gadgets with processing abilities to transport their elements without any foundation, by special appointment of networks. Some authors have also suggested that ACO was used to arrange the voyage business issue against the cutting edge in the zone and ACO was deployed to show the pheromone ants for complex enhancement issues. A large number of existing studies in the broader literature of hyper-heuristic ACO were used for behavioural and system colonies in the 1990s. After decades of research on heuristic ACO, reducing energy consumption in WSN routing protocols with the ant system (AS) were proposed (Derakhshan and Yousefi 2019; Nayyar and Singh 2019). The elitist strategy for ant colony (EAS) approaches with maximum and minimum ant colony systems (ACS) with the use of deposits were proposed to trace the shortest route (Wang and Tong 2020).

ACO aids the depiction of cooperative behaviour exhibited by ants to find the shortest path Anandh and Baburaj 2020). However, some authors suggested that they be multi-agent systems wherein every unique agent is revealed by the characteristics of an actual ant. Previous studies have demonstrated that traditional ACO has been added to combinatorial optimizing issues which assisted to achieve universal success in solving various problems such as planning, delivery and allocation. Prior research suggests that the ant behaviour of using aggregated performance characteristics for difficult tasks such as food transportation and locating the quickest routes to food sources is key in the ACO function (Janakiraman 2018).

The ACO algorithm uses the behaviour of ants to locate the shortest trail between the source and the destination and the same approach to explore the opportunities for survival (Zhao *et al.* 2019). This has resulted in the monitoring process of ants putting down a specified amount of pheromones on their way from their nest (source) to food (destination). On their return, the living organism is expected to trail the shortest trails with marks by the pheromones that are deposited and, on the way, back, the ant follows the shorter path is projected to return sooner and produce more pheromone deposition in its mapping trail at a slower pace than a living organism following a longer path (Wang *et al.* 2015).

The ants have been seen to deposit a specific quantity of pheromones along their path when moving from their source to destination. The ants' operations are expected to ply the shortest path that is identified by the pheromones, which are deposited, while the other categories of ACO pheromones of ants on the way back follow the smaller path that leads to a growth in the number of pheromones that are deposited in the path at a faster pace than the ants going through a longer path. The foraging activity of numerous ants is an inspiration for ACO. The ephemerides that are deposited can be identified by the fellow ants to know their routing source and destination. For this reason, ACO with its different engineering applications has long been thought to be a high-quality solutions algorithm. Mobile and wireless networks, data mining, database systems, grid computing, multicore processing, image processing, artificial intelligence, and biomedical applications are all examples of peer to peer computing that can make use of ACO (Gajalakshmi and Srikanth 2016; Xie and Pan 2016).

Ant Colony Optimization was offered as a way to learn about sensor node localization for WSN applications in order to find the best critical path for data transmission (Sun, Dong and Chen 2017). Similarly, the EHO algorithm was employed to solve the WSN's node localization issues (Strumberger *et al.* 2018a).

Recent innovative advancements have empowered smaller gadgets with greater processing abilities to transport their elements without any foundation by special appointment of networks. Some authors have also suggested that ACO was used to arrange the voyage business issue against the research in the zone and ACO was deployed to show the shortest path pheromone for complex enhancement issues. A large number of existing studies in the broader literature of hyper-heuristic ACO was used for behavioural and system colonies in the 1990s (Gupta and Sharma 2019). Decades of research has shed light on heuristic ACO processes to minimize power energy consumption in WSN routing protocols with the approach of the AS (Shankar *et al.* 2021). Tian, Gao and Ge (2016) have also explored hybridized versions of ACO with a larger network rate of conversion for the energy efficiency grid, and some of its attributes of ACO on sensor localization have been explored (Gouda *et al.* 2021). Tian, Gao and Ge (2016) reported optimized coverage. More detail is shown below in Table 2-2.

Table 2-2: The Summary of ACO Solutions in WSNs

ACO WSN Problem Focus	Author	ACO Solutions
• Minimizing localization error. • The transportation of food location using shortest paths. • Search for unknown locations of sensors. • Compared performance of live ant behaviour with ACO.	Li, Keegan and Mtenzi (2018a); Derakhshan and Yousefi (2019); Sun, Yu and Wang (2019); Sefati, Abdi and Ghaffari (2021)	Sensor Localization
• The behaviour of optimal challenges. • Improvement to coverage and connectivity deficiencies • Unstable coverage and clustering problem.	Guleria and Verma (2019); Gupta and Sharma (2019); Yue, Cao and Luo (2019)	Optimal Coverage
• Improvement in the communication approach and their network energy lifetime. • Network availability and its diminished utilization techniques. • Routing and energy protocols. • Unequal clustering protocols consumption. • Alleviation of energy hole problems.	Tian, Gao and Ge (2016); Elhabyan, Shi and St-Hilaire (2019); Nayyar and Singh (2019); Zhao *et al.* (2019); Wang and Tong (2020).	Energy Efficiency Clustering and Routing
• Centralized method for data aggregation and communication using ACO.	Gouda *et al.* (2021); Nayak *et al.* (2021)	Data Aggregation

• Ant aggregation for optimal data communication • Make use of simple ACO. • Improvement in the system lifetime		

Table 2-2 shows the overview of energy efficiency and routing protocols, optimal coverage node sensor localization, and data aggregation in balancing the various algorithms approaches.

2.4.7.1 Elitist Ant System (EAS)

The EAS is an extension of the ant colony system (ACS) that is used for maximum and minimum distance calculation in the ant system. ACSs are used for tracing the shortest routes. Xu and Zhou (2020) indicated that mobile sink scheduling (MSS) is another proposed way to solve the challenge of energy efficiency in WSNs.

Aggregating ACO for optimum data aggregation within the WSN was investigated by looking into the complexity of the optimum aggregation of data that is NP-hard using the optimal search aggregation (Kaur *et al.* 2019). Consequently, the WSN's major problem is not energy consumption but how to effectively minimize the utilization by helping to conserve power capacity and battery life (Wang and Tong 2020). Sensor nodes have an irreplaceable battery with limited capacity. The model of dual sink optimisation used was for considering a single destination and multiple sources for communication within their various environments with the use of multiple hops (Kaur and Sharma 2020).

2.4.8 Genetic Algorithm (GA)

The evolution of computation is collectively referred to as several computing methods on natural inspired evolution. This process explores various computational media to carry out search and optimization types of gaps. The genetic algorithm (GA) has been used in different mobile and wireless networks in fields such as WSN, P2P computing, biomedical applications, data mining, multi-core processing, artificial intelligence, database systems, image processing, and grid computing. The GA is used for proffering solutions to natural selection process challenges. GAs comprise of three categories of rule sets, namely cross-over rules, mutation rules, and selection rules (Gupta, Rao and Venkatesh 2016; Gao *et al.* 2019).

Therefore, considering the problems associated with the great complexity of networks such as large-scale network processing, load balancing, resource constraints, controlling route congestion, heterogeneity, unattended operation and dynamic nature, more advanced strategies are needed to solve these problems because of their complexity and robustness. Insufficient energy consumption is a critical concern for WSNs due to the power capacity of each sensor. The use of sequence detecting activities to increase the lifespan of WSNs is an effective way to do so (Gu *et al.* 2020).

The deployment of GAs helps resolve key issues which include maintaining the confidentiality of information and protecting it from unauthorized users, as well as regulating the number of nodes in the WSN. To improve sensor network performance, it is vital to manage node mobility in movable sensor networks. The GA based approaches in WSNs can be used to extend the lifetime of sensor nodes and quality of service in order to reduce the energy consumption rate. GAs further proffer advantages that help in deciding what sensor are to be managed in transmission within the specified range due to their ease of implementation (Hamidouche, Aliouat and Gueroui 2018).

Ashween, Ramakrishnan and Joe (2020) stated that WSNs are used for monitoring environmental conditions, that collect data in an analytical form then convert it into digital information to assist the GA converters and it routes to SNs either directly or indirectly. Scheduling protocols help nodes to listen to various channels. Idle listening time division multiple access (TDMA) protocols are deployed to reduce energy consumption when carrying out the application of GA algorithm deployment (Kaur and Kumar 2018).

Routing protocol improvement such as speed protocol and ear protocols on ACO was proposed in WSN to balance the power node consumption. Consequently, with the recent advancement in speed and memory, WSNs have been an emerging technology, assisting humans to perform various tasks such as environment and habitat monitoring, using various health care applications, carrying out wild ecological studies, and ensuring traffic control (Arya and Sharma 2018; Hassan et al. 2019). The limitation of GA is a scatter mutation. Table 2-3 sheds light on the full characteristics of GA solutions. Optimal utilized coverage and sensor localization are also explored (Arya and Sharma 2018; Elhoseny and Hassanien 2019).

Table 2-3: The Summary of the Genetic Algorithm Solution in WSNs

GA WSN Problem Focus	Author	GA Solutions
• Distance mapping for localization • Improvement in DV-Hop localization accuracy with the use of GA.	Ayadi *et al.* (2016)	Sensor Localization
• Minimization of the sensing redundancy with cross mutation. • Investigation of optimal coverage. • Investigation of the sensor node deployment for larger scale. • Incorporation of fitness functionality with WSN' parameters.	Gupta, Rao and Venkatesh (2016); Chamanian *et al.* (2019)	Optimal Coverage
• Minimization of the various communication distances within the sensor networks through the route of clustering. • Investigation of the gradual energy depreciation. • Acquisition of the location dimension with the use of GA. • Reduction of power consumption and improvement of the parameters for fitness functionality. • Lifetime improvement and QoS in WSN.	Hamidouche, Aliouat and Gueroui (2018); Kaur and Kumar (2018); Hassan *et al.* (2019)	Energy Efficiency Clustering and Routing
• Balancing energy efficient data gathering for bandwidth estimation in WSN. • Making use of simple GA. • Maximization of network lifetime by data aggregation in network processing techniques • Transfer of packets from one random sensor to the base station.	Arya and Sharma (2018); Gao *et al.* (2019)	Data Aggregation

2.4.9 Kestrel-based Search Algorithm (KSA)

The kestrel-based search (KSA) approach is a nature-inspired clustering algorithm that combines the qualities of a bird with the features of a distributed system form. The distributed system form model is a mathematical model for utilizing energy to the optimal level into different stages of clustering. The KSA deploys the half-life of radioactive elements at a random generation which uses heterogeneous energy requirements for optimizing usage (Agbehadji *et al.* 2018; Agbehadji *et al.* 2019).

2.4.9 Artificial Bee Colony (ABC)

The artificial bee colony (ABC) is a nature-inspired approach mainly used for fitness value calculations in WSN routing and energy optimisation problems (Hasnat *et al.* 2015). The ABC algorithm is tagged as part of bio-inspired classification due to its technique of searching in the space. Different information communication distributions of bee swarms are utilized to get the desired outcomes (Basturk 2016; Bui *et al.* 2020). ABC algorithm use bees' tactics for selecting the shortest path for packets to reach their destination within WSNs. They are also deployed for energy cost savings to evenly distribute energy scheduling in WSNs (Bui *et al.* 2020).

2.5 Non-Nature Bio-Inspired Algorithms

A non-nature bio-inspired algorithm is mainly used for different multi-hop modelling simulations for sending and acknowledging sensor node packets from the neighbouring sensors. Some examples of non-nature-inspired algorithms are Gaussian elimination algorithm and K-means algorithms. Non-nature bio-inspired algorithm is used for distance and energy related calculations within the WSN. One of the limitations of non-bio-inspired algorithms is that they repeat solutions via the same route in the WSN (Rodriguez-Zurrunero *et al.* 2018; Dattatraya and Rao 2019).

2.5.1 Gaussian Elimination Algorithm

The Gaussian elimination algorithm is the linear form deployed for multiple matrices in the row of echelon equation for eliminating variables, until one variable is left identified. The Gaussian elimination algorithms help to substitute another member of the echelon matrix equations. The Gaussian elimination algorithm is used to remove computation, to get the desired outcome (Zhang *et al.* 2017; Hassan *et al.* 2019).

2.5.2 K-Means Algorithm (KMA)

The KMA is a non-bio-inspired clustering algorithm that is used for placing or gathering nodes in the formation of clusters in WSN. KMAs are deployed to self-organize sensor nodes into different sets as a cluster to select their alternative nodes to form the CH. However, the KMA algorithm is the unsupervised class approach with the use of Euclidean distance for sensing and calculating residual power (Ray and De 2016; Hassan *et al.* 2019).

2.5.3 LEACH Algorithm

The LEACH algorithm was designed by Manikandan and Chinnadurai (2021) used for a greater measure of system performances. However, a reduction in information quality transmission is a significant setback (Joshi *et al.* 2016). LEACH helps to increase machine network performances to maximize data quality, minimize acknowledgment delay and to aid traffic monitoring processes (filtering, decompression, decryption, prediction, and filtering processes) in WSNs. The routing protocols are heuristics in nature that help to reduce power usage (Fawzy *et al.* 2016). The process is shown below in Figure 2-8.

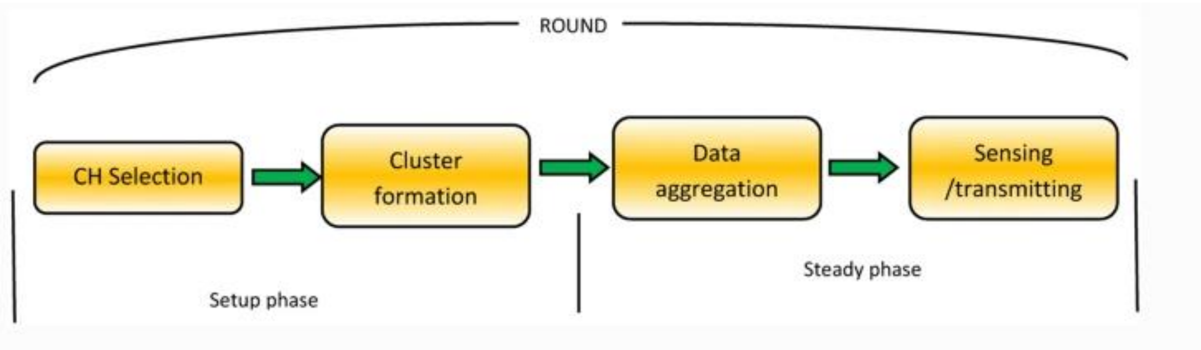

Figure 2-8: LEACH Operational Function
Source: Extracted from Devika, Ramesh and Karegowda (2021)

Routing protocols are used for updating data routing, localisation, cluster selection, data aggregation, and the hierarchy of protocols in transmitting (Rajput, Sharma and Khatri 2017). LEACH protocols enhance initialization broadcasting in energy efficiency maximization calculation. Routing protocols follow a single-path route that does not allow traffic load and constraints that are attached to the network. Single routing protocols, flat routing, data-centric, address-centric, hierarchical routing protocol, and multiple sink protocols are the various channels used in WSNs (Jayanthi and Valluvan 2018).

The Fuzzy-based Energy Efficient Clustering Approach (FEECA) was deployed alongside LEACH to select the CH according to its probability with the different parameters to reduce power enhancement longevity and to maximize its utilization with better throughput in WSNs (Singh and Soni 2017; Dwivedi and Sharma 2020; Oktaviani 2021). In LEACH protocols, data transfer is carried out within the time division multiple access (TDMA) schedule, and the CH executes the data gathering via the local machine computing systems to determine the energy utilization.

2.5.4 Routing Algorithm

Routing algorithms are discussed widely and are divided into two classes which are flat and hierarchical. These are used to solve energy routing issues associated with the WSN. For flat communication to take place all the sensor nodes communicate directly with the BS within a short time framework to replicate the packet of information delivered. Meanwhile, hierarchical routing procedures involve monitoring the various fields in different segments termed clusters which enable all the sensor nodes to communicate through the CH. These are amongst the sensor nodes in the clusters and every other node is called a cluster associate member. The communication of operations is passed across to the BS to extend the network lifetime (Devika and Karegowda 2015; Naeimi *et al.* 2017; Devika, Ramesh and Karegowda 2021). The operation is shown in Figure 2-9.

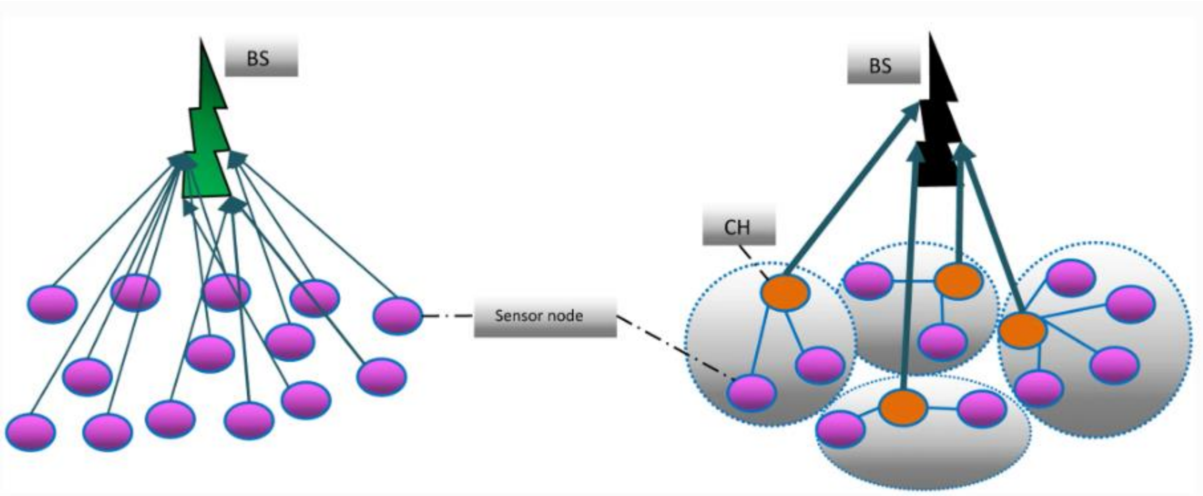

Figure 2-9:Flat and Hierarchical Routing Communication
Source: Extracted from Devika and Karegowda (2015)

2.5.5 Enhance-LEACH (E-LEACH) Algorithm

The E-LEACH algorithm is an approach used for improving the LEACH methods in terms of performance and the segmentation selection for assessing the residual usage of energy usurpation by the sensor node that is greater than 50% during the assessment of residual usage. These sensor nodes identify the direction of threshold value that is channelled by the LEACH. Once the residual energy level decreases below 50% another quota of value that is consumed values is likely to be picked as one of the CH in the formation processes. E-LEACH election of clustering is always based on its residual energy average usage operation, which is a relay in the data sent to the base destination. Cluster heads then proceed to elect and carry out a poll within their group and broadcast data to the BS, as shown in Figure 2-10 (Prabowo, Abdurohman and Erfianto 2015; Rai, Deswal and Singh 2016).

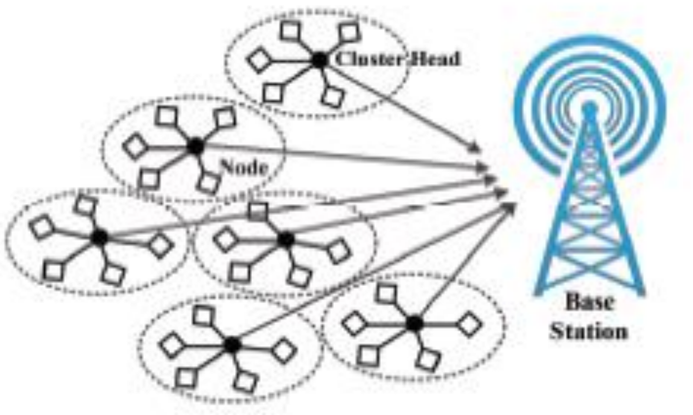

Figure 2-10: E-LEACH Topography
Source: Extracted from Prabowo, Aburohman and Erifianto (2015)

2.5.6 Power-Efficient Gathering in Sensor Information System (PEGASIS) Algorithm

The WSN are tools that are used for aggregating data from various hubs of sensor nodes in a natural world and it expedites the power efficiency leading to power-efficient gathering in sensor information system (PEGASIS). The PEGASIS is an alternative algorithm used for energy dissolution with various metrics such as a packet of delivery ration, throughput with different functionality of sensor node temperatures and their BS environment. PEGASIS is more efficient in performance when compared to the LEACH algorithm. The PEGASIS is used for analysing the sensor energy usage, lifetime availability, and the total cost of the overheads. Some researchers refer to PEGASIS as the routing protocol that extends networks compared to

LEACH (Al-Sodairi and Ouni 2018; Koteswara and Nanda 2018; Pawar and Khandelwal 2021).

2.5.7 Gradient Distance Algorithm (GDA)

The GDA is used for measuring accuracy, decent spotting of sensors positions that are in iterative nature and coordination of both known and unknown sensor nodes for localization in WSNs. The GDA inter-distance nodes are used to receive signal strength and time of arrival measurement. Multi-alteration employs gradient algorithm for its density of the various anchors. If the anchor nodes are not sufficient during the operation, the use of proximity matrix distance help to transform the distance estimate for every unknown proximity matrix distance. The gradient approach does optimize the most efficient position of nodes to determine their distance measurement and target functionality. The combination of approaches for iteration are refined for improvement for node coordination positions. The more the anchors, the more the adaptative convergence in the process of gradient distance computation with regards to nodes in WSNs (Wei *et al.* 2017; Zhang *et al.* 2018b; Mukherjee *et al.* 2020).

2.6 Power Management in Wireless Sensor Networks

The sensor nodes of WSNs are self-powered sources, and the amount of power source stored in the battery determines the sensor node's lifetime. As a result, the most difficult task in sensor data collecting is making good use of the available power. To lower the power consumption rate, researchers suggested a method of selecting CHs for a collection of sensor nodes (Alarifi and Tolba 2019). Random cluster head selection is used in the heuristic ensemble methods, with the shortest distance between sensor nodes being reported. The CH is then assigned to the node with the shortest distance, which will help to reduce the energy necessary to hop data. The programming will include an optimization approach for minimal buffering and a controlled mobile sink (Goyal 2016; Estrada-López *et al.* 2018).

2.6.1 Mobile Sink Scheduling (MSS)

According to Zhou, Wang and Xiang (2017), mobile sink scheduling (MSS) is a proposed potential solution to the problems of power efficiency in WSNs. The sensor depleting power operates from the SN using a single hop communication. This creates latency problems and inaccurate energy consumption within the WSN. The MSS is simulated using linear programming methods and the greedy maximum residual energy (GMRE) algorithm (Zhou, Wang and Xiang 2017).

A WSN's major problem is energy consumption but how to effectively minimize the energy utilization and to conserve power capacity and battery life remains a challenge (Wang *et al.* 2018; Wang *et al.* 2020). Therefore, considering the problems associated with the tremendous complexity of networks, such as their dynamic nature, resource limits, heterogeneity, load shedding balancing, routing congestion control, unattended operation, and robustness more advanced solutions to tackle these challenges are required (Gao *et al.* 2019). Since each sensor has a limited battery supply, power consumption is one of the most significant issues for WSN efficiency. Sensor activity scheduling is an excellent approach to extend the life of WSNs. Due to the importance of maintaining the integrity and confidentiality of information, as well as protecting against unauthorized users, regulating the number of nodes is crucial (Iwendi, Zhang and Du 2018).

Managing the MSS of nodes in WSNs is important to increase the WSN’s performance in setups having multiple applications with different network requirements running concurrently over the same underlying networks (Gao *et al.* 2019; Solangi *et al.* 2019). Al-Janabi and Al-Raweshidy (2017) stated that WSNs are used for monitoring environmental conditions, where data collected in an analytical form is converted into digital information. The MSS protocols also help nodes to listen to various channels with idle listening. TDMA protocols are deployed for energy consumption optimization (Kumar, Edalatpanah and Mohapatra 2020; Kumar, Kumar and Batra 2020). Sensors closer to the SN are burdened with a large quantity of data and high the energy consumption of nodes (Pal, Yadav and Karnwal 2020). The approach is to use an effective mobile sink to achieve a better outcome.

2.6.2 Improved Routing Protocols

In WSN, a better routing protocol based on ACO that considers node communication transmission distance, residual energy, and other factors has been developed and recommended for further research (Sun, Dong and Chen 2017). Similarly, node localization in WSNs using the butterfly optimization algorithm approach was compared to other existing particle swarm algorithms and firefly algorithms with the recommendation that further hybridized methods be used to minimize the location estimation error (Arora and Singh 2017). Yick, Mukherjee and

Ghosal (2018) worked on WSNs for monitoring the environment and its vicinity by sensing its physical elements and used ad-hoc deployment, topology, dynamic spatial distribution, and reduction in the bandwidth of WSNs. The FPA has contributed to improving node localization but gaps still exist in the research (Pan *et al.* 2017; Yick, Mukherjee and Ghosal 2018).

2.7 Cluster Head Selection

The cluster head election problem (CHEP) is amongst the most frequently identified lifespan difficulties in WSNs because if a specialize group of sensor nodes are picked as the CHs too frequently these sensor nodes will quickly deplete their battery power storage (Heinzelman, Chandrakasan and Balakrishnan 2010). To solve this problem, a simple and easy-to-implement clustering technique known as LEACH was deployed, which has since become a well-known clustering approach. LEACH does not always choose the same sensor as a CH, and any sensor can be picked as a CH. According to LEACH's CH election regulation, every sensor should have an equal chance of being elected as CHs through a fair procedure. As a result, even though a sensor has been designated as a CH, it will not run out of energy quickly while utilizing the LEACH approach (Abdurohman, Supriadi and Fahmi 2020).

Hoang *et al*. (2010) noted that LEACH may not be able to find the optimum answer for the CHEP. If one CH is far from the others, for example, other sensors will deplete this CH's energy. To investigate this difficulty, we must consider carefully the selection of a sensor as a CH. Multiple finding of meta-heuristic algorithms demonstrated that by utilizing a clever guess and check technique might find better outcomes than standard rule-based and deterministic algorithms in addressing complex optimization problems. This type of method has been employed in a number of engineering research projects (Hoang *et al.* 2010).

However, many meta-heuristic algorithms have both advantages and disadvantages. As a result, there is no single meta-heuristic algorithm that can consistently outperform all others according to the hierarchical heritable vicinity. When a sensor node's contextual information is insufficient to make an adaptation assessment, the CH assists in determining the environment based on information received from nodes in its cluster. If the CH's existing information is not suitable for habitable reasoning, the SN is in charge of ensuring that the CH informs the temperature sensor nodes to reduce the sampling rate (Nam and Kim 2021).

2.8 Data Aggregation

Data collection is a medium of acquiring data over a long period and transmitting the generated series of data from emerging applications from the networks. Data aggregation helps to make meaningful use of energy resources (Mejia *et al.* 2020). When data aggregation was applied to the original message size media data, it was apparent that energy efficiency is related to the various source of nodes in correlated sensors media data. Two elements considered for data gathering are the shortest path tree (SPT) and the centre at nearest source (CNS). The number of source nodes used range from 20 moderate sources to 40 large sources. Hence, the simulated solution for the optimal aggregation problem was implemented and the results showed energy is conserved, saved by up to 45% as a result of fewer sensor nodes (Shahina and Vaidehi 2018).

Seminal contributions have been made that ACO algorithms be applied to NP-hard problems to effectively manage the routing algorithm (Osamy, Salim and Khedr 2020). The mathematical scenario for dependence was calculated with an output of logarithm functions of GA fitness growth and it was recommended to redefine the problem for sensors anywhere in the field instead of being in a static position (Ullah and Youn 2020). Local synergy helps the sensor nodes to identify the filter and process sensors to read before transporting them to the BS. In conclusion, this procedure can help to mitigate the counts of packets sent to the BS (Ghate and Vijayakumar 2018).

Data gathering is further classified into four categories for example, chain based, grid based, cluster based, and tree based as shown below in Figure 2-11:

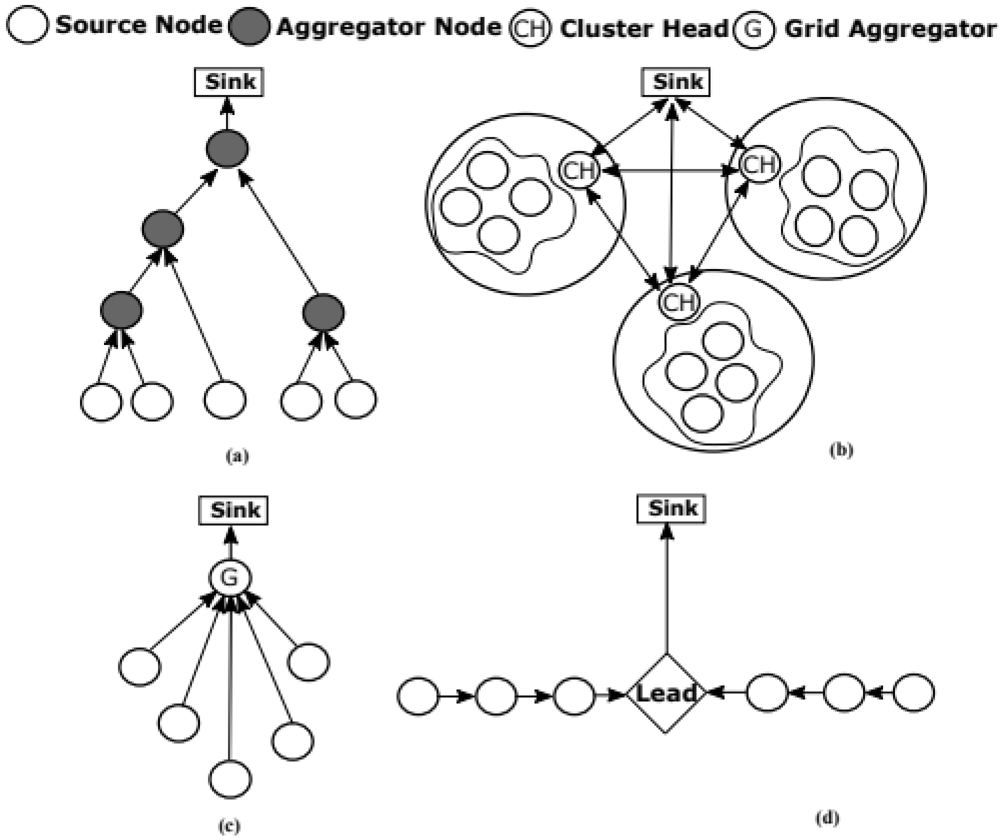

Figure 2-11:A aggregation classes: (a) Tree-based, (b) Cluster-based (c) Grid-based (d) Chain based
Source: Extracted from Singh, Sharma and Singh (2021)

The tree-based class uses the tree structure for sourcing the node as a director and the packet of information gathered is called the node aggregator. The cluster-based approach uses the clustering method architecture to segregate the clusters into smaller chunks with the help of CH. The grid-based approach sub-divides the occurrences in the energy consumption to deploy the aggregation into several central nodes, also known as grid nodes. The chain-based technique makes use of the node transfer to its environment to lead the data gathering in a circular form (Singh, Sharma and Singh 2021).

One of the sources of energy expenditure occurs in the transfer of data within the transmission process of the network. Data is delivered over capacity-limited fronthaul links from a baseband unit in the core network to numerous remote radio heads, via a set of edge routers (Norouzi, Babamir and Orman 2018). The data compression-based approach is employed to minimise the challenges in a wireless cellular network (Langner *et al.* 2020). Data compression is important with the emergence of social network platforms, blogs, wearable devices and high usage of the internet.

The BS is the aggregation centre that collects network data and information from its environment that are from different sources within the network, processes them and sends them to the desired destination after analysis. They have a significant impact on energy dissipation lifetime in WSN. A BS is responsible for calculating the parameters that are associated with the sensor nodes, communication, and processes of information received (Tamandani, Bokhari and Kord 2017). The BS is often referred to as the anchor node, which is used for satellite positioning (Wang and Tu 2020). In a few cases, all the routing clusters are monitored via CH and the CH in turn sends feedback to the BS for network expansion (Devika, Ramesh and Karegowda 2021). The simple operational process is shown in Figure 2-12.

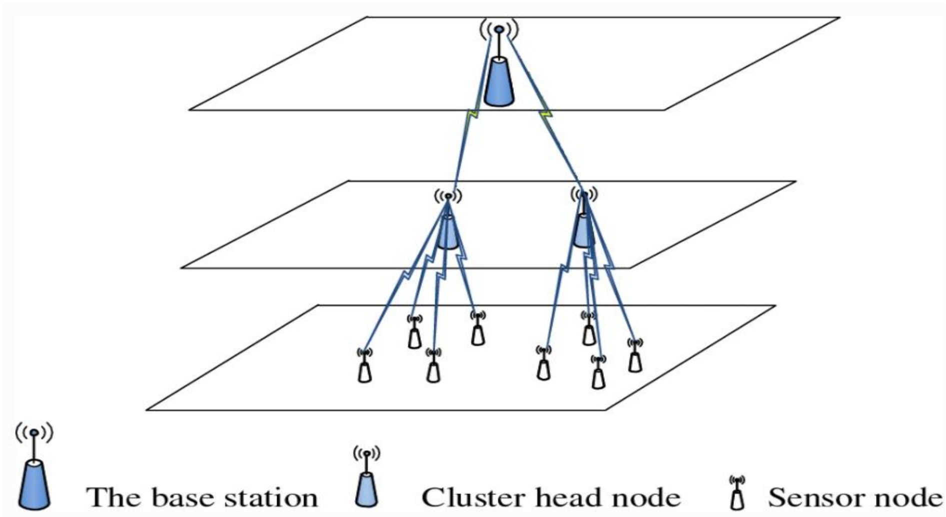

Figure 2-12: Base Station Network Model
Source: Extracted from Dou, Chen and Long (2021)

2.9 Performance Metrics

Performance measures are used for revealing the hyper-heuristic optimization project evaluation such as optimization of energy efficiency, node localization, estimation error of sensors that are in the entire network space. The performance metrics are sometimes referred to as requirements in the applications that are used to gauge measures, independently and compared against each other (Jayanthi and Valluvan 2018). First node dead (FND) is usually referred to as the stability period while the tenth node dead (TND), probability of error (PoE) are commonly called the instability period (Reddy and Rajan 2017; Guntupalli, Martinez-Bauset and Li 2018; Pallapothu and Mehta 2018; Kaur, Aggrawal and Lal 2020).

Dead nodes are generated as sensor nodes, and they are not explored for any further analysis. The offspring of a dead node can always be expanded. There are some limitations in the dead node which are the high cost needed for implementation (Saini, Kansal and Randhawa 2019; Aroba, Naicker and Adeliyi 2021b). The dead node significantly utilizes more power because the energy source of sensors is mainly from the batteries that are attached to them. It is difficult to recharge the batteries due to the significant number of dead sensor nodes which affects the network lifespan in WSNs (Aroba, Naicker and Adeliyi 2021a).

Network Lifetime are an evaluation of operations or tasks carried out by distance for all the sensor nodes and the CH, with the various calculations of their time spent during the operation. It is one of the metrics that are used for measuring performance in nodes, to know the time taken for an execution to be completed. One of the existing approaches for extending the network lifetime of WSN focuses mainly on the devices, data performance, network topology control that perform a vital duty in the optimization of energy management (Mohajerani and Gharavian 2016; Wu *et al.* 2016; Naranjo *et al.* 2017; Jiang and Zheng 2018).

2.10 Heuristic Approaches

In the growing wireless sensor networks applications heuristic techniques are a significant component. The growth of heuristic techniques in WSNs over the last decade has resulted in different solutions for challenges around sensors (Arora and Singh 2017). Wireless sensor networks are a self-paced network procedure that is made up of many micro nodes that have low-cost data processing and wireless communication component. Node localization is widely used in WSN to determine the current location of nodes with minimal energy usage (Sun, Dong and Chen 2017).

Heuristic approaches are used in the solution of a variety of network problems. Many heuristic algorithms are explored to solve the localization problems in WSN, which drastically reduce the localization issues for example the FPA strategy was deployed to optimize localization issues in WSNs (Sun, Dong and Chen 2017). The EHO approach is the preferred solution in the realm of geographical coordinates within the sensor nodes in WSN (Strumberger *et al.*

2018a). Other examples of heuristic algorithms are firefly algorithm, particle swarm algorithm, help in hurled leaping algorithm, cuckoo search algorithm and bat algorithm. These algorithms help to improve the network performance (Kaur and Mahajan 2018). Heuristic algorithms belong to the family of optimization problem solvers, which will help in iterative processes that provide a feasible solution in identifying the nearest optimal solutions to the various problems in WSN nodes.

2.10.1 Meta-Heuristic Approach

Meta-heuristic approaches are high-level methods that create an optimization solution using a variant of a single state-of-the-art algorithm which researchers have used to solve problems of sensor nodes (Sorensen, Sevaux and Glover 2017; Samorani *et al.* 2019). Most researchers have centred on meta-heuristic methods to overcome clustering of sensor nodes problems and energy depletion of sensor nodes that cause packet delays, and delays in information communication from the origination to the end point (Shah-Hosseini 2011; Rao, Jana and Banka 2016; Yuan *et al.* 2017; Kaur and Kumar 2018; Bozorgi and Bidgoli 2019; Mhatre, Kumar and Jha 2019).

An example of meta-heuristic approaches used by researchers was the unique artificial swarm intelligence approach in the investigation of localization challenges in WSNs (Strumberger *et al.* 2018b). The krill herd method was used to optimize localization for a wider number of issues in order to beat established approaches and create predictive abilities (Biswas *et al.* 2017). The cuttle optimization algorithm are also meta-heuristic bio-inspired optimization algorithm. The following meta-heuristic methods have been presented in solutions for routing, energy consumption, node localization inefficiency and clustering, namely, algorithms for colliding bodies, harris hawk optimization, mass and energy balance, emperor penguin optimization and momentum balance algorithms and finally, memetic algorithm (Chawra and Gupta 2020S; harma and Gupta 2020).

The fundamental reason that meta-heuristic approaches are limited in their growth is their high energy consumption and, as a result, short network lifetime. Improvements are still required in terms of power usage, clustering of packets, and energy lifetime in meta-heuristic approaches.

2.10.2 Hybrid-Heuristic Approach

Hybrid-heuristic is the combination of two meta-heuristic algorithms with one search approach to get the desired outcome (Tharwat and Hassanien 2019). Hybridizing classic algorithms, such as a combination of any two of the following, has been used to strengthen the heuristic method namely, meta-heuristic and sim-heuristic (de León *et al.* 2017; Garcia *et al.* 2018).

In recent papers, hybrid-heuristic approaches have been employed to look at job scheduling to reduce jet lag and speedup the sensor power usage during information dispatch in the WSN. Hybrid algorithm comprises the PSO and ACO algorithms to offer the best possible solutions to WSN problems (Yin, Luo and Luo. 2018). Furthermore, for both the best and average sensor nodes, a hybrid-heuristic approach to the multi-dimensional DB-scan were developed, with potential for further expansion and improvements (García *et al.* 2020). The unified heuristic bat algorithm and panacea no collision detection algorithm (PNCDA) were introduced to provide synchronous and asynchronous performance (Cai *et al.* 2019).

2.10.3 Hyper-Heuristic Approach

A hyper-heuristic is a combination of two or more heuristic approaches into a single implementation. A hyper-heuristic approach is a way for selecting and constructing heuristics using a combinatorial optimization resolution (Burke and Qu 2019). Researchers have made use of different algorithms to provide some solutions in node localization. Wang *et al.* (2019) formulated mobile sink algorithm to optimize the sum of stay time of the node at every candidate's site with the use of a linear programming method. The hyper-heuristic model focuses on encompassing a variety of methodologies with the common purpose of piloting heuristic model adaptation and designs to tackle tough mathematical search deficiencies (Aroba, Naicker and Adeliyi 2021c).

The level of normality for formulas on comparative analysis is being raised. In addition, only a few works demonstrate the scheduling, flat classification routing protocol with the use of a hyper-heuristic approach with different algorithms such as block-additive constrained optimization problem (BCOP) algorithm and monte carlo damage simulation (MCDS) for the efficient minimum connected dominating set (Rai, Deswal and Singh 2016). Research approaches for TDMA two centralise heuristic algorithms for WSNs and possible classical multi-hop scheduling were discovered for improvement of nodes that do not have any packet

(Tsai, Liu and Wang 2018). Considerably, a novel hybrid algorithm single annealing machine was used for the optimal solutions of 1 000 iteration cases in wireless nodes (Zlobinsky and Cheng 2018).

2.10.4 PRISMA

The Preferred Reporting Item for System Meta-Analysis (PRISMA) technique was used in this study (Page *et al.* 2020). During the systematics review, the PRISMA provided a checklist of items that should be addressed. The systematic review involved looking for relevant publications in Web of Science and Google Scholar databases. We were able to streamline more than 306 citations, articles, and patents on meta-heuristic, hyper-heuristics, and hybrid heuristics in WSN with the use of PRISMA. The meta-analysis report analysed and identified publications from databases published between 2010 and 2020. The relevant studies in the findings were manually analysed with electronic source search as part of the evidence method. According to Aroba *et al.* (2020), the notable factors that are identified after conducting the meta-analysis from the google scholar and web of science using the PRISMA techniques were presented and the hyper-heuristic approach was the best model when compared to hybrid-heuristic and meta-heuristic approaches. It is with clear evidence that the hyper-heuristic outcome is the best model and gap for energy efficiency optimization and for the node localization approach in WSN (Aroba *et al.* 2020).

2.11 Chapter Summary

This chapter situated the research in the context of WSNs with publications primarily focused on contemporary WSN issues. WSNs is one of the vital points discussed within the IoT space for over a decade and the issues associated with it are wide ranging including, energy efficiency, fluid communication between the base station and sensor nodes, nodes localization and load balancing. The literature review exposed the problems in WSN research and confirmed the need for critical research in node localization and energy efficiency.

The literature research found this problem to be consistent, and the three basic ways to addressing it were considered. This research looked at various heuristic approaches based on the three main heuristic methods, namely, meta-heuristic, hyper-heuristic, and hybrid-heuristic that are used to improve localization and energy optimization in WSNs. The meta-analysis outcome demonstrated that research investigations using hyper-heuristic techniques produced the best evidence for enhancing node localization and energy efficiency, resulting in increased WSN success. We can now say from our review of the relevant literature on optimization of localization in the WSN that the hyper-heuristic approach is the best algorithm when compared to classic approaches. The result does not imply that the meta-heuristic, hybrid heuristic approaches are inefficient but when compared to the hyper-heuristic result performance, the hyper-heuristic outperforms both hybrid heuristic and meta-heuristic methods in reforming node localization and energy optimization elaboration challenges within the WSN. The next chapter will give details on the research methodology.

CHAPTER THREE: THEORETICAL FRAMEWORK AND CONCEPTUAL MODELS

3.1 Introduction

The concept of theoretical models is important to underpin the research providing a basis to evaluate complex systems (Wieringa 2014). Some researchers suggest that a theoretical framework helps to generalize systems and provides ideas on how to explain the phenomenon under study (Jozkowski 2017; Zeigler, Muzy and Kofman 2018). The theoretical framework underpinning this research worked along with a well-explained analysis for the hyper-heuristic optimization procedures.

A conceptual framework on the other hand is the total logical orientation of one's own line of thought taken about specific decisions by comparing the variables identified in the study. Conceptual models use of an outline of inputs and procedures in the project investigation. The conceptual framework is termed as research paradigm which supports a theory in a research project (Jozkowski 2017; Zeigler, Muzy and Kofman 2018; Alarifi and Tolba 2019). The conceptual model helps to validate the theories from the researcher's observations with facts to achieve a meaningful situation (Uhl-Bien and Arena 2018; Nord, Koohang and Paliszkiewicz 2019).

Figure 3.2 provides a framework of the process involved in designing a conceptual model.

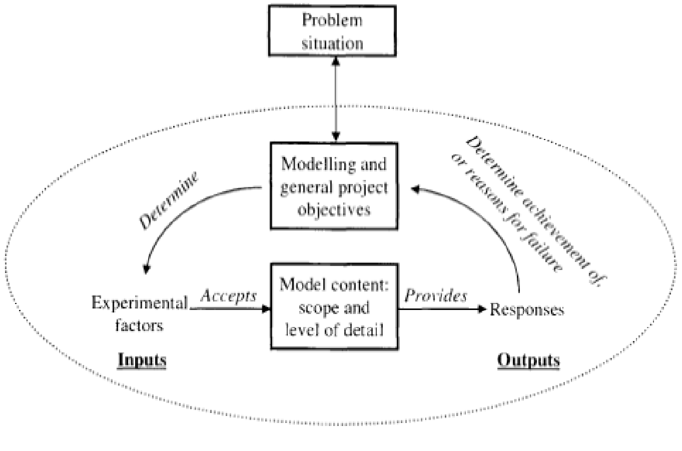

Figure 3-1: Conceptual Model
Source: Extracted from Robinson (2008)

Figure 3-1 provides the overview of designing a conceptual framework as extracted from Robinson (2008). In designing a conceptual framework, it is important to understand the research problem. A thorough introspection into the problem situation would help to determine the modelling and project objectives. General project objectives can be refined by revisiting the problem situation. Using the project objectives, the model inputs (experimental factors) and outputs (responses) are identified. Finally, determine the model content (scope and level of detail). Ensure that all assumptions are identified. It is important to examine the conceptual model to see if it can be simplified (Robinson 2008).

Conceptual modeling is the starting point for simulation (Robinson 2008). The conceptual model will enable subject matter experts to develop a clearer understanding of the problem. The following characteristics are important in the simulation, namely, flexibility, run-speed, visual display, ease of use and component reuse (Robinson 2008).

3.2 Design Research (DR)

Information systems (IS) research has a relevant methodology such as design research (DR) that brings about the theoretical contribution and applicability checks to provide solutions for the identified research objectives (Plomp and Nienke 2013). The DR processes do re-echo the general processes that are not limited to the identification of the research problem, simulation, analysis and evaluation until the desired result is produced (Plomp and Nienke 2013).

This sub-section provides in-depth knowledge about the methodology and overview of the design research that was further expatiated into six phases. Design research is a type of interdisciplinary research where more than two scientific specialties are grouped into two, parts namely, conceptual model and theoretical design (Tobi and Kampen 2018).

Design Research (DR) is used to solidify the thoroughness with regards to learning and its associated entities that took place in the process of the design, redesign, and evaluation. The authenticity of real-life theories and improved practical scenarios are tailored to test and refine theoretical assumptions and their advancement. The DR approach includes researchers with different expertise that interact on reporting techniques (McKenney and Reeves 2021). DR is of importance for the creation of successful models which will help to incorporate principles, practices, procedures to carry out the research objectives as shown in Figure 3-2 (Wieringa 2014).

3.3 Design Research (DR) Model

The DR model is an outcome-based information technology research methodology that helps to offer specific guidelines for iteration and evaluation within research projects (Wieringa 2014). Design research is used for the development and performance of artefacts (algorithms, human-computer interfaces, design methodologies and process models). Design research is a result-based research methodology that offers specific guidelines for evaluation, concepts, inputs, specifications, and iteration (Burnap *et al.* 2015). Design research enables support, processes, in ideation that are deployed into one or more algorithms for hyper-heuristics and enhance the capability to create the design. The description, methods, simulation and outcomes, are scientific (Downton 2003). The DR methodology is used for providing nominal framework processes, building up pieces of literature about design and information systems, and providing researchers with a mental model for the research output (Geerts 2011).

Design research comprises six phases that are displayed as a diagrammatical representation in Figure 3-1. The phases are *Identify the problem*, *Describe the objectives, Design and develop the artefact*, *Test the artefact, Evaluate testing results and Communicate the testing results* (Ellis and Levy 2010).

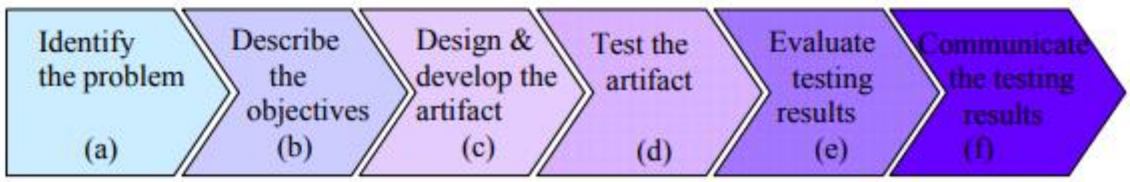

Figure 3-2: The Design Research Model
Source: Extracted from Ellis and Levy (2010)

3.3.1.1 Phase 1: Identify the Problem

The first phase of the design research model addresses the problem that is compiled at the preliminary stage of the research work. For purposes of research, the identification of the problems helps to guide the development of the potential solution to ensuring energy efficiency and node localization in WSNs (Hevner *et al.* 2004; Kuechler and Vaishnavi 2006; Sein *et al.*

2011). The identified research problem comprises the problem statement, problem definition, and its importance. This phase one is used to pre-empt the research aim and objectives. This is described in Chapter One.

Node localization has been a prominent challenge in WSNs. This challenge gets heightened due to high bandwidth usage, high energy consumption rate, poor sensor estimations, and poor quality of service solution (Yang and Wu 2015; Sun, Yu and Wang 2019). This challenge necessitates a novel approach to combat the energy efficiency and node localization problems. At this phase, statements and review of relevant findings guides in detecting the gap and conceptualizing the research opportunities according to the laid-out theories and technologies.

3.3.1.2 Phase 2: Describe the Objectives

This section is phase two of the design research model. It presents insight into the aim and objectives as stated in Chapter One that are developed from the problem statement. This phase enabled a deeper understanding of the problem in the context of the potential solutions and the various techniques (Eekels and Roozenburg 1991). In this phase, we substantiated the design, understanding, and sought possible ways to solve node localization problems in WSNs by adopting a hyper-heuristic algorithm approach to improve the node localization accuracy using of the ***DEEC-GAUSS Distance Elimination Algorithm (DGGDEA)***. This method improves the distance error calculations.

3.3.1.3 Phase 3: Design and Development of the Artefact

This phase presents insight into the design and development solutions that will be created, in relation to the models (Hevner *et al.* 2004). The theory and the simulations will guide the achievement of solutions that are being identified and contributed to this research work. This phase four provides the design and development of the proposed approach using MATLAB R2020a software. The design details include hyper-heuristics that was proved as the best option during the literature review. Hyper-heuristic algorithms have an advantage with the combination of two or more meta-heuristic algorithms to solve the problems of node localization and energy efficiency (Aroba, Naicker and Adeliyi 2021a; Aroba, Naicker and Adeliyi 2021b; Corchado and Juan 2021; Reddy, Puttamadappa and Suresh 2021). The combination of three algorithms, namely, DEEC algorithm, GAUSS algorithm and GDA are used to maximize node localization and energy optimization of the network as shown in Figure 3-3.

3.3.1.4 Phase 4: Test the Artefact

At the Test the Artefact phase, the potency of the proposed artefacts in solving the research problem are tested. At this phase we simulated the WSN environment to test the performance of the proposed models (artefacts) for node localization and energy optimization using the MATLAB environment (Pfeffers et al. 2006; Sein *et al.* 2011). The DEEC algorithm, GAUSS algorithm and GDA were adapted to improve on the existing gaps of the node localization and energy efficiency optimization.

3.3.1.5 Phase 5: Evaluate Testing Result

At the evaluation phase, performance evaluation metrics were used to evaluate the effectiveness of the presented artefact against other well-known algorithms (Hao *et al.* 2021; Pfeffers et al. 2006). The proposed algorithms introduced at phase 3 was benchmarked with other state of the art algorithms using performance evaluation metrics such as FND, tenth node dead (TND), number of packets sent to BS, the execution time during the process and probability of error (PoE).

3.3.1.6 Phase 6: Communicate the Testing Result

This sixth phase presents a concise analysis of results and the contributions of the proposed artefacts to the body of knowledge (Ellis and Levy 2010). This study presents an additional new knowledge in optimizing energy efficiency and minimizing node localization error in wireless sensor networks. The result of this research study shows that the presented artefacts outperformed state-of-the-art algorithms when benchmarked with well-known performance evaluation metrics. These results were reported through the publication of several peer-reviewed journal articles.

3.4 Justification of Design Research for the Study

The DR was adopted to guide the research and the artefacts were developed using the phases of DR, namely, *Identify the problem, Describe the objectives, Design and develop the artefact, Test the artefact, Evaluate the testing results and Communicate the testing results.* The hyper-heuristic approach was selected as the best method using phases 1-3 of DR. The DR is the most suitable methodological approach to achieve the aim and objectives of the research. Moreover, DR is inter-disciplinary involving several fields such as Engineering, Sociology, Economics, and Information Technology. DR explores, justifies, utilizes, validates, and describes knowledge with the proposed model (Teegavarapu, Summers and Mocko 2008; Hancock and Algozzine 2017; Micheli *et al.* 2019).

3.5 Conceptual Model: Hyper-Heuristic Framework

In this research work, the hyper-heuristic framework was adopted to enhance the poor transmission, node localization, network lifetime, and to reduce energy consumption. A typical hyper-heuristic framework includes a high-level approach as well as a set of lower-level heuristics. In this research methodology, the metrics parameters were the unit of nodes, localization error, processing time, transmission radius, throughput sent by packet and the energy consumption calculated. The framework for this research study is displayed in Figure 3-3. The framework displayed the hyper-heuristic solution created using three state-of-the-art algorithms. Figure 3-3 serves as the conceptual model for the study.

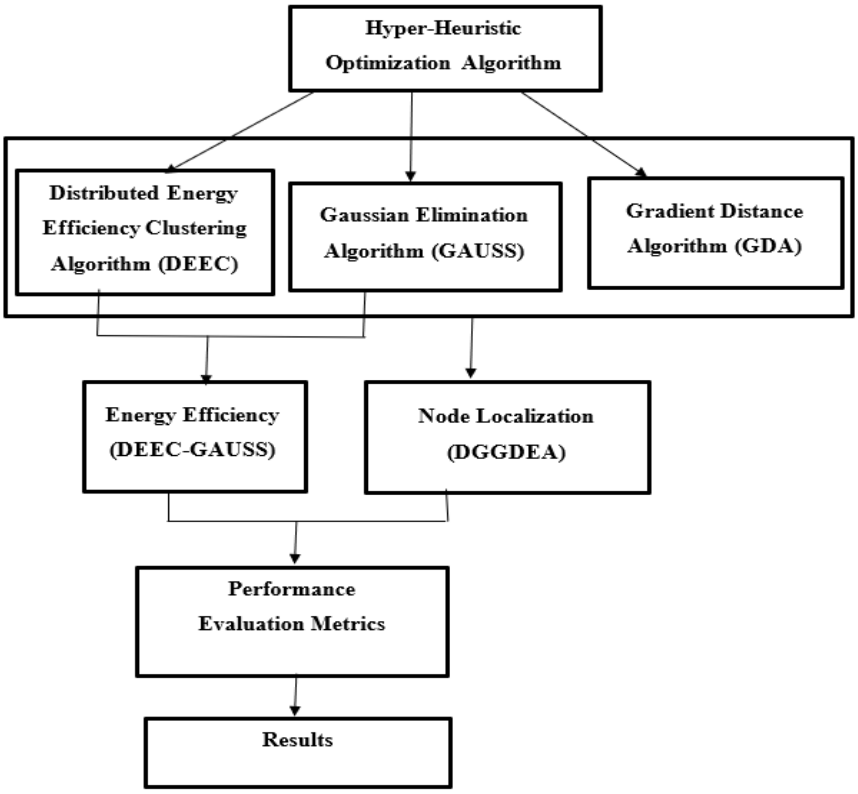

Figure 3-3: Conceptual Model: Hyper-Heuristic Framework
Source: Researcher's own construction

3.6 Theory of Modelling and Simulation

Modelling and simulation is used extensively in Computer Science and sub fields of Computer Science such as Artificial Intelligence as method of solving complex scientific problems. Models are built inductively by observing the real system. In the theory of Modeling and Simulation the following constructs are significant, namely:- a *system, which* is described as specific aspects of an object in the real world under study; the *experimental frame*, which is a limited set of circumstances under which a system is to be observed or subject to experimentation; *experimentation,* which is the act of carrying out an experiment and getting results while *simulation* is building a model of a real world system to mimic the output of the system in response to input parameters (Vangheluwe, De Lara, and Mosterman, 2002).

The problem faced while implementing real life complex systems include cost and error prone implementation. To address this problem, modelling and simulation as somewhat replaced potentially risky experiments and implementation of complex systems that are exceptionally or nearly impossible to implement in real life (Vangheluwe, De Lara and Mosterman 2002).

Figure 3-4 presents a simulation and modelling paradigm of a real-world problem that deals with complicated systems. An abstract model can be constructed using the inductive and deductive approach to simulate the real-world scenarios in order to attain the project objectives. Theoretical techniques based on the analysis of the simulation properties will continue to have a substantial impact on node localization and energy efficiency in WSNs (Coveney *et al.* 2012).

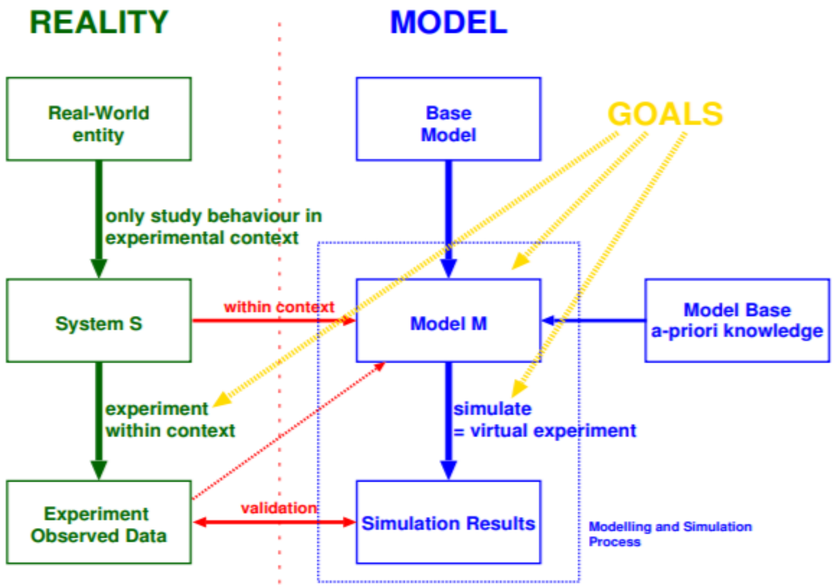

Figure 3-4: The Simulation and Modelling Paradigm
Source: Extracted from Vangheluwe, De Lara and Mosterman (2002)

3.7 Justification of the Theory of Modelling and Simulation for this Study

Node localization and energy efficiency are real life challenges encountered in wireless sensor networks. This study has adopted the theory of modelling and simulation to represent the real-life problem of this study. A virtual experiment of the energy efficiency and node localization real life problem was simulated in the MATLAB R2020a environment. Consequently, the novel models of this research were benchmarked with other state-of-the-art model for us to solve the energy efficiency optimization and node localization deficiencies. The contributions of the theory of modelling and simulation were to tackle the basic difficulties in energy efficiency optimization and node localization error.

Different authors have presented the essential content of the theory of modelling and simulation as the assertion, prediction, description, and behaviour or characteristics that qualify for logical coherencies within visual operations (Kivunja 2018). Simulation modelling helps to describe, compare empirical data, formulas, claims of proven theories that are carried out with an outcome from the result that is compared with the modern-day approaches (Fetters and Molina-Azorin 2017). Modelling and simulation are also thought to be a powerful method for carrying out large-scale complex systems. Hence, the presented models were used in a simulation environment for smaller networks (up to 100 nodes) and larger networks (1 000 nodes to 1 500 nodes) for energy efficiency while 200 to 450 sensor nodes and 20 static anchor nodes were used for node localization error in WSNs.

3.8 Construction and Simulation Construct

The construction and simulation construct are relatively fast and easy for implementation in MATLAB software for decision making (Abar *et al.* 2017; Farmer *et al.* 2017). The simulated result was contrasted against the modern techniques, which proposed to improve the estimation and detection of node localization problems, consumption time, and affect the attentiveness of the connection lifespan in the WSN. This proposed framework helped to identify the current location with more accurate node localization, optimize connection lifetime, advance the power efficiency of the networks, improve the number of iterations and ensure more packets are delivered, and increase the speed of the network for different organizations. The MATLAB 2020a environment is where the simulation model was carried out and it is used to show the contrast between the findings and some form of elements that were observed from the literature and the meta-analysis that are deemed credible (Kivunja 2018; Zeigler, Muzy and Kofman 2018).

3.9 The Emergent Conceptual Model for the DEEC-GAUSS and Gradient Distance Algorithm (DGGDA)

The conceptual model as displayed below typifies the phases involved in the DR model as stated earlier.

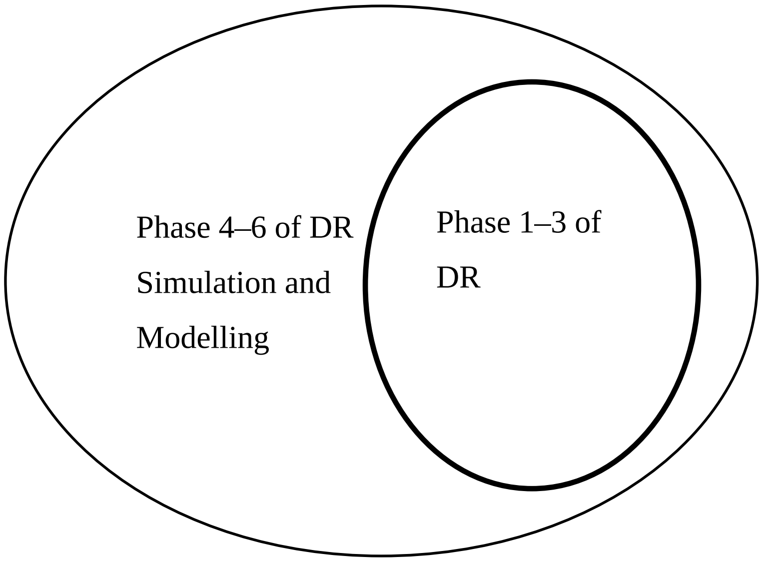

Figure 3-5: The Embryo for the Hyper-Heuristic Model
Source: Researcher’s own construction

Simulation largely takes place in Phases 4-6 of the DR model. The Figure 3-5 shows the hyper-heuristic model as a combination of DR and the theory of modelling and simulation. Combining the theoretical framework and conceptual model gives a broader path of the research work by offering the foundation for their credibility, definition and guideline for the structure that support methodology and the process of a research study (Ravitch and Riggan 2017; Adom, Hussein and Agyem 2018; Bammer *et al.* 2020).

In this chapter, the theoretical framework and a collection of researchers' ideas from the works of literature and methodological algorithms that are related to WSN are presented. The outcome from the PRISMA results proved that the hyper-heuristic approach was the most suitable method for solving challenges of node localization and energy optimization within WSNs. The combination of the three different comparative algorithms, namely, ***the Distributed Energy Efficiency Clustering (DEEC) algorithm; Gaussian Elimination (GAUSS) algorithm; and the Gradient Distance Algorithm (GDA)***, were simulated with the use of MATLAB 2020a to accomplish the performance criteria, node localization and enhanced energy efficiency as required.

In this research study, algorithms in the family of swarm intelligence and non-swarm intelligence, namely, the DEEC algorithm, the GAUSS algorithm, and GDA was adopted to consist of high-level hyper-heuristics. Applying them to bring a unified solution to prolong the network lifetime, calculate the shortest path, reduce energy consumption which helped to improve node estimation error and determine the lowest cost of communicating between anchor nodes and the target node. Metrics such as the sum aggregate of packets dispatched to BS, first node dead (FND), time of arrival to the BS, probability of error of sensor within the connection are used to show superior performance compared to the results in the literature, where there are established heuristic methods.

3.10 Justification for Preferred Programming Language for the Simulation

C programming language is an object-oriented programming (OOP) used in the MATLAB environment because it has re-useable properties (inheritance) while providing modular functionalities when compared to Python. C programming helps the software development in the MATLAB environment by being used as a prototype language to support fast development.

Furthermore, using C, security is enhanced, and cost of development is reduced (Hardin 2017; Stueben 2018).

The purpose of using MATLAB R2020a was to have a scholarly foundation from which the approach and combination of the various advantages were deployed. The authenticity of the graphical programming interface when using the code line editing with the table display during simulation running, made it relatively easy to detect the error line. The MATLAB environment used with C does supports the Windows Operating System allowing for easy design, and development during the implementation process (Abar *et al.* 2017). MathWorks being the organization behind MATLAB R2020a is able to carry out analysis of code generations with a simple real-world scenario presented with the easy graphical user interface (GUI). MATLAB R2020a comes loaded with different toolboxes for simulation depending on the area of focus for each study and diversity for implementation. The state flow coder generates efficient compilation in real-time. The MATLAB R2020a tools are a reliable means to test, evaluate, automate processes, producing real-time executable files and results. The optimized C language supports hyper-heuristic systems, real-time node localization, and energy efficiency in an easier way when compared to modern programming languages on a stand-alone Windows Operating System. The code style functionality and code addition are examples of the functionalities that come with a MATLAB R2020a environment (Naghashzadeh *et al.* 2021).

3.11 Comparative Algorithms

The comparative analysis of the novel DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA) for this research work is stated in Table 3-1.

Table 3-1: Advantages of the three State-of-the-art Algorithms

Gaussian Elimination (Gauss) Algorithm	**Distributed Energy Efficiency Clustering (DEEC) Algorithm**	**Gradient Distance Algorithm (GDA)**
GAUSS algorithm will help to identify the minimum cost of the path in the graph	DEEC stability in energy consumption in the network is great when compared to other categories of energy efficiency algorithm protocols (Vançin and Erdem 2018)	GDA was used to measure the unknown locations of sensor nodes (Qiao and Pang 2011)
Gauss algorithm will help to calculate the shortest path, the first node dead, the tenth node dead.	DEEC is used for optimizing and balancing energy depletion of the nodes pattern during the process of utilization (Krishna, Babu and Kumar 2016)	GDA was used to optimize the accuracy estimation of localization (Qiao and Pang 2011)
GAUSS algorithm is used for considering node communication and number of packets sent or transmitted and the distance from source to destination	DEEC is used to determine the current velocity of the energy compared to another algorithm in the energy hierarchies (Reddy and Rajan 2017)	GDA was used to calculate the cluster centre of each node
GAUSS algorithm will help to optimize the targets for nodes to save energy	DEEC helps in the aspect of the probabilistic model when compared to stable election protocol (SEP) and its characters are enormous in an ideal solution (Reddy and Rajan 2017)	

The DEEC algorithm and GDA helped to improve node localization and determined the best cost from source to destination, initialized particles used for calculating velocity, found the position of particles, provided the best solution needed. Both algorithms mimic swarm intelligence, based on the natural behaviour of organisms which was deployed in this research work. The results were compared with the modern techniques, regarding estimation, transmission, and detection of node localization problem in WSNs.

3.11.1 Distributed Energy Efficiency Clustering (DEEC) Algorithm

The DEEC algorithm is an energy management protocols algorithm that is used for solving the impediments of sensors battery lifespan in WSNs such as memory information management, information routing, data detection, and the processing of information (Babayo, Anisi and Ali 2017; Engmann *et al.* 2018; Vançin and Erdem 2018).

The DEEC is a clustering algorithm where the CH aids selection with probability ratio for residual energy deployed to minimize the overhead utilization in the energy management. The DEEC is assumed to be a selection of node that guarantees the CH energy circulation is ascertained before the last node energy depreciates during the WSN operations. DEEC is sometimes regarded as the steady state when the population size of the sensor nodes is being minimized to enable it to display the robustness of the nodes in the CH election.

The DEEC algorithm uses flat and reduced standard deviation when compared to LEACH. DEEC stability in energy consumption in the network is great when compared to other categories of energy efficiency algorithm protocols used in WSNs (Saini and Sharma 2010; Aderohunmu, Deng and Purvis 2011; Reddy and Rajan 2017).

The DEEC algorithm is considered to be multi-level heterogeneous because it comprises two or more kinds of nodes in the area of energy hierarchy (Aslam *et al.* 2016; Vançin and Erdem 2018). One of the DEEC algorithm's limitations is that it cannot make use of advanced sensor nodes and supervise the super-nodes which are sometimes called CH. In most cases, the super-nodes utilize the same energy just like the normal nodes (Gupta, Rao and Venkatesh 2016). The DEEC algorithm is heterogeneous in nature, comprising of normal nodes and advanced sensor nodes which have high energy consumption capacity. The only limitation of the DEEC algorithm is that it has a low performance level when differentiated to developed distributed energy efficiency clustering (DDEEC), enhanced distributed energy efficiency clustering (EDEEC) (Qureshi *et al.* 2012; Singh, Malik and Kumar 2017).

3.11.2 Gaussian Elimination (GAUSS) Algorithm

The Gaussian Elimination is mainly used in solving linear determinant calculations and is used to explain the history and living mutation of mathematics (Sasaki and Murao 1982; Grcar 2011). Some researchers also use GAUSS elimination for analysing the network performance for small distance linear details (Schotsch, Schepker and Vary 2011; Wang *et al.* 2019.). The Gaussian elimination algorithm was deployed to reduce the matrices row of fractions rather than the traditional approach (Gharib *et al*. 2015) so that $AX = B$, as presented in Equation 3-1 below:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & & a_{1k} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2k} \\ a_{31} & a_{32} & a_{33} & & a_{3k} \\ & \vdots & & \ddots & \vdots \\ a_{k1} & a_{k2} & a_{k3} & \cdots & a_{kk} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_k \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_k \end{bmatrix} \qquad (Eq. 3-1)$$

3.11.3 Gradient Distance Algorithm (GDA)

The Gradient Distance Algorithm (GDA) was incorporated into the hyper-heuristic approach to optimize the energy consumption of sensor nodes within the wireless sensor networks (Banerjee *et al.* 2017). The GDA sensor node hop distance is placed at random within the anchor node environment which produces the optimal route for node localization and improves the transmission delay in the hyper-heuristic approach when compared to similar traditional approaches. The GDA enhances the sensor node accuracy and the cluster centre node estimation error optimization (Hijazi *et al.* 2019; Jin, Zhou and Wang 2020). The GDA processes for calculating hop sizes for the distances between the sensor nodes are computed using the following equations (Heinzelman, Chandrakasan and Balakrishnan 2010; Oliveira, Miranda and Miranda 2020):

$$AvgHopSize_i = \frac{\sum_{j=1\ j\neq i}^{m} \sqrt{(X_J - X_I)^2 + (y_J - y_i)^2}}{\sum_{j=1\ j\neq i}^{m} Hopij} \qquad (Eq. 3-2).$$

For computing the average size of the hop, where *u* and *I* are variable and *j* is constant (Liu, Nayak and Stojmenovic 2010):

$$d_{iu} = AvgHopSize_j \times hop_{iu} \qquad (Eq. 3-3).$$

The weighted centroid method for the sensor localization as m, is determined to be the anchor's nodes for the total sum

$(X_{u,} Xy_u)$ $, m\ is\ assumed\ to\ be\ the\ total\ number\ of\ anchor\ nodes$ and

$w_i = \frac{1}{mHop_{ui}} is\ assumed\ to\ be\ the\ weighted\ factor\ for\ the\ i$ and the sensors that are unknown are computed using the following equation (Qiao and Pang 2011):

$$X_u = \frac{\sum_{i=1}^{m} w_{ix_i}}{\sum_{i=1}^{m} w_i}, \quad , \quad y_u = \frac{\sum_{i=1}^{m} w_{iy_i}}{\sum_{i=1}^{m} w_i} \qquad (Eq.\,3{-}4).$$

The factor of *Wi* for the remote sensor for unknown sensor nodes are localized (Vidyasagar, Atif and Elizabeth 2009)

$$w_i = \frac{\sum_{i=1}^{m} Hop_{ui}}{mHop_{ui}} \qquad (Eq.\,3{-}5).$$

3.12 Chapter Summary

The chapter presented the theoretical framework of DR and the methodological processes taken to bring into reality the goals and objectives of this study. The chapter presented in detail the six phases of DR, namely, Identify the problem, Describe the objectives, Design and develop the artefact, Test the artefact, Evaluate testing results and Communicate the testing results. The justification for this theoretical framework is discussed in this chapter. In the third phase, the artefacts, namely, the DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA) and DEEC-GAUSS algorithm for node localisation and energy efficiency respectively were designed and developed. The algorithms were writen using the MATLAB software in the C programming language. Justification for use of MATLAB R2020a was discussed in this chapter. In the Evaluate testing results phase all the results were observed, analysed and evaluated to enable the optimum conclusions to be drawn. The theory of modelling and simulation as well as the hyperheuristic framework were presented in this chapter. The huperheuristic framework represented the conceptual model of the study. The next chapter presents the research methodology for the study.

CHAPTER FOUR: RESEARCH METHODOLOGY-A SCIENTIFIC APPROACH USING HYPER-HEURISTIC MODELS

4.1 Introduction

Scientific approach is a systematic framework that researchers use to find solutions to research problems. Scientific theories through scientific processes are used to understand the research problem and present solutions using tools such as algorithms (Dodig-Crnkovic 2002). This study, considering the aim and objectives was suited to scientific approaches such as Design Research and the Theory of Modelling and Simulation. The Hyper-Heuristic Framework is the conceptual model used in this research study. These scientific theoretical frameworks and conceptual models are discussed in Chapter Three. Figure 4-1 shows the alignment of the theoretical frameworks, conceptual model, research methods and research objectives of the study.

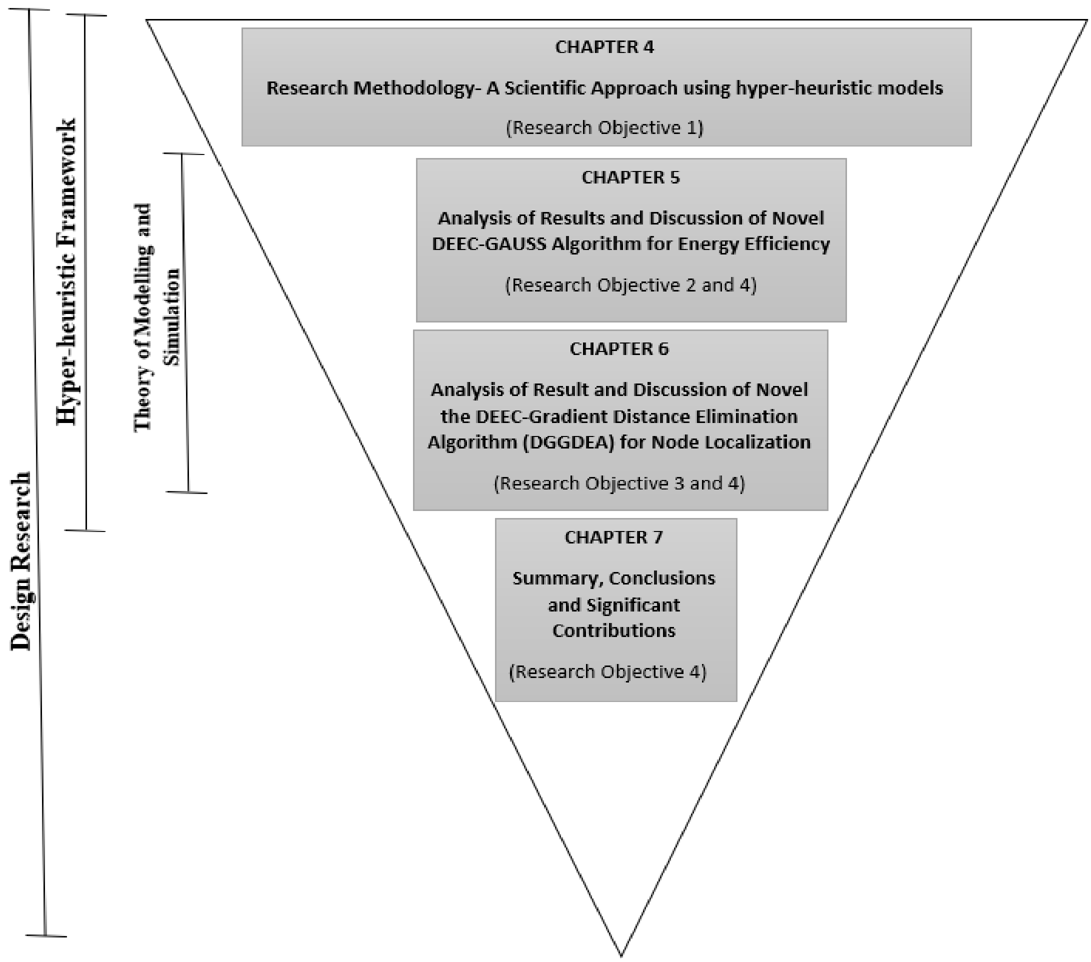

Figure 4-1: Alignment of Theories with Research Objectives

Source: Researcher's own construction

This chapter describes the scientific methodological procedures, namely algorithms that were used in this study. The first section introduces the algorithms used for optimizing energy efficiency for 100 sensor nodes. Hyper-heuristic methods were proposed to solve the energy efficiency and node localisation problem. Figure 4-2 presents the novel ***DEEC-GAUSS method*** which is discussed in the second section of this chapter.

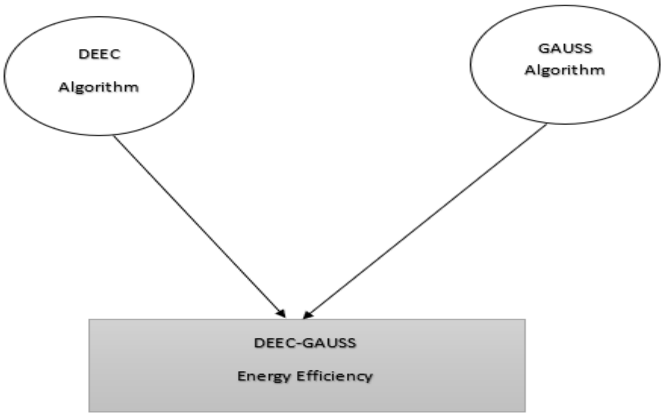

Figure 4-2: Hyper-heuristic DEEC-GAUSS for Energy Efficiency
Source: Researcher's own construction

Figure 4-2 shows the combining of the ***Distributed Energy Efficiency Clustering (DEEC) algorithm and the Gaussian Elimination (GAUSS) algorithm***. The novel DEEC-GAUSS represents the hyper-heuristic solution for energy efficiency. The third section presents energy efficiency for larger networks comprising between 1 000 and 1 500 sensor nodes. Simulation experiments were conducted using the novel DEEC-GAUSS method on larger networks.

Figure 4-3 presents the novel ***DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA)*** method for node localization for WSN which is discussed in the fourth section of this chapter.

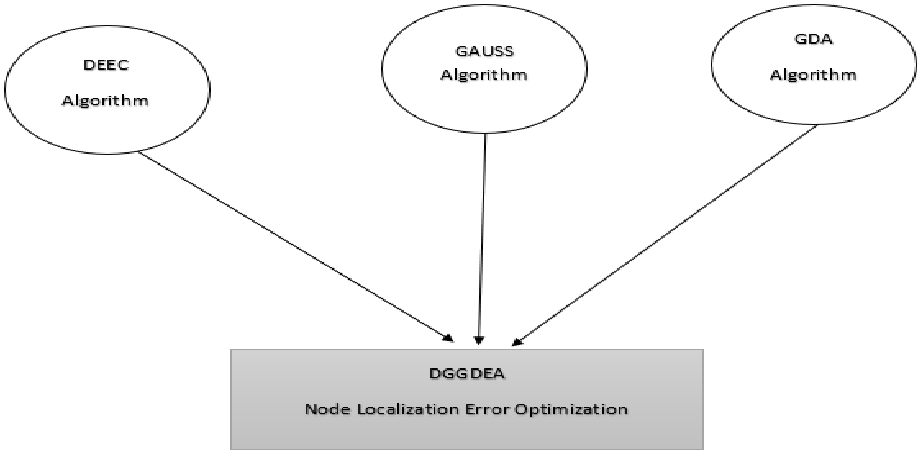

Figure 4-3: Hyper-heuristic DGGDEA for Node Localization
Source: Researcher's own construction

Figure 4.3 shows the combining of the ***Distributed Energy Efficiency Clustering (DEEC) algorithm; the Gaussian Elimination (GAUSS) algorithm and Gradient Distance Algorithm (GDA)***. The novel DGGDEA represents the hyper-heuristic solution for node localization having 20 anchor node and 200 to 450 sensor nodes. The fifth section looks at the MATLAB R2020a environment, and finally the conclusion for the chapter is presented.

4.2 Energy Efficiency of WSN using a Maximum of 100 Sensor Nodes

The centre of sensing circumference is the cluster head (CH). The BS has assigned a certain number of sensor nodes, which is where all data packets are intended to go. The data arrives at the CH before the data has aggregated, making it difficult for the CH to determine where they are going. When network nodes acknowledge or transfer data, this power model assists in determining the energy delivered. A clustering-based technique called Gaussian Elimination and the criteria formulae were used in this study work to expand on the DEEC's cutting-edge findings. The number of simulation rounds was kept constant at 5,000, and the initial energy was varied between 0.5J and 0.8J. The network lifetime was calculated throughout the simulation when it comes to rounds and the first node dead for various sensor nodes of 100. The details step by step is displayed in Figure 4-4 showing the procedures followed to be able to get the desired results.

4.3 The Heterogeneous Optimized DEEC-GAUSS Algorithm for Energy Efficiency

The proposed DEEC-GAUSS model was developed as effective solution for energy efficiency. The steps for the novel DEEC-GAUSS is stated mathematically below:

Step 1: Configure the required criteria that are necessary.

Step 2: Get the initialization energy requirements for all sensor nodes using the equation below (Al-Janabi. and Al-Raweshidy 2017):

$$E_{Total} = \sum_{i=1}^{n} E_0(1 + a_i) = E_0\left(\left(n + \sum_{i=1}^{n} a_i\right)\right) \qquad (Eq. 4-1)$$

Step 3. Begin iterating the rounds in the following manner:

i. Examine the single dead nodes and record the round in which the initial node died.

j. Check to see if the 10% of the nodes are dead, then record the rounds if this happens.

k. Check to see if all of the nodes are dead before moving on to the next phase and save the round.

l. Check if there is life in a node, denote it with a “N”.

m. Each round, the list the dead sensor nodes, living sensor, clustered heads set to zero is counted.

n. Continue this process for each node.

o. Compute the p_i for composite nodes using the equation below (Heinzelman, Chandrakasan and Balakrishnan 2002; Heinzelman, Chandrakasan and Balakrishnan 2010):

p. $$p_i = \frac{p_{opt}N(1+a)E_i(r)}{(N+\sum_{i=1}^{N} a_i)\bar{E}(r)} \qquad (Eq. 4-2)$$

q. Compute the power required by the transmitter amplifier (Heinzelman, Chandrakasan and Balakrishnan 2010)

$$E_{TX}(l,d) = \begin{Bmatrix} lE_{elec} + l\varepsilon_{f_s}d^2, & d < d_0 \\ lE_{elec} + l\varepsilon_{mp}d^4, & d \geq d_0 \end{Bmatrix} \qquad (Eq. 4-3)$$

and calculate the power required by the receiver $E_{RX}(l)$

using $E_{RX}(l) = lE_{elec}$ $\qquad (Eq. 4-4)$

u. In the next round, calculate the energy for the sensor node (Heinzelman, Chandrakasan and Balakrishnan 2010)

$$E_{Total} = \sum_{i=1}^{n} E_0(1 + a_i) = E_0((n + \sum_{i=1}^{n} a_i)) \qquad (Eq. 4-5)$$

Let *ni* be the number of rounds for the nodes *si*, rotating individual CHs for the node and we name it to be the rotating epoch, super-node, or normal node. The energy dissipated within the network cutting edge is measured using *Ei* in the modern DEEC algorithm. The dissipated in the network energy of node *si* at round *r is represented* by Ei in our proposed scheme. When the heads of the cluster appear using DEEC, the nominated CHs is the central focus on the GAUSS approach.

The number of CHs chosen is assumed to be *q*; matrix *A* denotes the energy usage of single node chosen as CH and *q* the number of CHs. *Aij to* represent the energy consumed by a CH *i has* assumed to be a normal node if CH *j* is its CH. Furthermore, *bi* denotes the residual energy of CH *i*, which is believed to be a node *xi* expresses the times when CH *i* will become a CH. This way, matrices *B* and *X* are formed, according to Gharib *et al*. (2015) so that *AX* = *B*, as shown in Equation (4 - 6) below:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & & a_{1k} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2k} \\ a_{31} & a_{32} & a_{33} & & a_{3k} \\ & \vdots & & \ddots & \vdots \\ a_{k1} & a_{k2} & a_{k3} & \cdots & a_{kk} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_k \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_k \end{bmatrix} \qquad (Eq. 4 - 6)$$

The code is used to find the optimal number of clusters and the number of rounds in the network (Gharib *et al.* 2015).

```
For (k=1; k<m+1; k++)
I_max:= argmax(i=k…m, abs(A[i,k]));
If (A[i_max,k] = 0)
Error “Matrix is singular!”;
Swap rows (k,i_max);
```

The code below is used to figure out how many packets were sent to the BS as well as the state of the tenth node, which is currently dead (Gharib *et al.* 2015).

```
For (i=k+1; i<m+1; i++)
    For (j=k+1; k<n+1; j++)
        A[i,j]:= A[i,j] – A[k,j] x (A[i,k]/A[k,k]);
        A[i,k]:=0;
```

The proposed DEEC-GAUSS Algorithm for energy efficiency in WSNs is given below using pseudocode using the steps outlined in Section 4.3.

<u>Sequential Algorithm 1: The DEEC-GAUSS Algorithm (Gharib *et al.* 2015)</u>

Input: The DEEC-GAUSS algorithm Matrix b[1 : m, 1: m+1]

Output: y[1 : m]

1. for c = 1 to m-1
2. for i = c+1 to m
3. u = bic/bcc
4. for j = c to m+1
5. bij = bij – u * bcj
6. proceed next for j
7. proceed next for i
8. proceed next for c
9. ym = bm,m +1/amm
10. for i = m to 1 step -1
11. proceed sum = 0
12. for j = i+1 to m
13. Then sum = sum + bij * yj
14. proceed next for j
15. yi = (bi, m+1-sum)/bii
16. proceed next for i
17. end

Figure 4-4 shows the system model of the novel DEEC-GAUSS Algorithm for energy efficiency.

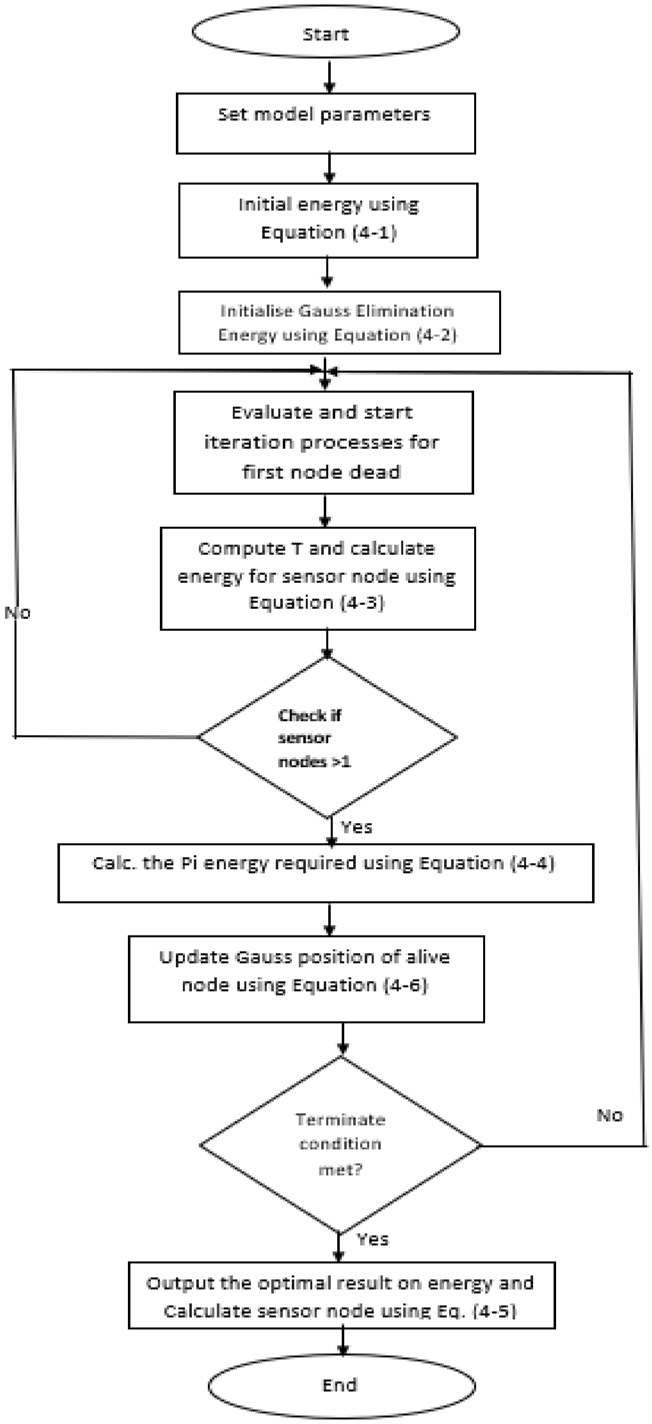

Figure 4-4: The DEEC-GAUSS Algorithm System Model

Figure 4-4 represents an illustration of the steps to be followed using a flow diagram to obtain the results for the novel DEEC-GAUSS Algorithm. The equations that are used in the flow diagram is shown in processing boxes of the flow diagram. These equations can be referenced in Section 4.3.

Table 4-1 shows the simulation parameters for the experiments.

Table 4-1: Simulation Parameters for Energy Efficiency

Parameters	Value
Network Field	(100,100) m^2
Number of sensor nodes	100; 1000 -1500
Eo (Initial energy of normal nodes) Optimization algorithm Transmission Range ®	0.5J – 0.8J
Unknown node (N) Message Size	100 4 000 Bits
E*elec*	50 *nJ/bit*
Efs	10 *nJ/bit/*m^2
E*amp*	0.0013pJ/bit/m^4
EDA	5Nj/bit/signal
D*o* (Threshold Distance)	100m
P*opt*	0.1

The size of the area of interest is set to m-by-m, meter equal to 100 as displayed in Table 4-1 and the process taken is displayed in Figure 4-4. The BS is situated in the centre of the location’s field.

4.4 Simulation Environment: MATLAB Technicalities

The first simulation was initially carried out with 100 sensor nodes with starting energy between 0.5J to 0.8J, while the second simulation was carried out for 1 000 to 1 500 sensor nodes for energy optimisation. The novel DEEC-GAUSS was run multiple times for the best results to be obtained.

Furthermore, we added node localization error with 20 anchor nodes and varieties of sensor nodes between 200 and 450 with the random deployment of the nodes. DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA) was run multiple times consecutively for the best results to be obtained. The novel DGGDEA) simulation results was benchmarked with classical node localization algorithms such as Weighted Centroid Localization (WCL), DV-Hop, Compensation Coefficient (CC), Weighted Centroid (WC). The simulation was carried out in the MATLAB 2020a environment to achieve the desired result. The system was configured with an Intel Core i7, 8650U CPU running at 1.90GHz, and 8.00GB of installed memory (RAM) (7.85GB usable). Windows 10 is running on a 64bit operating system with an x64-based processor.

4.5 DEEC and Gaussian Elimination Method

The DEEC-GAUSS method is a combination of two homogeneous algorithms, namely, DEEC and Gaussian Elimination Method that form a heterogeneous method for clustering of sensor nodes that are deployed to locate the energy stability and performance of the node coverage operations (Aroba, Naicker and Adeliyi 2021b; Aroba, Naicker and Adeliyi 2021a). We assume a unique DEEC-GAUSS design model that facilitates network connectivity which includes power optimization clustering with their position from the CH and sensors. In the DEEC-GAUSS technique, one of the individual criteria utilized for timing mode Popt.=0.1, where Popt. represents the optimum probability. All of the sensor nodes, including those that are stationary at one time are used and deployed at random. Each of these individual nodes contains an equal amount of energy, ranging from 0.5J to 0.8J.

In this area, we present a distinctive DEEC-GAUSS algorithm model that assists the connection with energy-efficient clustering with focus on the path between the CHs and the sensor nodes. Popt=0.1 is one of the period mode parameters used by the DEEC-GAUSS. All of the sensor nodes, including those that are stationed in one location, are used and deployed, at random. Each of these separate nodes has a fixed quantity of energy ranging from 0.5J to 0.8Joules. Both inside and outside of the sensing environment, the BS is considered to be homogeneous. These sensor nodes are frequently merged and then moved to the CH. The sensor's environment is unknown, including the location in which it is situated. As a result, the self-organization is placed on closed monitoring before being deployed to the next batch of procedures.

When the task is done at an individual round, the uniform nodes conduct tasks as the CH, and the sensors are delivered at random to identify the connection agedness of node with the long-awaited energy result. The CH is located within sensing area's centre. The number of sensor nodes distributed from the BS has been dramatically reduced, which is where all information is expected to go. The nodes arrive at the CH before the data assemble, making it difficult for the cluster leader to figure out where they are. The capacity for nodes to calculate the coverage between BS and the nodes by differentiating the received signal intensity are all features of this simulation, which was run in the MATLAB server, which are determined by their GPS co-ordinated. As a result, the sensor nodes have increased with a significant amount that does collaborate with the CHs that are closest to them.

Both inside and outside of the sensing environment, the BS is homogeneous. The data collated within various nodes is collected and delivered to CH on a regular basis. The sensor node's location, as well as the position in which it is placed is also collected. As a result, before moving on to the next phase of operation, the self-organizing nodes are monitored. The consistent nodes can act as CHs, and the sensor node are to determine the moment of deployment at random time as the sensor node's connection lifetime based on the expected power output when the work is done in a single round.

4.6 Node Localization for 200-450 Sensor Nodes

The node localization aspect of this research work is by considered by using the approach of balancing the energy and the accurate localization approaches. It is implemented by using the hyper-heuristic **DEEC-GAUSS Gradient Distance Elimination Algorithm (DGGDEA)** which metrics that are considered as the packet of data, the anchor locations including the hop-count, when the packets are being received. The second phase of the programming for each anchor node looks for the distance on each hop with the average size, the third phase focuses on the converted unknown sensor nodes that were not localized with the use of the multiliterate method applied for getting their locations. In the fourth phase the variant of the DV-Hop for calculation of the weighted centroid was determined for full localization to take effect while the fifth phase which was the localization error computation for the nodes and the actual estimated location for the nodes are calculated within the transmission range. The overall DGGDEA processes were established fully to outperform other state-of-the-art algorithms WCL, WC, and DV-Hop respectively.

4.7 Node Localization using the Novel DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA) Method

Node localization in wireless connected networks is a modern trend of technology for targeting unknown node location acquisition for further analysis and development (Zhao, Cheng and Zhou 2021). Node localization helps to reduce the communication within the known main sensor nodes and unidentified location of nodes by utilizing the calculation of the size of hop for all the unknown locations of the sensor nodes (Kanwar and Kumar 2021). Location estimation is of great importance in WSN along with range-based approaches such as Time Difference of Arrival (TDOA), Time of Arrival (TOA), Receive Signal Strength Indicator (RSSI) and the Angle of Arrival (AOA) (Shahbazian and Ghorashi 2017). Node localization is the latest trend in WSN technology. Major problems in WSNs related to node localisation are: location error, lack of accuracy, and distance estimation implementation (Risteska Stojkoska 2017; Zhang *et al.* 2021).

The proposed DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA) for node localisation is described mathematically using the steps below:

Step 1. Set the network model criteria.

Step 2. The homogenized energy for every sensor nodes is calculated using the equation below (Wang *et al.* 2018)

using $E_{Total} = \sum_{i=1}^{n} E_0(1 + a_i) = E_0\left((n + \sum_{i=1}^{n} a_i)\right)$ (Eq. 4-7)

Step 3. Start iteration the computation of p_i for heterogeneous nodes (Heinzelman, Chandrakasan and Balakrishnan 2002)

using $p_i = \frac{p_{opt} N(1+a) E_i(r)}{(N+\sum_{i=1}^{N} a_i)\bar{E}(r)}$ (Eq.4-8)

a. Calculate the energy that is needed by the transmit amplifier (Heinzelman, Chandrakasan and Balakrishnan 2002; Wang *et al.* 2018)

$$E_{TX}(l,d) = \begin{Bmatrix} lE_{elec} + l\varepsilon_{f_s} d^2, & d < d_0 \\ lE_{elec} + l\varepsilon_{mp} d^4, & d \geq d_0 \end{Bmatrix} \quad \text{(Eq. 4-9)}$$

And the computation of power required by the receiver using

$E_{RX}(l)$ using $E_{RX}(l) = E_{elec}$ (Eq. 4-10)

Step 4. Then calculate the average hop size (Heinzelman, Chandrakasan and Balakrishnan 2010)

$$(AvgHopSize_i\,) \quad \text{(Eq. 4-11)}$$

Step 5. The average hop size for the distance between the sensor nodes is computed with equation 6 (Heinzelman, Chandrakasan and Balakrishnan 2010; Oliveira, Miranda and Miranda 2020)

$$AvgHopSize_i = \frac{\sum_{j=1\ j\neq i}^{m}\sqrt{(X_{J}-X_{I})^2+(y_J-y_i)^2}}{\sum_{j=1\ j\neq i}^{m} Hopij} \quad \text{(Eq. 4-12)}$$

Step 6. We computed the average size of the Hop, where *u* and *I* are variable and *j* is constant (Liu, Nayak and Stojmenovic 2010)

$$d_{iu} = AvgHopSize_j \times hop_{iu} \quad \text{(Eq. 4-13)}$$

Step 7. The weighted centroid method for the sensor localization as m is determined to be the anchor's nodes for the total sum $\left(X_{u,}Xy_u\right), m\ is\ assumed\ to\ be\ the\ total\ number\ of\ \ anchor\ nodes$ and $w_i = \frac{1}{mHop_{ui}} is\ assumed\ to\ be\ the\ weighted\ factor\ for\ the\ i$ and the sensors that are unknown are computed from (Qiao and Pang 2011)

$$X_u = \frac{\sum_{i=1}^{m} w_{ix_i}}{\sum_{i=1}^{m} w_i}, \quad , \quad y_u = \frac{\sum_{i=1}^{m} w_{iy_i}}{\sum_{i=1}^{m} w_i} \quad \text{(Eq. 4-14)}$$

Step 8. The factor of *Wi* for the remote sensor for unknown sensor nodes are localized (Vidyasagar, Atif and Elizabeth 2009)

$$w_i = \frac{\sum_{i=1}^{m} Hop_{ui}}{mHop_{ui}} \quad \text{(Eq. 4-15)}$$

Step 9. We assume the number of anchor nodes to be CH as *q*; matrix *A to* signify energy consumption for every node selected as CH and *q is the* amount of CHs. *aij* denotes energy consumed by a CH, *i* represent usual node, if CH *j* is its CH. Additionally, b_i denotes used energy of CH *i*, similarly*xi* represent the times that CH *i* can become a CH (Singh *et al.* 2016;

Rawat, Chauhan and Priyadarshi 2020). Likewise, matrices *B* , matrices *X* are formidable, to make $A \cdot X = B$, as shown in Equation (4-16) below:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & & a_{1k} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2k} \\ a_{31} & a_{32} & a_{33} & & a_{3k} \\ & \vdots & & \ddots & \vdots \\ a_{k1} & a_{k2} & a_{k3} & \cdots & a_{kk} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_k \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_k \end{bmatrix} \qquad \text{(Eq. 4-16)}$$

Snippet code presented below is used for computing number of rounds (Singh *et al.* 2016).

```
For (k=1; k<m+1; k++)
I_max:= argmax(i=k…m, abs(A[i,k]));
If (A[i_max,k] = 0)
Error "Matrix is singular!";
Swap rows (k,i_max);
```

Step 10. The code displayed below is use for computing packets dispatched to BS and their tenth node dead (Gharib *et al.* 2015).

```
For (i=k+1; i<m+1; i++)
For (j=k+1; k<n+1; j++)
A[i,j]:= A[i,j] – A[k,j] x (A[i,k]/A[k,k]);
A[i,k]:=0;
```

Step 11. The localization error is computed and the estimated position of the various unknown nodes are estimated (Oliveira, Miranda and Miranda 2020)

$$\frac{1}{n \times r} \sum_{i=1}^{n} \frac{Gauss\ localization\ error=}{\sqrt{(X_{ai} - X_{ui})^2 + (y_{ai} - y_{ui})^{\ 2}}} \qquad \text{(Eq. 4-17)}$$

The proposed DEEC-GAUSS Gradient Distance Elimination Algorithm (DGGDEA) for node localisation in WSNs is given below using pseudocode using the steps outlined in Section 4.7

<u>Sequential Algorithm 2: The DEEC-GAUSS Gradient Distance Elimination Algorithm</u>

Input: Given Matrix for DEEC-GAUSS Gradient Distance b[1 : m, 1: m+1]

Output: y[1 : m]

1. for c = 1 to m-1
2. for i = c+1 to m
3. u = bic/bcc
4. for j = c to m+1
5. bij = bij – u * bcj
6. if c∇f(y τ c)c < √ ϱ then
7. return(y τ c), if c∇f(y τ c)c
8. Generate y τ k+1 = B (f, yτ c ;L τ 1 , Lτ 2 ; y τ 0 , D, d), which satisfies

   cy τ 0 − B (f, yτ c ;L τ 1 , Lτ 2 ; y τ 0 , D, d)c ≤ D.
9. if cy τ c+1 − y τ 0 c ∈ [D − d, D] then

10 y τ+1 0 = y τ c+1.

11. proceed next for j
12. proceed next for i
13. proceed next for c
14. ym = bm,m +1/amm
15. for i = m to 1 step -1
16. Then sum = 0
17. Then sum = sum + bij * yj

18.proceed next for j

19. for xi = (bi, m+1-sum)/bii
20. proceed next for i
21. End

The Figure. 4-5 below present the **DEEC-GAUSS Gradient Distance Elimination Algorithm (**DGGDEA) flow process.

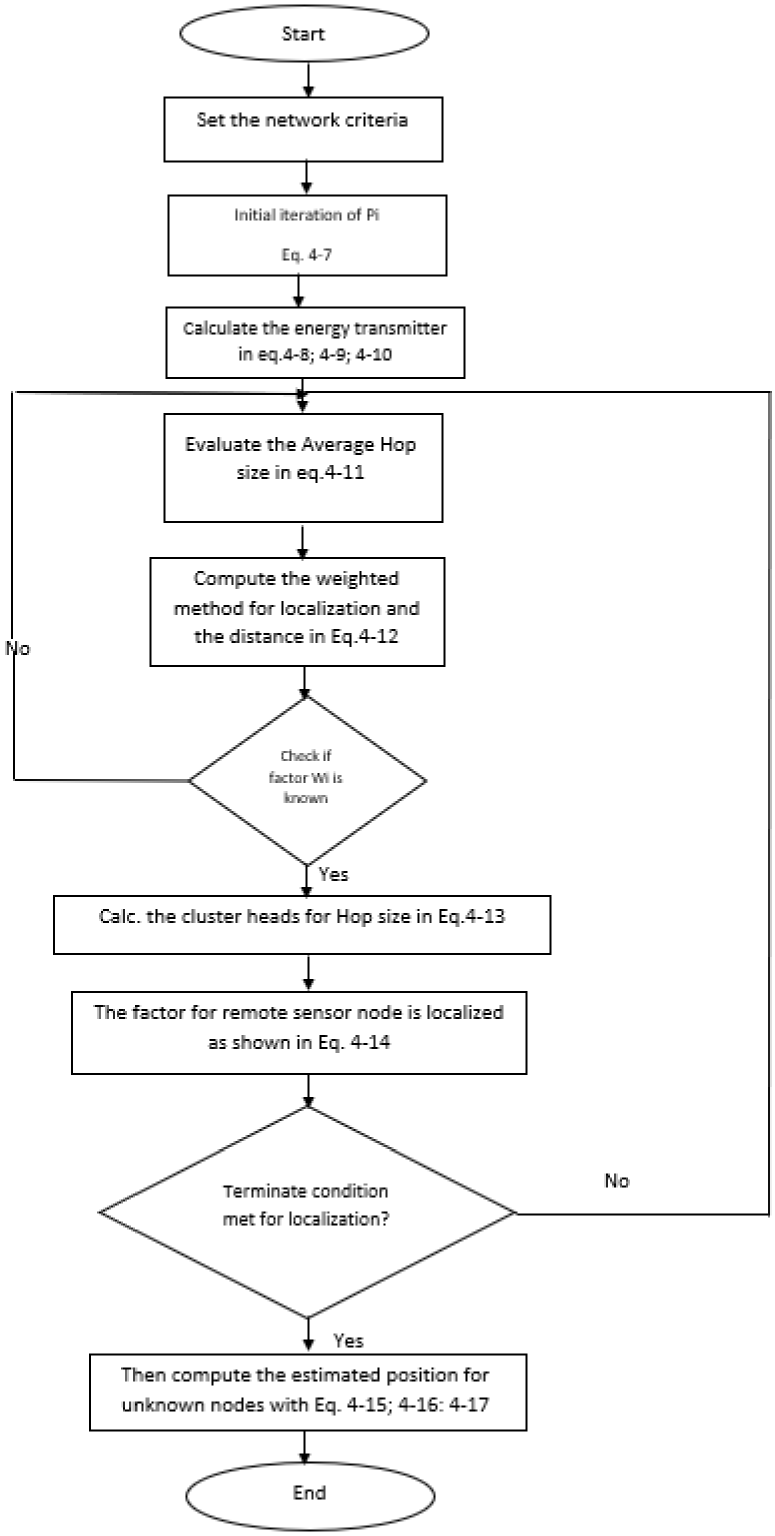

Figure 4-5: System model of proposed DEEC-Gaussian Gradient Distance Elimination Algorithm
Source: Researcher's Own Construction

The Table 4-2 shows the location error and the number of anchor nodes used during the simulation performances.

Table 4-2:Simulation Network Parameters for Node Localization

Parameters	**Value**
Network Field	(100,100) m^2
Number of nodes	200 to 450
Eo (Initial energy of normal nodes)	0.5J
Message Size	5 000 Bits
Anchor node numbers	The num
Efs	10 *nJ/bit/m*^{2}
E*amp*	0.0013pJ/bit/m^4
EDA	5Nj/bit/signal
D*o* (Threshold Distance)	100m
P*opt*	0.1
Total number of simulations	450

The Table 4-2 is the network simulation parameters that are used for carrying out the experiments for 200 to 450 sensor nodes in determining the node localization using DGGDEA.

4.8 The Node Localization Errors Model

The localization of nodes estimation **DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA)** error approach dissertates information on the power to be received and dispatches the number of information to the BS that is within the area covered by 100m by 100m. We place 10% of the number of nodes that are attached to the CHs. Hop count is placed at zero for the (X*i*, Y*i)* and the anchor nodes (i) which is the identity with the Hop*ij* that is assumed to be the hop count number sent to the BS.

We present the approach of localizing the probability of error with the use of the DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA).

Step 1: Set the sensor nodes to be deployed in a scattered form so that the position will not be static when they are being deployed.

Step 2: The CHs which comprise 20 anchor nodes have an equal number of initial energies.

Step 3: Consequently, we use the same initial energy for sensor nodes.

Step 4: All nodes are assumed to be bi-directional and the parameters for DGGDEA is *Popt=0.1* for the periodic time mode when all the nodes are deployed at random. The sensor nodes are dispatched from a BS to their various destinations at an equal energy capacity of *0.5J*.

Step 5: Probability of Error (PoE) is divided by the location error with the total sum of sensor nodes from 200 to 450 used.

4.9 Chapter Summary

The chapter commenced with a recap of the scientific methods and models used in this study. This chapter presented a unique method using **DEEC-GAUSS for optimizing energy and DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA**) model for reducing node localization error in WSNs. Each hyper-heuristic solution was explained in terms of pseudocode, equations and system models. The processes to be followed to get the desired results are described step by step in this chapter. In the next chapter, the analysis and discussion of results are presented.

CHAPTER FIVE: ANALYSIS OF RESULTS AND DISCUSSION OF NOVEL DEEC-GAUSS ALGORITHM FOR ENERGY EFFICIENCY

5.1 Introduction

This chapter presents the analysis of results and discussion of the simulation experiments to accomplish the second [RO 2] and fourth [RO 4] objectives of the study. Section 5.2 presents the results of energy efficiency using DEEC-GAUSS for small (100 sensor nodes) networks and Section 5.3 presents the results for energy efficiency for larger networks (1000 to 1500 sensor nodes). The results for network throughput, first dead node and all dead nodes and the execution time during the simulation analysis are presented in the results.

5.2 Results of the Energy Efficiency of WSNs using Maximum of 100 Sensor Nodes

The simulation result of the unique DEEC-GAUSS technique with correlation analysis and state of the art clustering approaches are shown, such as Developed Distributed Energy-Efficient Clustering Extended (DDEEC_E), Distributed Energy Efficiency Clustering (DEEC), and Distributed Energy Efficient Clustering Extended (DEEC_E) with natural, intermediate, and super node classifications. The number of rounds in the network before first node dead (FND) was used to evaluate a clustering strategy in terms of connection establishment and the number of rounds in the connection until the tenth node depleted and their power dissipates or depreciates. This is represented in the tables below with the TND abbreviation.

The simulation model output for DEEC_E: Developed Energy-Efficient Clustering Extended, DDEEC_E: Developed Distributed Energy-Efficient Clustering Extended, DEEC: Distributed Energy-Efficient Clustering, and DEEC GAUSS: Distributed Energy-Efficient Clustering Gaussian Elimination Clustering algorithms are displayed in Table 5-1. The acronym BS refers to the base station, Popt refers to periodic time mode and Time (S) refers to time taken. Table 5-1 below shows the outcome of our novel proposed DEEC-GAUSS algorithm with the modern algorithms, namely, DDEEC_E, DEEC_E, DEEC for composite initial energy values of 0.5J to 0.8J respectively.

Table 5-1: Alive Nodes During the Network Lifetime for 100 Nodes with an Initial Energy of 0.5J

Algorithms	Popt	FND	TND	Packets to BS	Time (S)
DEEC_E	0.1	1 444	1 693	82 268	8.17027
DDEEC_E	0.1	1 344	1 440	89 892	8.727181
DEEC	0.1	1 282	1 552	136 305	9.984828
DEEC-GAUSS	0.1	1 617	1 832	133 944	5.088432

Table 5-1 presented the results of FND, TND, packets to BS and execution time. The DEEC-GAUSS algorithm, recorded the shortest time to carry out the sensor node operation with an initial energy of 0.5J. DEEC-GAUSS recorded the highest number of packets sent to BS (133 944) compared to other cutting-edge clustering algorithms. When the first node fails, the network's performance suffers, and it becomes unstable. The invented DEEC-GAUSS produced the best results for FND and TND. The FND was reported in round 1 617, and the tenth node died in round 1 832.

Table 5-2 displays the outcome of 100 nodes using an initial energy of 0.6J.

Table 5-2: Alive Nodes Within the Network Lifetime with 100 Nodes with an Initial Energy of 0.6J

Algorithms	Popt	FND	TND	Packets to BS	Time (S)
DEEC_E	0.1	1 308	1 514	89 892	8.727181
DDEEC_E	0.1	1 451	1 719	112 310	9.210859
DEEC	0.1	1 768	2 114	138 482	9.187751
DEEC-GAUSS	0.1	2 064	2 236	159 276	6.719211

Table 5-2 showed that the novel DEEC-GAUSS (159 276) sends more packets to BS than the state-of-the-art clustering algorithms, namely DEEC_E, DDEEC_E, and DEEC. For FND (2 064 rounds) and the tenth node dead, the proposed DEEC-GAUSS produced the best results (2 236 rounds).

Table 5-3 presents the results of 100 nodes using an initial energy of 0.7J.

Table 5-3: Alive Nodes During Network Lifetime for 100 Nodes with an Initial Energy of 0.7J

Algorithms	Popt	FND	TND	Packets to BS	Time (S)
DEEC_E	0.1	1 484	1 918	174 625	7.66522
DDEEC_E	0.1	1 827	2 023	152 256	9.187751
DEEC	0.1	1 585	1 868	110 453	11.17691
DEEC-GAUSS	0.1	2 028	2 292	185 463	7.794244

According to Table 5-3, the number of packets sent to the BS is higher on the DEEC-GAUSS (185 463) than the other clustering algorithms, namely: - DEEC_E, DDEEC_E, and DEEC. For FND (2 028 rounds) and TND, the DEEC-GAUSS presented the best results (2 292 rounds).

Table 5-4 presents the results of 100 nodes using an initial energy of 0.8J.

Table 5-4: Alive Nodes During network Lifetime for 100 Nodes with an Initial Energy of 0.8J

Algorithms	Popt	FND	TND	Packets to BS	Time (S)
DEEC_E	0.1	2 190	1 693	82 268	7.260549
DDEEC_E	0.1	2 005	2 370	171 984	10.27297
DEEC	0.1	1 894	2 150	142 979	10.37544
DEEC-GAUSS	0.1	2 480	2 751	213 305	10.43691

According to Table 5-4, the number of packets sent to BS is higher on the DEEC-GAUSS (213 305) than on the other clustering algorithms, DEEC_E, DDEEC_E, and DEEC. The novel DEEC-GAUSS also has the advantage of producing the best results for FND (2 480 rounds and a TND of 2 751 rounds with 0.8J of initial energy).

5.2.1 Comparative Analysis of First Node Dead and All Dead Nodes for 100 Nodes

Using the DEEC-GAUSS from Tables 5-1 to Table 5-4, we were able to note that the network stability period over the period before it gave up the first dead node was decreasing. The results are presented in Tables 5-1 to 5-4 for composite initial energy within the ranges of 0.5J, 0.6J, 0.7J, and 0.8J. Tables 5-1 to Table 5-4 show the FND performance for DEEC_E, DDEEC_E, DEEC, and the novel DEEC-GAUSS for various energy schemes. On the other hand, as shown in Figures 5-1 to 5-4, the FND of DEEC_E, DDEEC_E, and DEEC is inferior to the proposed DEEC-GAUSS.

Correspondingly, we examined the consummation of the proposed DEEC-GAUSS algorithm in selecting the best CH, employing the same 0.1 Popt parameters throughout the program, which were generated at random. Notwithstanding, the network administration, displayed on the bar chart demonstrated the algorithm's crystal clarity when differentiated to our novel DEEC-GAUSS clustering method, for FND, all dead nodes, and initialization, at initial energies of 0.5J, 0.6J, 0.7J, and 0.8J.

Furthermore, we can draw our conclusion from the simulation and analysis displayed in Figures 5-1 to 5-4 with the initial energy ranging from 0.5J to 0.8J. The comparison for the first node, tenth node, and the times it took for each round to run, revealed that our proposed DEEC-GAUSS algorithm performed well in all cases. Thus, equivalently, Figure 5-1 depicts the results for the FND and all dead nodes for DEEC_E, DDEEC_E, DEEC, and the novel DEEC-GAUSS at 0.5J of energy.

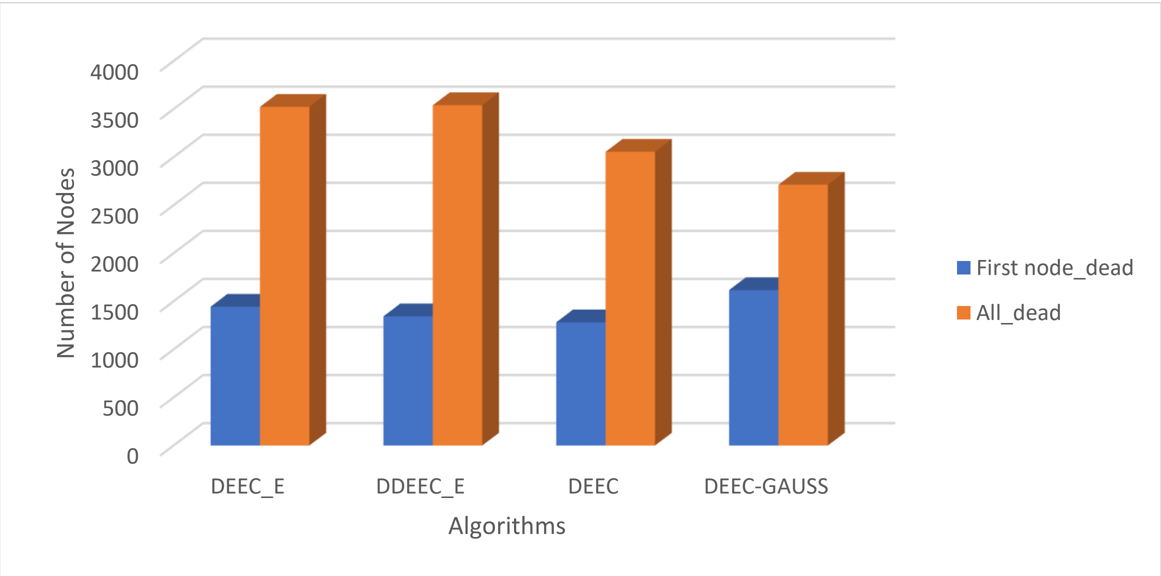

Figure 5-1: First node_dead, All _dead at 0.5J of energy

The Figure 5-1: First node dead at 0.5J shows that DEEC-GAUSS proved the best outcome for the FND and all dead nodes.

The Figure 5-2 depicts the results for DEEC_E, DDEEC_E, DEEC, and the novel DEEC-GAUSS for the FND and all dead nodes at 0.6J of energy.

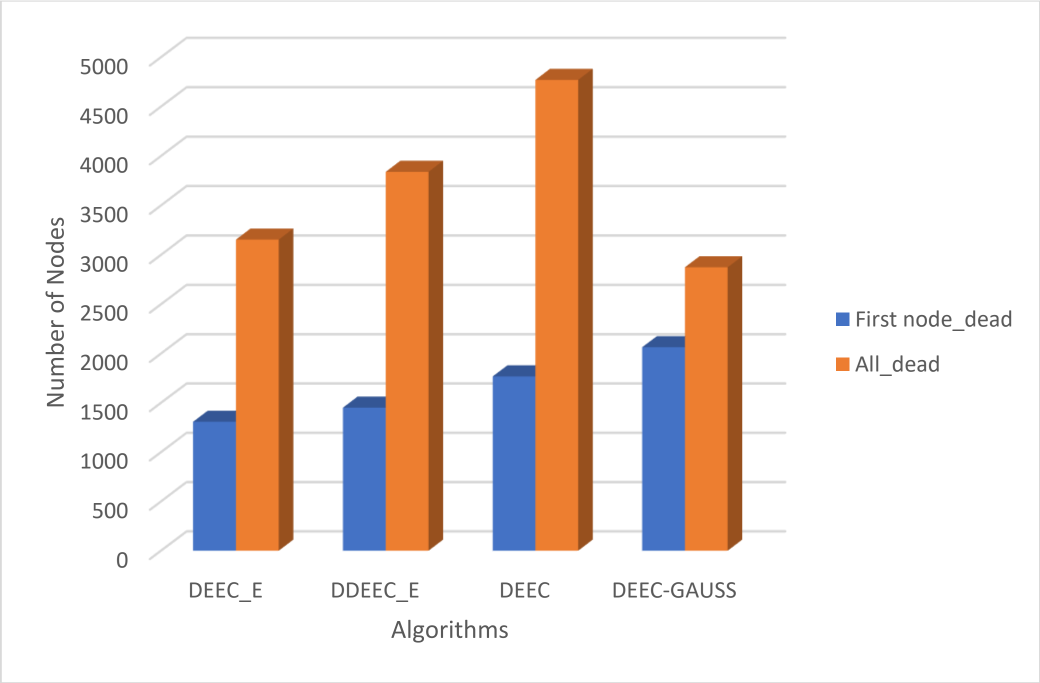

Figure 5-2: First node_dead, All_dead node at 0.6J of energy

Figure 5-2 above shows that DEEC-GAUSS produced the best results for the FND and while DEEC has the best result for all dead nodes for 0.6J of energy.

Figure 5-3 shows the results for the FND and all dead nodes for DEEC_E, DDEEC_E, DEEC, and the novel DEEC-GAUSS at 0.7J of energy.

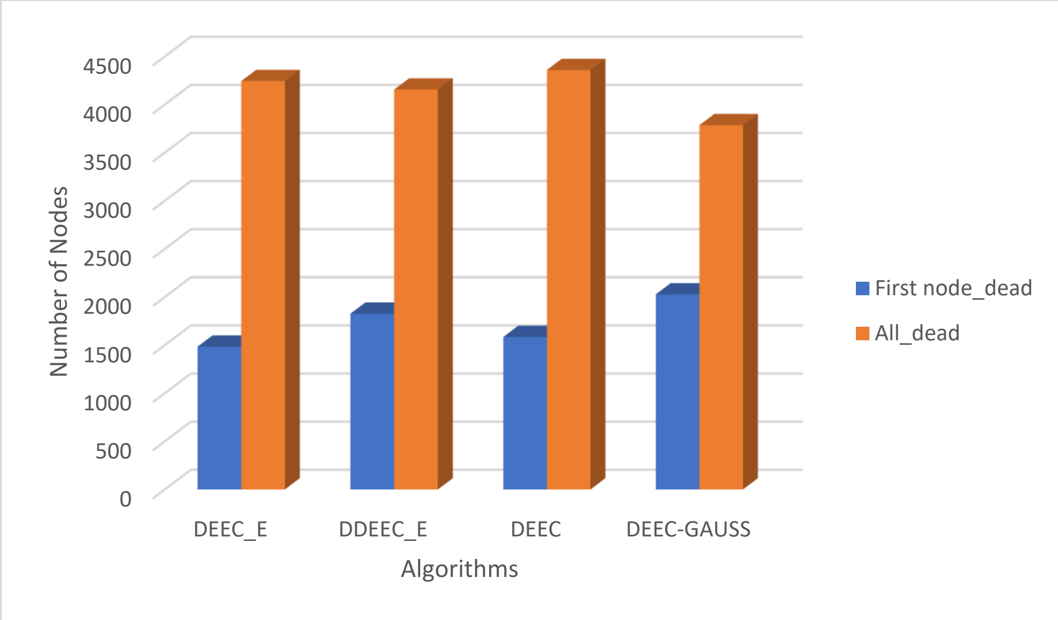

Figure 5-3: First node_dead, All_dead node for 0.7J of energy

Figure 5-3 above shows that DEEC-GAUSS produced the best results for the FND and DEEC produced the best results for all dead nodes for 0.7J of energy.

Figure 5-4 shows the results for the FND and all dead nodes for DEEC_E, DDEEC_E, DEEC, and the novel DEEC-GAUSS at 0.8J of energy.

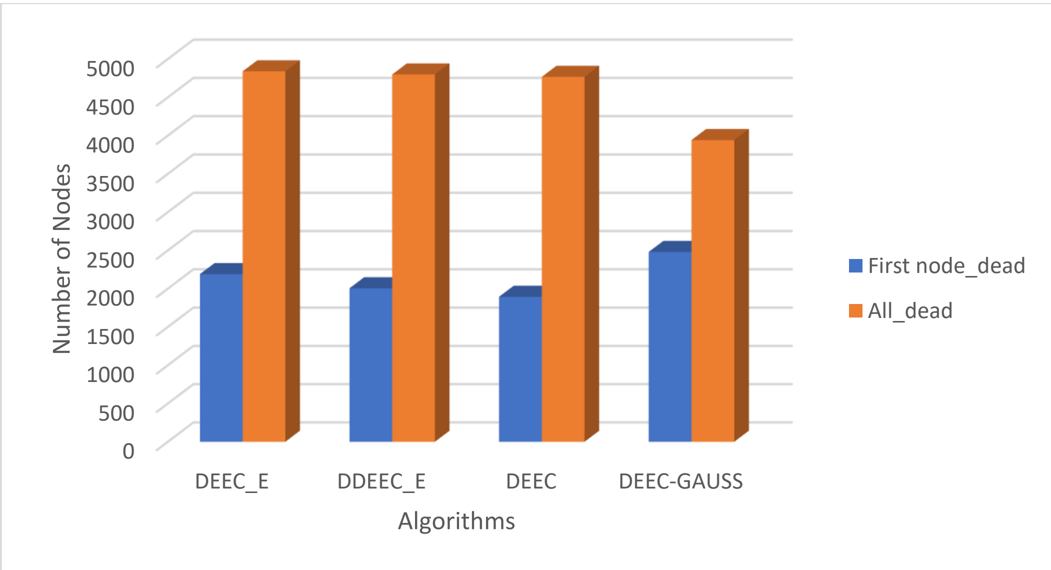

Figure 5-4: First node dead, All_dead node for 0.8J of energy

Figure 5-4 shows DEEC-GAUSS evidenced the best results for FND and DDEEC_E produced the best results for all dead nodes for 0.8 J of energy.

5.2.2 The difference in network throughput for DEEC-GAUSS for 100 Sensor Nodes

Network throughput is one of the most basic needs in WSN for evaluating the results of distinguishing algorithms. Several data packets are successfully transported throughout the network. The data from the CH is sent to BS, and the CH can fuse the data and send it to the stations within the timeframe. The CH's energy must be sufficient at this stage to accept or send packets.

This simulation is run with the four algorithms DEEC_E, DDEEC_E, DEEC, and the novel DEEC-GAUSS on 100 nodes with varying heterogeneous initial energies ranging from 0.5 to 0.8J.

Figures 5-5 depicts the increase in the number of packets sent to the BS as the number of rounds increases.

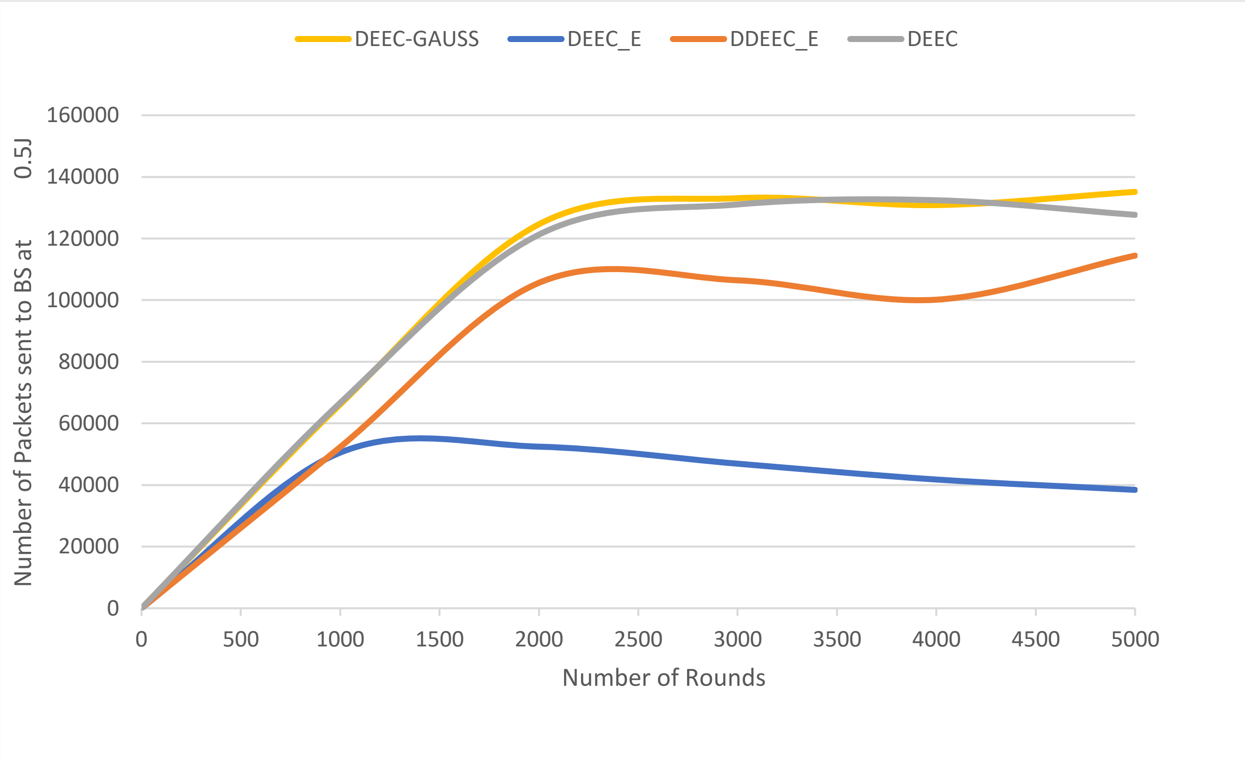

Figure 5-5: Number of data sent to Base Station vs Number of rounds at 0.5J of energy

Figure 5-5 displays that for 0.5J of initial energy, the DEEC-GAUSS achieves a network throughput of 135,134 packets in 5 000 rounds, the highest of the four tested.

Figure 5-6 below depicts the number of packets sent to the BS with respect to the number of rounds at 0.6J of energy.

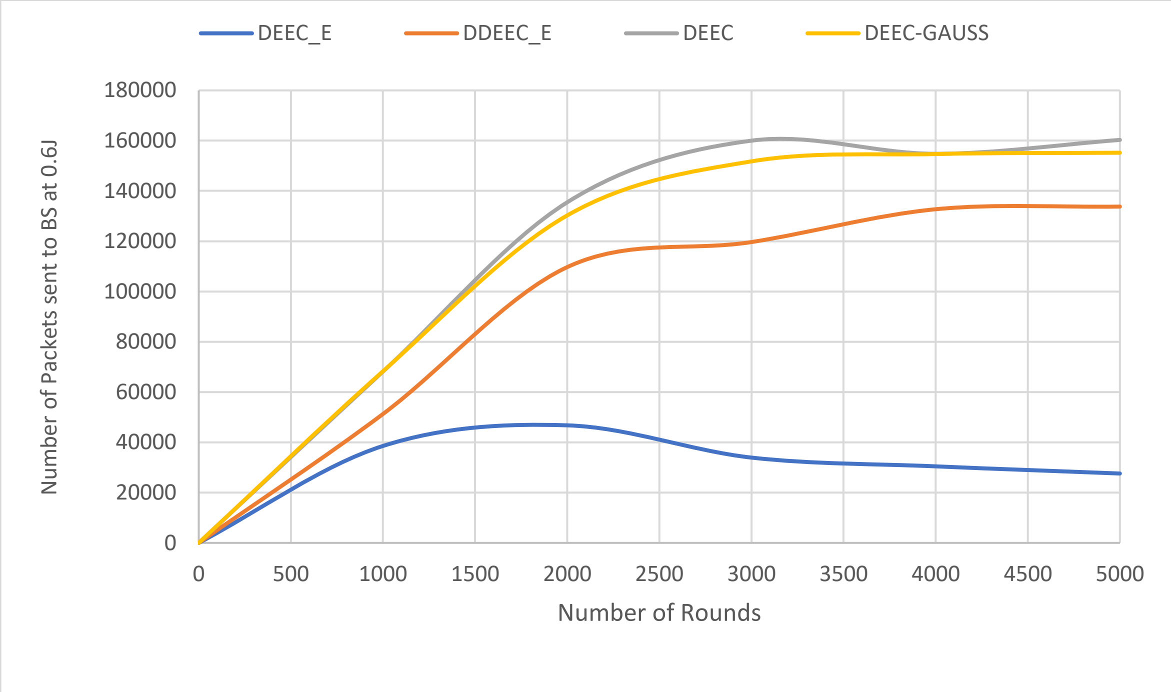

Figure 5-6: Number of Packets sent to Base Station vs Number of rounds at 0.6J of energy

Figure 5-6 depicts that the proposed DEEC has the highest network throughput of 160 289 packets, followed by DEEC-GAUSS with 155 196 of throughput packets in 5 000 rounds at 0.6J of initial energy.

Figure 5-7 depicts the number of packets sent to the BS versus the number of rounds for 0.7J of energy.

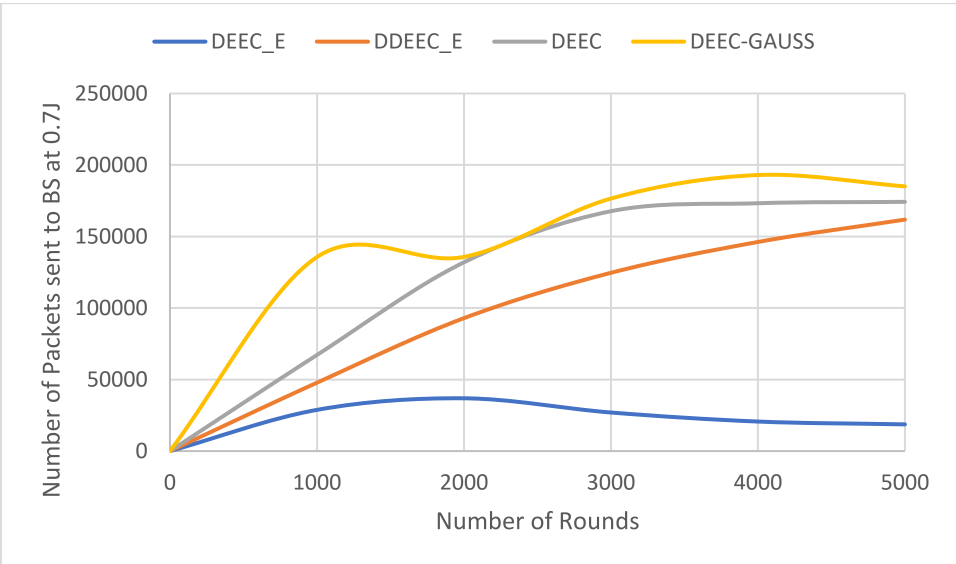

Figure 5-7: Number of Packets sent to Base Station vs Number of rounds at 0.7J of energy

Figure 5-7 shows that for 0.7J of initial energy, the proposed DEEC-GAUSS achieves the highest throughput of 185,083 packets in 5 000 rounds.

Figure 5-8 depicts the number of packets sent to the BS versus the number of rounds at 0.8J of energy.

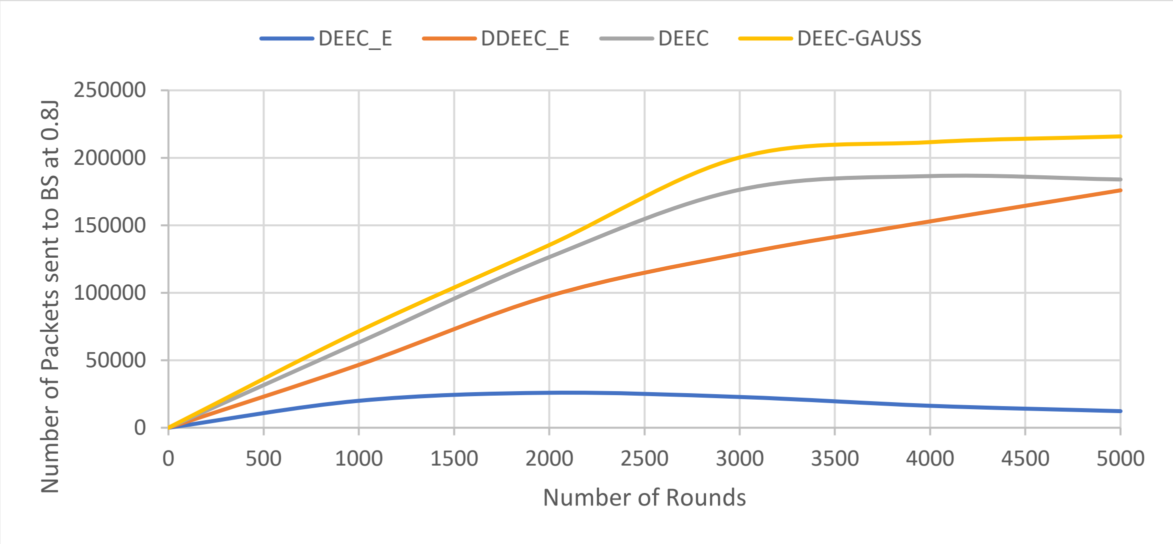

Figure 5-8: Number of Packets sent to Base Station vs Number of rounds at 0.8J of energy

Figure 5-8 shows that for 0.8J of initial energy, the proposed DEEC-GAUSS achieves the highest throughput of 215 844 packets in 5 000 rounds.

Figures 5-5, 5-7, and 5-8 shows the number of packets successfully sent to the BS, compared to number of rounds and different energy levels. The proposed DEEC-GAUSS produced the optimal network throughput initial energy in 0.5J, 0.7 and 0.8J, except in Figure 5-6 at the initial energy of 0.6J of the simulation results. Overall, the simulation results shows that DEEC-GAUSS is the most efficient algorithm because it sends the most packets to the BS.

5.3 Results of energy efficiency DEEC-Gaussian Elimination Algorithm for Larger Network (1 000 to 1 500 Sensor Nodes)

The clustering algorithms were assessed in terms of network stability for the FND, the number of rounds in the entire network when all sensor nodes die and their energy reduction, and finally the tenth node dead (TND). Throughout the simulation rounds, the number of rounds was fixed at 5 000 with energy ranging from 0.5J to 0.8J. In this simulation experiment, the network lifetime was calculated in terms of rounds when the first node died for various sensor node counts ranging from 1 000 to 1 500 sensors.

The FND metric is critical for many applications where the feedback from the sensor network must be reliable in extending the time interval before the first node dies. Figures 5-9 to 5-12 showed the performance of clustering algorithms DEEC_E, DDEEC_E, DEEC, and DEEC-GAUSS over a series of simulation rounds with initial energies of 0.5J, 0.6J, 0.7J, and 0.8J for FND.

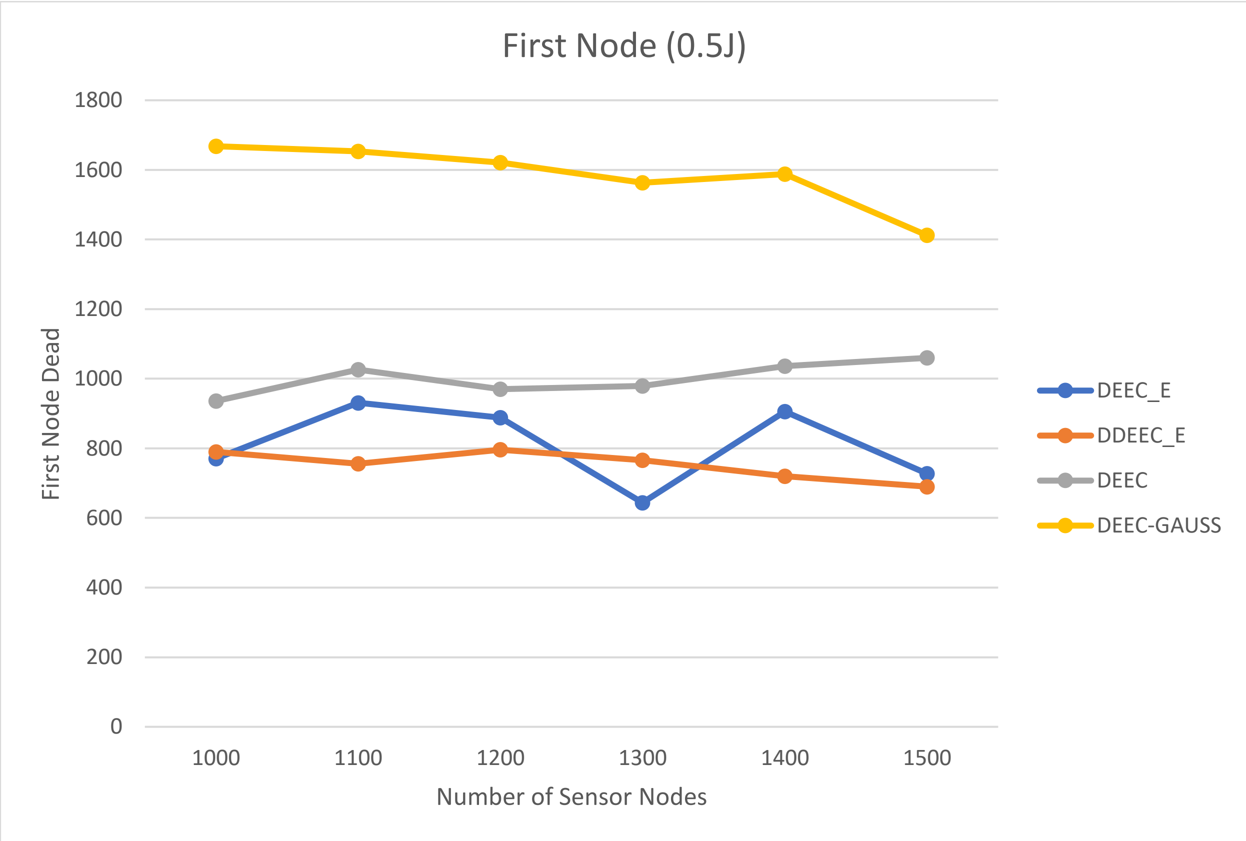

Figure 5-9: First Node Dead at 0.5J of energy

Figure 5-9 depicts the first node dead when sensor nodes are between 1 000 and 1 500 at 0.5J of energy. The higher the first node dead the better the algorithm, hence, the result of the simulation experiment depicts that the proposed DEEC-GAUSS shows a better performance than other state of the art algorithms. Figure 5-9 showed that the DEEC-GAUSS for FND at 0.5J of energy was the uppermost from 1 000 to 1 500 nodes, namely 1 668, 1 653, 1 621, 1 563, 1 588, and 1 412, while the DEEC for 1 000–1 500 sensor nodes was second at 936, 1 026, 970, 979, 1 036, and 1 060 respectively.

Figure 5-10 shows that the DEEC-GAUSS for FND at 0.6J of energy was greatest between 1 000 and 1 500 nodes.

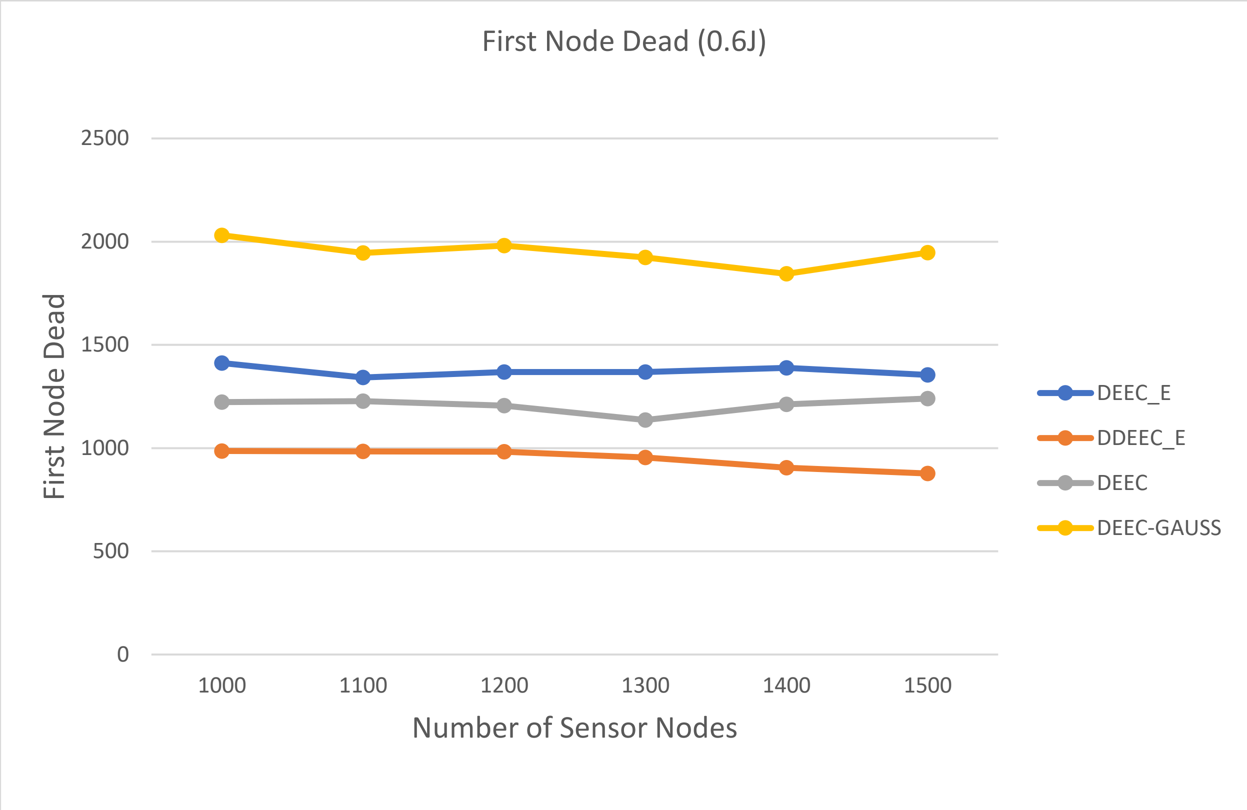

Figure 5-10: First Node Dead per 5 000 rounds at 0.6J of energy

Figure 5-10 shows that the DEEC-GAUSS for FND at 0.6J of energy was the uppermost from 1 000 to 1 500 nodes, namely 2 031, 1 945, 1 981, 1 923,1 844 and 1 947 while the DEEC for 1 000–1 500 sensor nodes was second at 1 222, 1 227, 1 205, 1 136,1 212 and 1 240 respectively.

Figure 5-11 shows that the performance of algorithms for FND at 0.7J of energy.

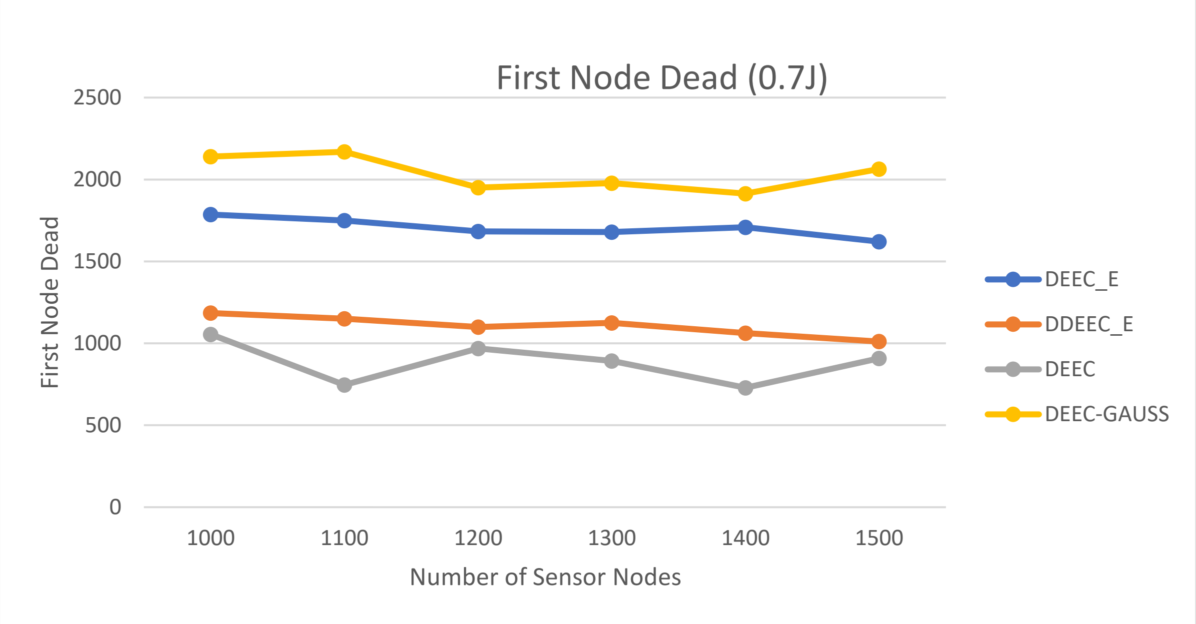

Figure 5-11: First Node Dead per 5 000 rounds at 0.7J of energy

Figure 5-11 shows that the DEEC-GAUSS for FND at 0.7J of energy was highest from 1 000 to 1 500 nodes at 2 140, 2 169, 1 951, 1 979, 1 914, and 2 063, while the DEEC_E for 1 000 to 1 500 sensor nodes was the second optimal, at 1 786, 1 749, 1 683, 1 709 and 1 621 accordingly in the performance results.

Figure 5-12 shows that the performance of algorithms for FND at 0.8J of energy

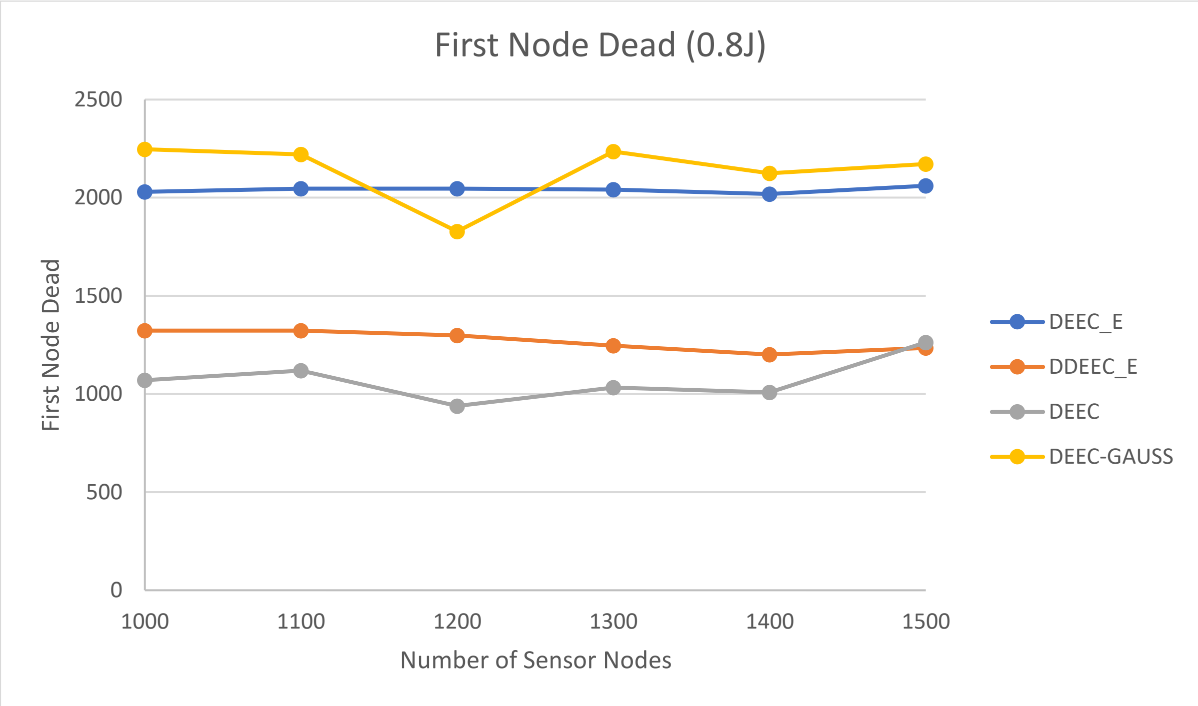

Figure 5-12: First Node Dead per 5 000 rounds at 0.8J of energy

Figure 5-12 shows that the DEEC-GAUSS for FND at 0.8J of energy was greatest for nodes 1 000 to 1 500 at 2 247, 2 221, 1 828, 2 235, 2 124 and 2 171 while the DEEC_E for 1 000 to 1 500 sensor nodes was the second optimal, at 2 030, 2 046, 2 046, 2 042, 2 019 and 2 061 respectively.

Figures 5-9 to Figure 5-12 demonstrate that the novel DEEC-GAUSS method outperformed other modern approaches for the FND for initial energies ranging from 0.5J to 0.8J. As a result, we can conclude that our approach does contribute to the WSN's longer stability period. Popt parameters (Popt=0.1) were generated at random. The DEEC-GAUSS has a significant advantage in that it delays the round of iteration by extending the time until FND.

Figure 5-9 to Figure 5-16 revealed that the DEEC-GAUSS algorithm was able to establish a stability period before the FND, TND, where the lifetime of the network performance tends to be minimized. Taking all of the simulation results into account, it can be concluded that the FND and TND of DEEC_E, DEEC, DDEEC _E are inferior to the DEEC-GAUSS.

As presented below for Figures 5-13 to 5-16 showed the performance of clustering algorithms in terms of TND for initial energies ranging from 0.5J to 0.8J over 1 000–1 500 sensor nodes.

It is evidenced that the most efficient clustering algorithm for dispatching a higher number of packets with lower energy consumption in WSN is DEEC-GAUSS. DEEC-GAUSS has a low energy consumption and the longest network stability duration for TND. As a result, the network lifetime is demonstrated by the number of rounds.

Figure 5-13 shows the performance of clustering algorithms in terms of TND for initial energy at 0.5J for 1 000 to 1 500 sensor nodes.

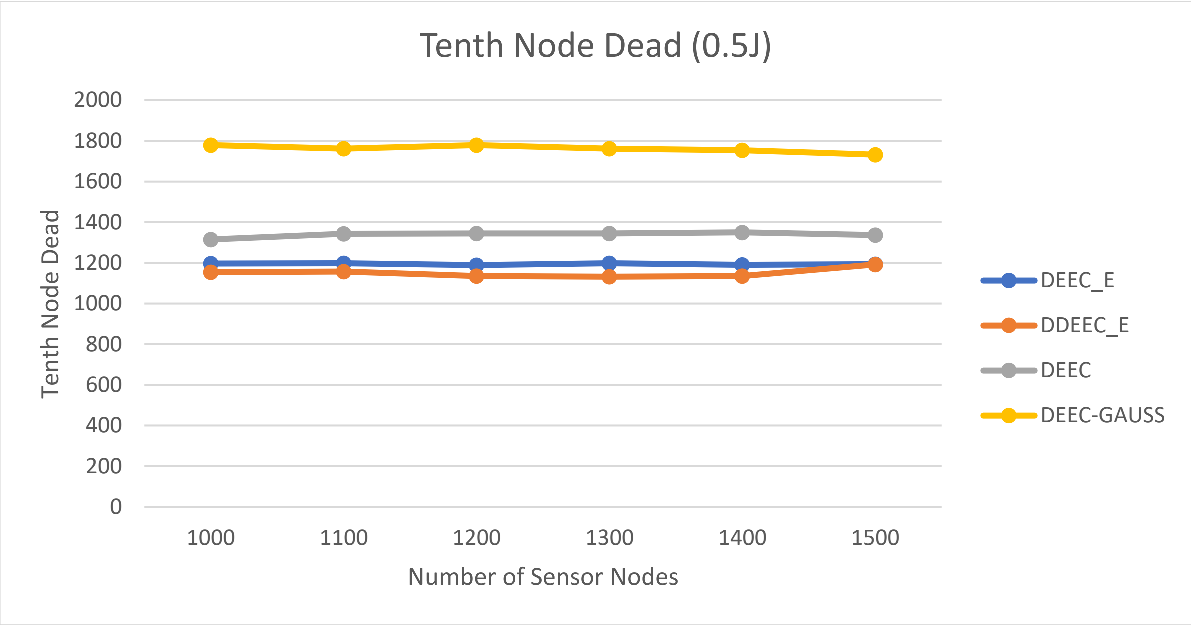

Figure 5-13: Tenth Node Dead per 5 000 rounds at 0.5J of energy

Figure 5-13 shows that the DEEC-GAUSS for TND at 0.5J of energy was greatest for nodes 1 000 to 1 500 at 1 779, 1 761, 1 779, 1 761, 1 753 and 1 732 while the DEEC for 1 000 to 1 500 sensor nodes while the second performing algorithm is DEEC, at 1 315, 1 343, 1 345, 1 345, 1 350 and 1 336 respectively.

Figure 5-14 shows the performance of clustering algorithms in terms of TND for initial energy at 0.6J for 1 000 to 1 500 sensor nodes.

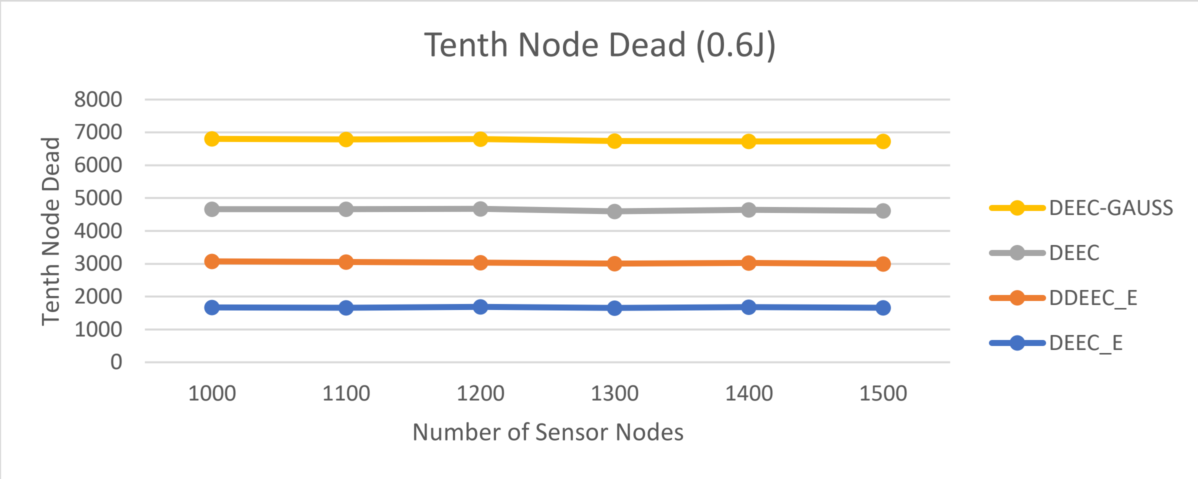

Figure 5-14: Tenth Node Dead per 5 000 rounds at 0.6J of energy

Figure 5-14 shows that the DEEC-GAUSS for TND at 0.6J of energy was greatest performing algorithm for sensor nodes of 1 000 to 1 500, at 1 779, 1 761, 1 779, 1 761, 1 753 and 1 732 from the simulation results while the DEEC of 1 000 to 1 500 sensor nodes is the second performing algorithm is at 1 590, 1 604, 1 636, 1 596, 1 614 and 1 618 respectively.

Figure 5-15 shows the performance of clustering algorithms in terms of TND for initial energy at 0.7J for 1 000 to 1 500 sensor nodes.

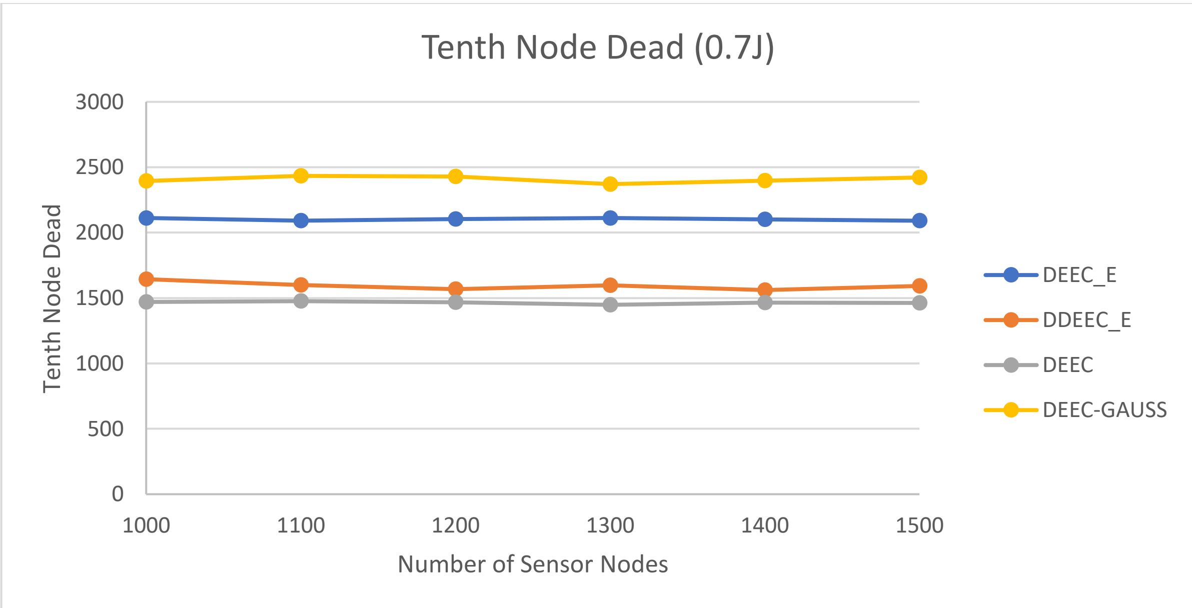

Figure 5-15: Tenth Node Dead per 5 000 rounds at 0.7J of energy

Figure 5-15 shows that the DEEC-GAUSS for TND at 0.7J of energy was greatest performing algorithm for sensor nodes of 1000 to 1500, at 2396, 2434, 2428, 2371, 2397 and 2423 from the simulation results while the DEEC_E of 1000 to 1500 sensor nodes is the second performing algorithm is at 2112, 2092, 2103, 2112, 2101 and 2091 respectively.

Figure 5-16 shows the performance of clustering algorithms in terms of TND for initial energy at 0.8J for 1 000 to 1 500 sensor nodes.

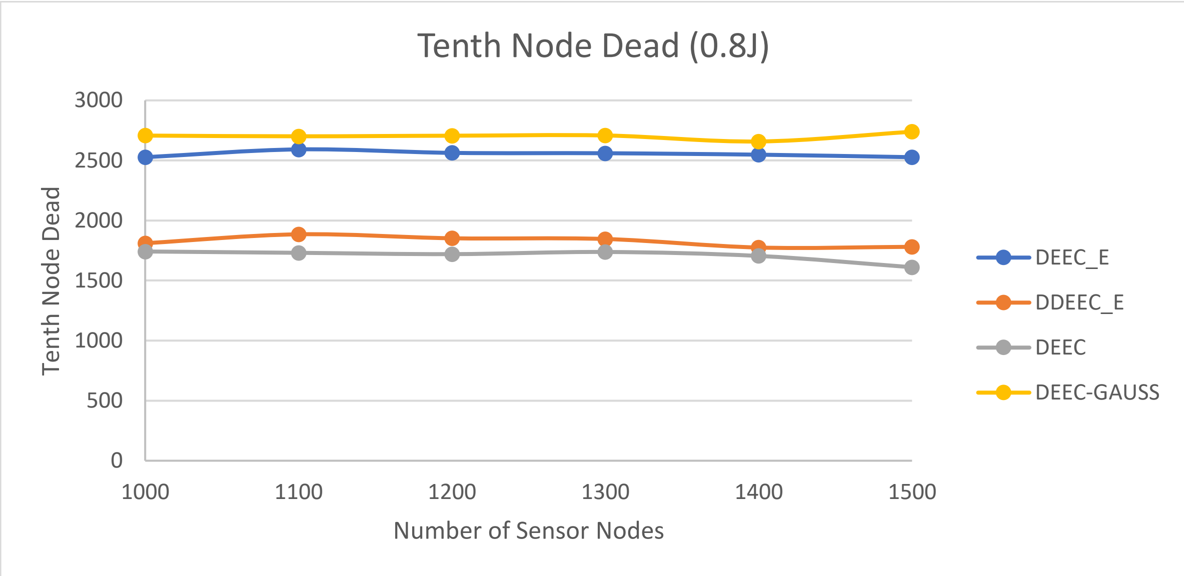

Figure 5-16: Tenth Node Dead per 5 000 rounds at 0.8J of energy

Figure 5-16 shows that the DEEC-GAUSS for TND at 0.8J of energy was greatest performing algorithm for sensor nodes of 1 000 to 1 500, at 2 707, 2 701, 2 706, 2 708, 2 658 and 2 739 from the simulation results while the DEEC_E of 1 000 to 1 500 sensor nodes is the second performing algorithm is at 2 527, 2 592, 2 563, 2 560, 2 548 and 2 527 respectively.

Figure 5-13 to Figure 5-16 demonstrated that the novel DEEC-GAUSS algorithm outperformed other state-of-the-art approaches in terms of the TND for initial energy ranging from 0.5J to 0.8J for 1 000–1 500 sensors. When a node's energy runs out, it is classified as dead, and it cannot send or receive data. When compared to other algorithms, DEEC-GAUSS aids in a longer stability period as it showed high energy efficiency, meaning less energy consumption.

5.3.1 Network Throughput (Packets sent to BS for 1 000 to 1 500 nodes at 5 000 rounds)

Packets sent to the destination from DDEEC_E DEEC_E, DEEC, and DEEC-GAUSS were calculated at 5 000 rounds for sensor nodes ranging from 1 000 to 1 500 sensors. Tables 5.5–5.9 show the outcome of packets sent to the BS with initial energies of 0.5J, 0.6J, 0.7J, and 0.8J.

Table 5-5: Simulation Parameters for 1 000 to 1 500 Nodes

Parameters	Value
Network Field	(100,100) m^2
Number of Anchor nodes	1 000 – 1 500
Eo (Initial energy of normal nodes) Optimization algorithm Transmission Range ®	0.5J – 0.8J
Unknown node (N) Message Size	1 000 4 000 Bits
E*elec*	50 *nJ/bit*
Efs	10 $nJ/bit/m^2$
E*amp*	0.0013pJ/bit/m^4
EDA	5Nj/bit/signal
D*o* (Threshold Distance)	100m by 100m
P*opt*	0.1

Table 5-6 presents the results of packets sent to the BS at 5 000 rounds using 0.5J of energy.

Table 5-6: The Packets Sent to the BS at 5 000 Rounds During the Network Lifetime for 1 000 –1 500 Nodes Using the Initial Energy at 0.5J

	(0.5J)	1 000 Nodes	1 100 Nodes	1 200 Nodes	1 300 Nodes	1 400 Nodes	1 500 Nodes
PACKETS TO BS	DEEC_E	2 299 147	1 747 222	1 812 327	1 897 495	2 972 858	1 044 212
	DDEEC_E	1 651 657	1 831 408	2 011 056	2 191 231	2 359 665	2 562 135
	DEEC	1 642 586	1 814 549	1 972 937	2 141 413	2 314 287	2 483 149
	DEEC-GAUSS	2 664 820	1 969 365	1 992 174	2 142 015	2 389 161	2 443 705

Table 5-7 presents the results of packets sent to the BS at 5 000 rounds using 0.6J of energy.

Table 5-7: The Packets Sent to the BS at 5 000 Rounds During the Network Lifetime for 1 000 –1 500 Nodes Using the Initial Energy at 0.6J

	(0.6J)	1 000 Nodes	1 100 Nodes	1 200 Nodes	1 300 Nodes	1 400 Nodes	1 500 Nodes
PACKETS TO BS	DEEC_E	2 883 808	2 176 074	1 621 066	1 677 306	2 732 089	2 794 223
	DDEEC_E	2 006 226	2 203 700	2 386 415	2 615 344	2 828 253	3 080 011
	DEEC	1 933 457	2 187 199	2 370 779	2 547 407	2 755 169	2 963 779
	DEEC-GAUSS	3 038 200	2 218 011	2 422 230	2 644 551	2 920 793	3 014 229

Table 5-8 presents the results of packets sent to the BS at 5 000 rounds using 0.7J of energy.

Table 5-8: The Packets Sent to the BS at 5 000 Rounds During the Network Lifetime for 1 000 – 1 500 Nodes Using the Initial Energy at 0.7J

	(0.7J)	1 000 Nodes	1 100 Nodes	1 200 Nodes	1 300 Nodes	1 400 Nodes	1 500 Nodes
PACKETS TO BS	DEEC_E	3 338 721	390 056	2 439 559	380 501	2 508 438	3 552 050
	DDEEC_E	2 362 573	245 102	2 800 331	3 044 108	3 306 804	3 568 250
	DEEC	2 246 848	2 499 249	2 725 818	2 966 581	3 216 831	3 447 189
	DEEC-GAUSS	2 247 434	3 653 446	2 822 387	3 970 148	3 450 988	3 618 760

Table 5-9 presents the results of packets sent to the BS at 5 000 rounds using 0.8J of energy.

Table 5-9: The Packets Sent to the BS at 5 000 Rounds During the Network Lifetime for 1 000–1 500 Nodes Using the Initial Energy at 0.8J

	(0.8J)	1 000	1 100	1 200	1 300	1 400	1 500
PACKETS TO BS	**DEEC_E**	3 723 029	249 673	281 766	312 635	331 763	3 355 506
	DDEEC_E	2 690 078	2 926 016	3 274 822	3 510 145	3 781 593	4 001 940
	DEEC	2 472 324	2 718 987	3 052 043	3 270 663	3 528 774	2 955 721
	DEEC-GAUSS	2 543 934	2 798 712	3 118 411	3 542 941	3 620 260	4 953 488

The innovative DEEC-GAUSS technique beat the previous methods in terms of packets dispatched to the BS for initial energies ranging from 0.5J to 0.8J, as shown in Table 5-6 to 5-9. The unique DEEC-GAUSS sends more packets to BS in a shorter time frame and with a higher number of packets, consuming less energy.

5.3.2 Execution Time

This section presents the execution time for 1 000 to 1 500 sensor nodes during the simulation experimentation. The DEEC-GAUSS spent the least amount of time to send the most packets at energy levels ranging from 0.5J to 0.8J for nodes ranging from 1 000 to 1 500, at a fixed 5 000 rounds throughout the simulation.

Figures 5-17 presents the energy execution time of nodes for the initial energy of 0.5J.

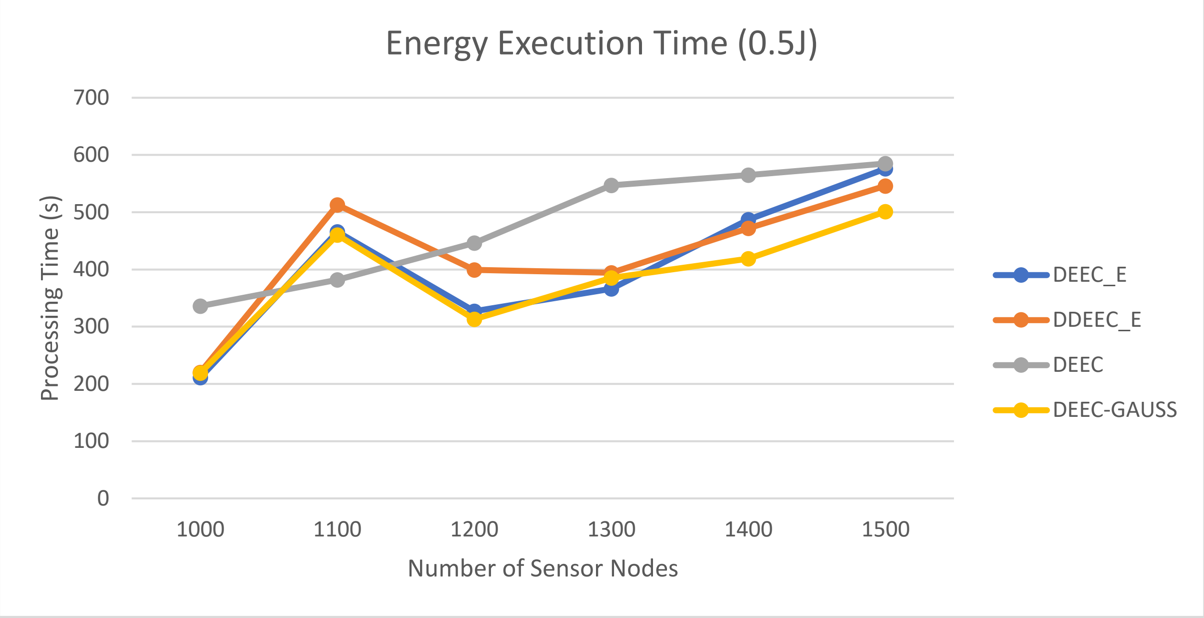

Figure 5-17: Execution Time at 0.5J of energy

Figures 5-18 presents the energy execution time of nodes for the initial energy of 0.6J.

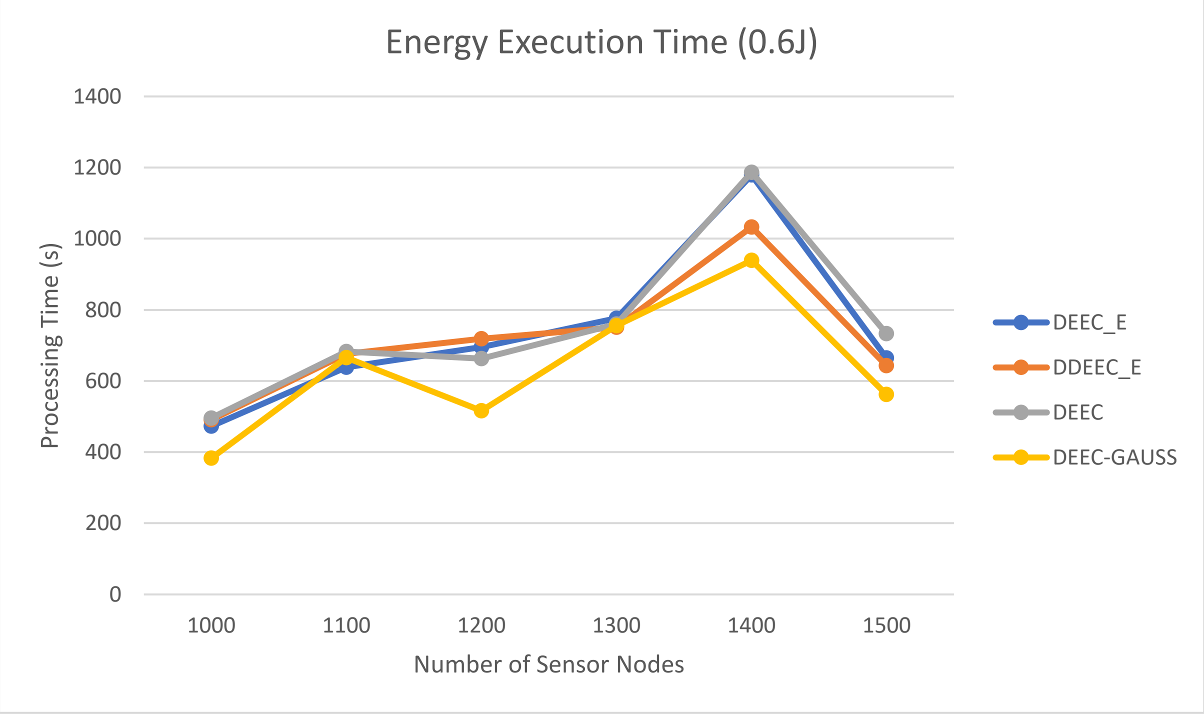

Figure 5-18: Execution Time at 0.6J of energy

Figure 5-19 presents the energy execution time of nodes for the initial energy of 0.7J.

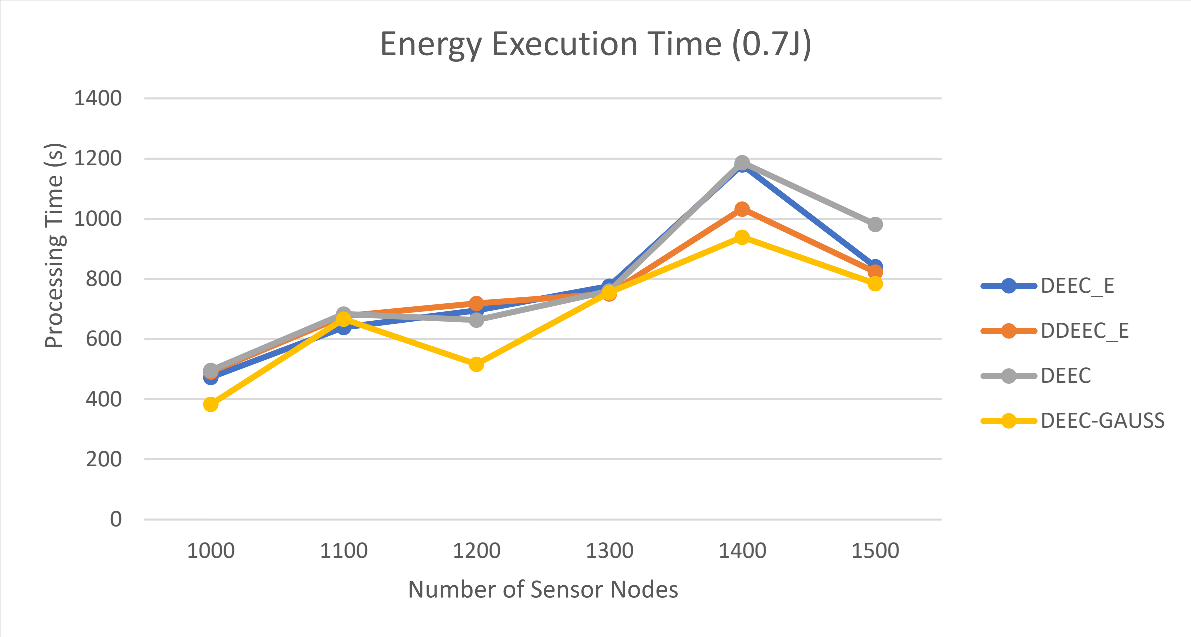

Figure 5-19: Execution Time at 0.7J of energy

Figure 5-20 presents the energy execution time of nodes for the initial energy of 0.8J.

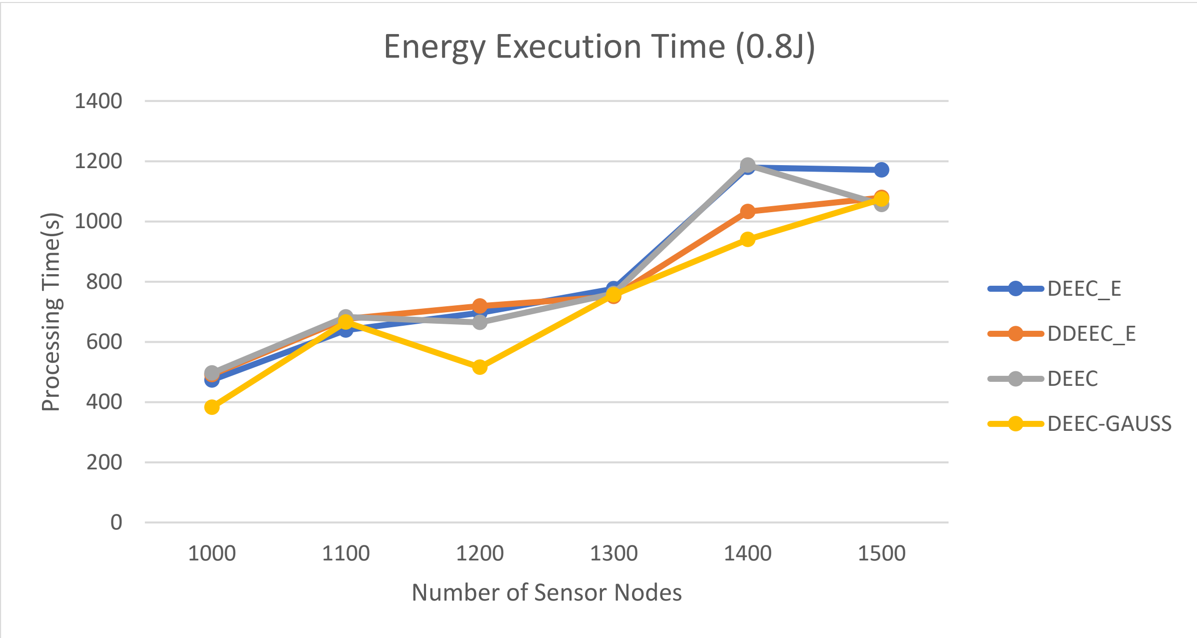

Figure 5-20: Execution Time at 0.8J of energy

According to the simulation analysis the time to send successful packets to the BS for the DEEC-GAUSS gave a better processing time than when executing the various algorithms as shown in Figures 5-17 to 5-20. The DEEC-GAUSS has an additional advantage of optimizing energy efficiency when compared to other algorithms. The order of performance as recorded during the simulation analysis are as follows: DEEC was second, followed by DEEC_E which is the third, while DDEEC_E is the fourth due to the complexity of the algorithm.

5.4 The Performance Metrics Components

The DEEC-GAUSS algorithm focuses on the objectives highlighted in Chapter One, Section 1.3 to develop a novel hyper-heuristic optimization for energy efficiency in smaller and larger network in a simulated environment of the WSN, compared to modern algorithms. The energy homogeneity is set from 0.5J to 0.8J for every clustering throughout the WSN connection of our model.

5.5 Chapter Summary

In this chapter, the analysis of results and discussion were presented with different sections that explained the energy efficiency of WSN using 100, then 1 000 to 1 500 sensor nodes. It was observed that the DEEC-GAUSS outperformed the other classic algorithms such as DEEC, DEEC_E and DDEEC. According to the simulation with a comparison of 100, 1 000, and 1 500 sensor nodes, DEEC-GAUSS surpasses the three other standard algorithms. The classes are normal, advance, and super node. The results showed that the suggested hyper-heuristic heterogeneous multi-sensor DEEC-GAUSS algorithm improved the tenth node dead (TND) by 3.0% and the first node dead (FND) by 4.8%. In addition, during the simulation and analysis it was further noted that the novel DEEC-GAUSS algorithm sent more packets to the BS in the least execution time. The network throughput rate was superb for DEEC-GAUSS. The DEEC-GAUSS algorithm has an advantage of maximizing the amount of data sent to the BS with minimal energy usage and cost effectively, when compared to other standard algorithms. The next chapter will present the analysis and results of node localization explicitly.

CHAPTER SIX: ANALYSIS OF RESULTS AND DISCUSSION OF THE NOVEL DEEC-GRADIENT DISTANCE ELIMINATION ALGORITHM (DGGDEA) FOR NODE LOCALIZATION

6.1 Introduction

This chapter presents the analysis of results and discussion on node localization, to accomplish the third and fourth objective [RO3 and RO4] of the research study. Node localization in wireless sensor networks (WSNs) is a recent trend in technique that is used to solve the deficiencies of unknown locations of sensor nodes' with self-powered batteries which are deployed in a scattered form without appropriate identification of their various locations. In this chapter we present the simulation analysis of results and discussion from node location to identify the unknown zones as a cost-effective solution. In this research simulation, we make use of our proposed DEEC-GAUSS Gradient Distance Elimination Algorithm (DGGDEA) to determine their sensing stations with minimal localization error with the use of 20 anchor nodes and 200 to 450 sensor nodes. We further compared other classic algorithms such as Weighted Centroid Localization (WCLS), Compensation coefficient (CC), Weighted Centroid (WC) and DV Hop to our proposed DGGDEA. The comparative analysis is presented in this chapter.

6.2 Node Localization Error

Energy loss of sensor nodes result in their battery life being continually drained. This makes node localisation a formidable problem (Kaur, Aggrawal and Lal 2020; Gautam, Kumar and Kumar 2021). During the simulation analysis of 200 to 450 sensor nodes in the MATLAB 2020a environment, the proposed DGGDEA showed the best performance in terms of the number of data packets sent to the BS as well as in reduction of node localization error and the probability of error.

The Table 6-1 shows the localization error and the number of 20 to 80 anchor nodes used during the simulation performances.

Table 6-1: The Localization Error vs the Number of Anchor Nodes

No. of Anchor Nodes	Proposed DGGDEA	WCLS	CC	WH	DV-Hop
20	11.0%	48.3%	52.4%	54.9%	56.1%
30	15.6%	43.6%	47.8%	48.2%	50.7%
40	7.2%	37.4%	42.1%	43.4%	45.9%
50	10.3%	39.0%	43.3%	46.1%	46.5%
60	5.4%	35.7%	42.8%	40.0%	43.9%
70	5.9%	33.4%	38.1%	37.7%	41.9%
80	10.3%	31.2%	34.4%	35.1%	40.1%
Mean	**11.0%**	**44.8%**	**50.1%**	**50.9%**	**54.2%**

In Table 6-1 the DGGDEA was compared with four classical algorithms and the result presented shows that DGGDEA outperformed the other four algorithms. The lower the localization error, the better the performance of the algorithms (Tomic and Mezei 2016), hence, the DGGDEA significantly optimized the node localization accuracy by reducing the localization error.

In Figure 6-1 below, the node localization was simulated in the MATLAB 2020a environment with 20 to 80 anchor nodes and the overall sensor nodes deployed from 200 to 450. The results are presented in percentages compared to other algorithms. Figure 6-1, shows that the proposed algorithm outclasses the modern algorithms due to the optimization of localized sensor nodes for identifying the most preferred position of sensors.

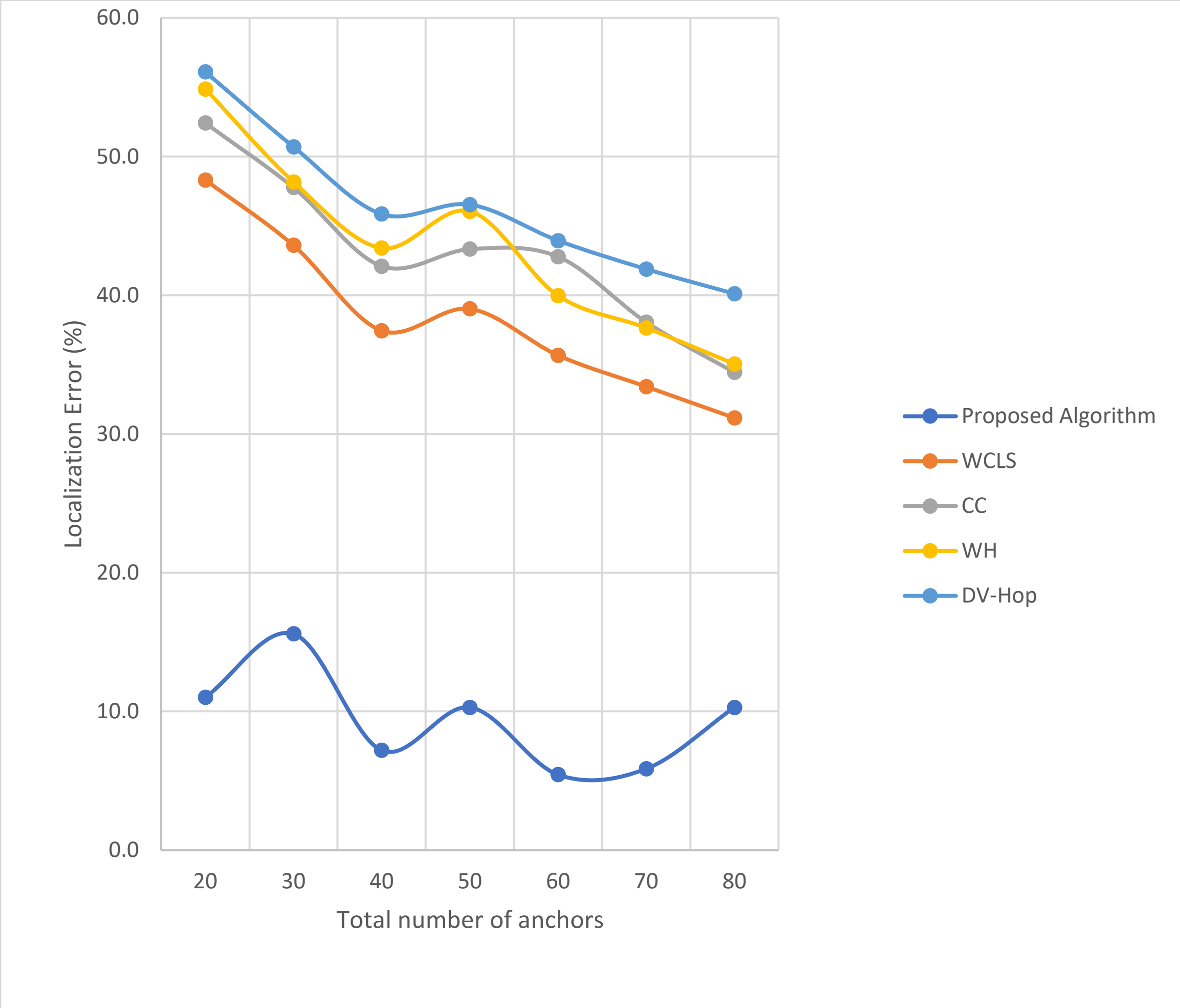

Figure 6-1: The Localization Error vs the Number of Anchor Nodes

Table 6-2 shows the results of the localization error vs the number of total sensor nodes ranging from 200 to 450 sensor nodes.

Table 6-2: The Localization Error vs the Number of Total Sensor Nodes

Total No. of Nodes	**Proposed (DGGDEA)**	**WCLS**	**CC**	**WH**	**DV-Hop**
200	11.0%	37.2%	40.6%	42.1%	46.2%
250	11.8%	33.6%	40.2%	41.1%	42.6%
300	9.2%	29.7%	36.8%	39.6%	37.2%
350	10.0%	31.4%	35.8%	37.1%	39.2%
400	15.5%	30.6%	34.4%	35.6%	37.7%
450	10.0%	29.4%	33.7%	34.1%	36.9%

Table 6-2 shows that the proposed algorithm outperformed all other algorithms for the total number of nodes from 200 to 450, while the second-best algorithm is WCL, followed by CC algorithm, and the worst algorithm is DV-Hop.

In Figures 6-2 to 6-7 below, the true position of the 20 anchor nodes' locations is localized. The small black circles represent the anchor nodes and the mobile sensor nodes are represented with the small open red circles. The cross symbols represent the mobile true locations, as displayed respectively at 0.5J energy simulation in the MATLAB 2020a environment with sensor nodes ranging from 200 to 450 mobile nodes. It was observed in the result presented from Figure 6-2 to Figure 6-7 that the number of sensor nodes does not directly impact on the localization error metric for the proposed DGGDEA.

Figure 6-2 shows the localized 20 anchor nodes with 200 sensor nodes.

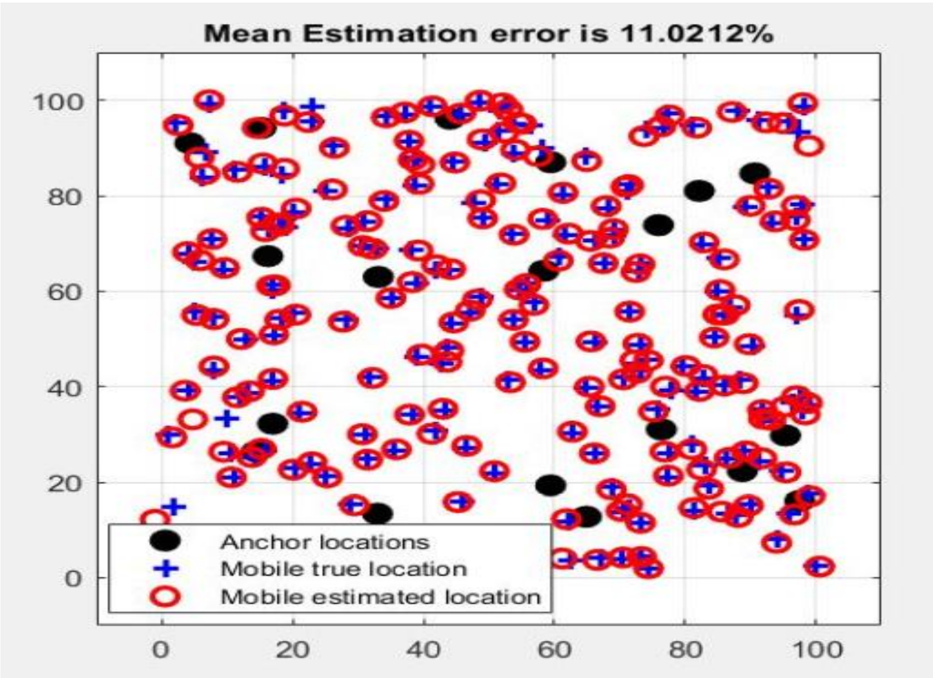

Figure 6-2: Localized Anchor Nodes with 200 Sensor Nodes

Figure 6-2 presents the 20-anchor node locations, the localized node and the 200 estimated localized sensor nodes. The DGGDEA produced a localization error of 11.02% hence improving the accuracy of the node localization.

Figure 6-3 shows the 20 localized anchor nodes and 250 sensor nodes.

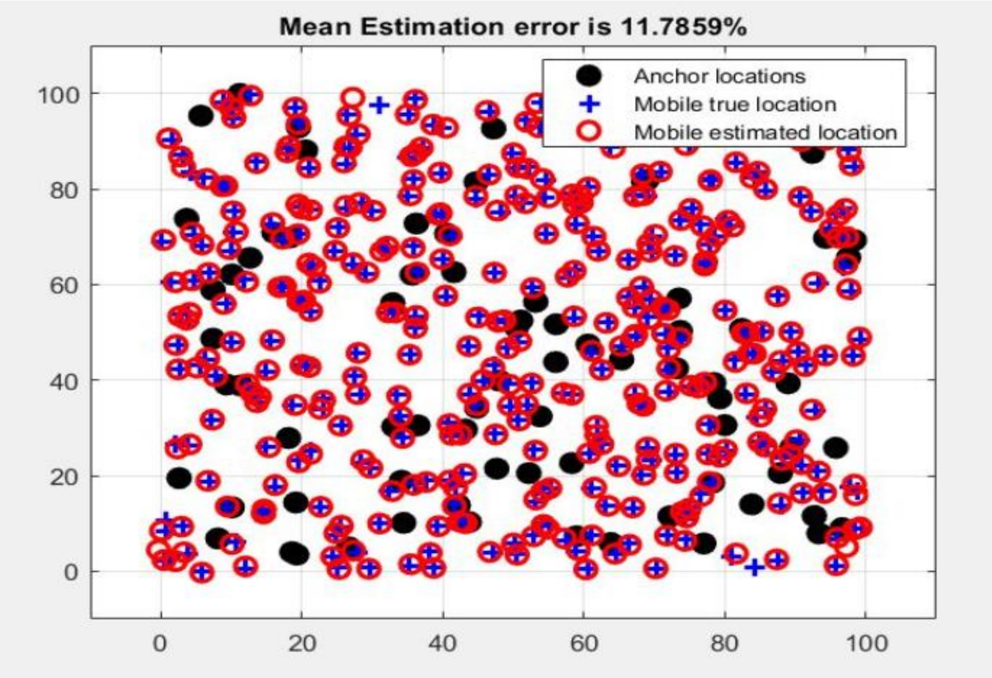

Figure 6-3: Localized Anchor Nodes with 250 Sensor Nodes

Figure 6-3 presents the 20-anchor node locations, the localized node and the 250 estimated localized sensor nodes. The DGGDEA produced a localization error of 11.78% hence improving the accuracy of the node localization.

Figure 6-4 shows the 20 localized anchor nodes with 300 sensor nodes.

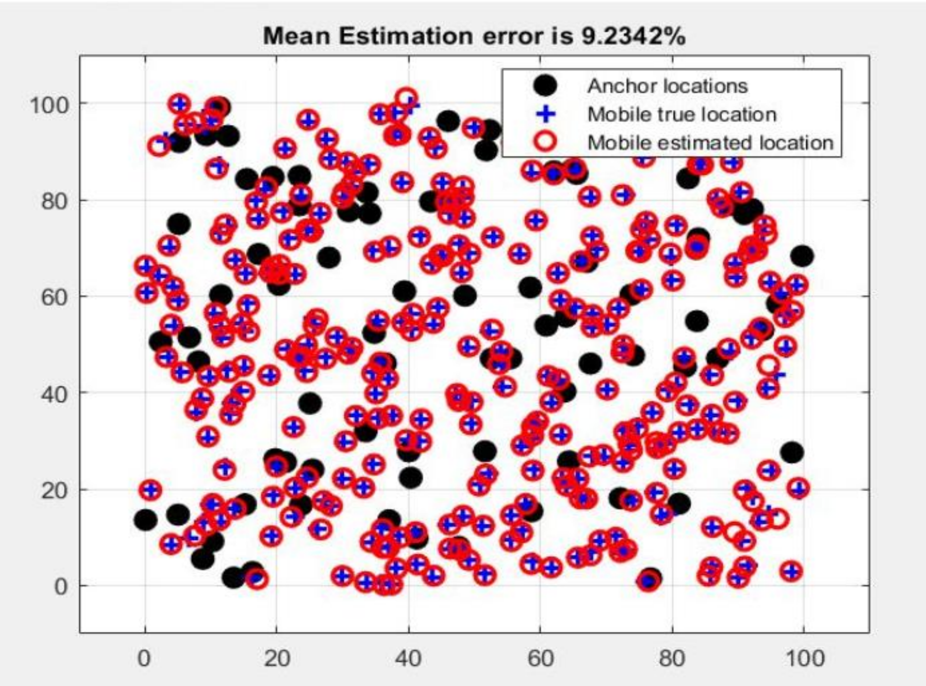

Figure 6-4: Localized Anchor Nodes with 300 Sensor Nodes

Figure 6-4 presents the 20-anchor node locations, the localized node and the 300 estimated localized sensor nodes. The DGGDEA produced a localization error of 9.23% hence improving the accuracy of the node localization.

Figure 6-5 shows the 20 localized anchor nodes with 350 sensor nodes.

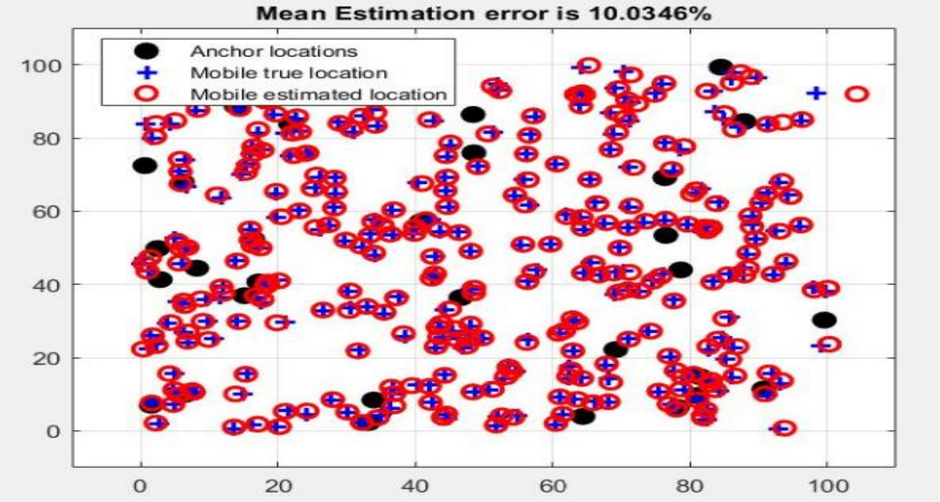

Figure 6-5: The 20 Localized Anchor Nodes with 350 Sensor Nodes

Figure 6-5 presents the 20-anchor node locations, the localized node and the 350 estimated localized sensor nodes. The DGGDEA produced a localization error of 10.03% hence improving the accuracy of the node localization.

Figure 6-6 shows the 20 localized anchor nodes with 400 sensor nodes.

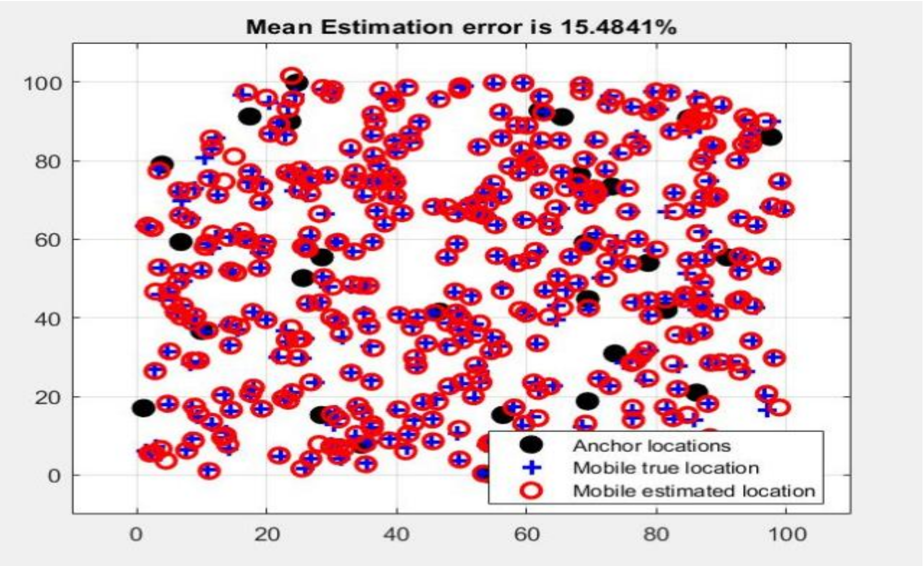

Figure 6-6:Localized Anchor Nodes with 400 Sensor Nodes

Figure 6-6 presents the 20-anchor node locations, the localized node and the 400 estimated localized sensor nodes. The DGGDEA produced a localization error of 15.48% hence improving the accuracy of the node localization.

Figure 6-7 shows the 20 localized anchor nodes with 450 sensor nodes.

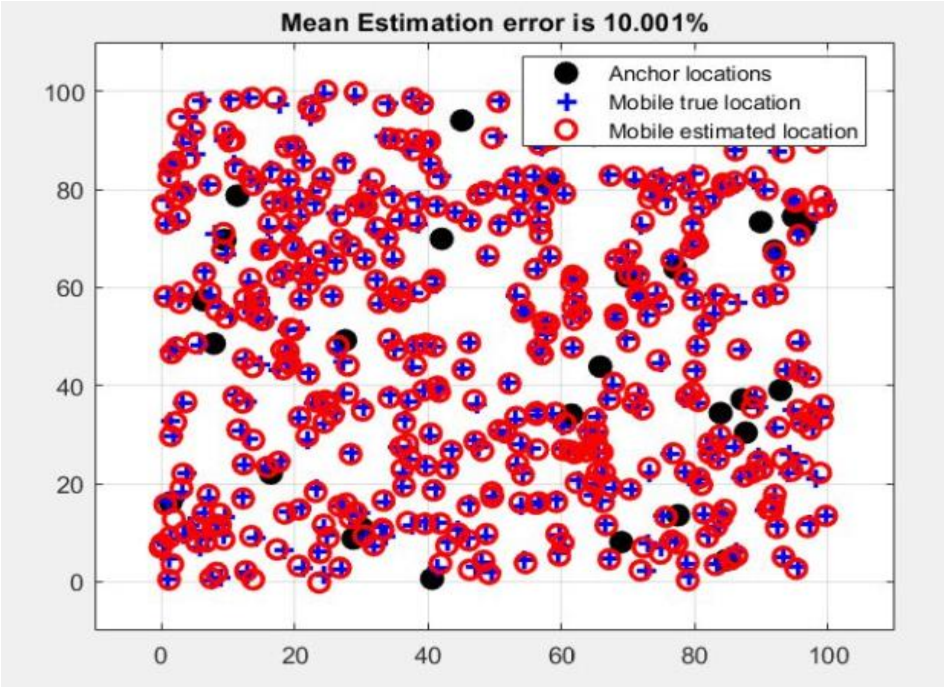

Figure 6-7:Localized Anchor Nodes with 450 Sensor Nodes

Figure 6-7 presents the 20-anchor node locations, the localized node and the 450 estimated localized sensor nodes. The DGGDEA produced a localization error of 10.00% hence improving the accuracy of the node localization.

Figure 6-8 shows the localization error versus the total number of sensor nodes.

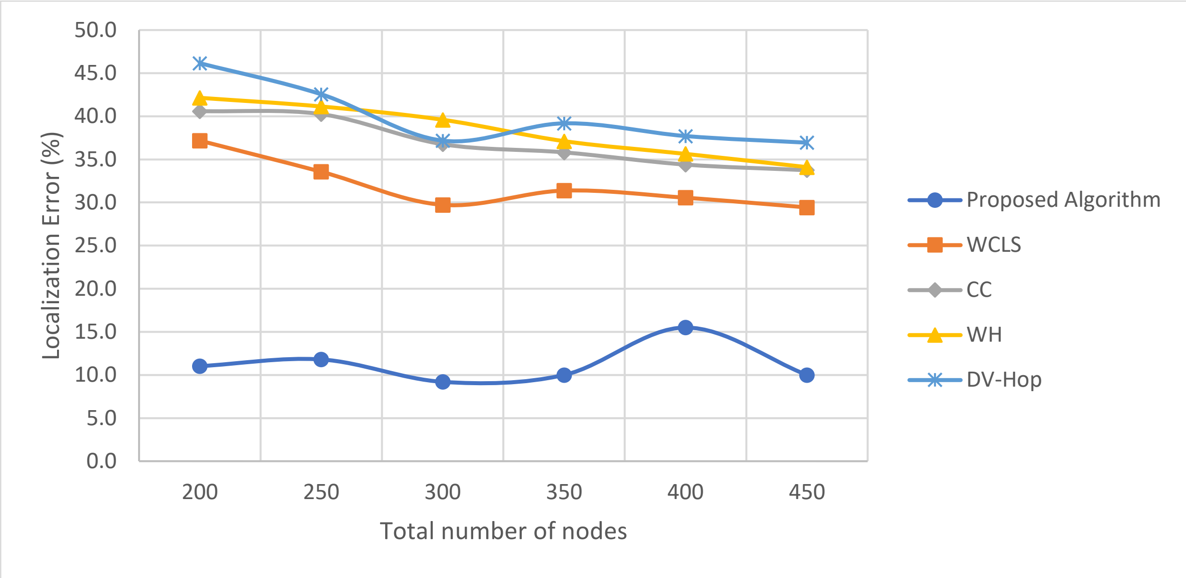

Figure 6-8:The Localization Error vs the Number of Sensor Nodes

In the above Figure 6-8, the proposed scheme outperforms all other algorithms for networks with node sizes 200, 250, 300, 350, 400 and 450.

In Table 6-3, we present the probability of error (PoE) during the simulation of the sensor node location detection. The presented data shows that the best performance is attained from the proposed algorithm when compared to the other selected algorithms.

Table 6-3: Localization Probability of Error for Node Localization

Total No. of Nodes	Proposed Algorithm PoE	WCLS PoE	CC PoE	WH PoE	DV-Hop PoE
200	0.0006	0.0019	0.0020	0.0021	0.0023
250	0.0006	0.0013	0.0016	0.0016	0.0017
300	0.0004	0.0010	0.0012	0.0013	0.0012
350	0.0003	0.0009	0.0010	0.0011	0.0011
400	0.0003	0.0008	0.0009	0.0009	0.0009
450	0.0003	0.0007	0.0007	0.0008	0.0008

The range-free approach of DGGDEA in contrast to classic state of the art algorithms such as WC, WCL, CC, WH and DV-Hop in the application of accuracy is 15% higher. It is evidenced from Table 6-3 that in 200 to 450 sensor nodes having a maximum number of 20 anchor nodes, DGGDEA was able to minimize their mean estimation error drastically from 54.2% (DV-Hop) to 11% (DGGDEA), as shown in Table 6-1.

6.3 Performance Metrics

The DEEC-GAUSS Gradient Distance Elimination Algorithm (DGGDEA) focuses on the objectives highlighted in Chapter One to simulate an effective maximization of node localization for WSN with the novel algorithm compared to other modern algorithms. The energy homogeneity was set to 0.5J for every clustering throughout the WSN connection of the novel model.

Received signal strength indicator (RSSI): The RSSI aids in the transmission of data broadcasts where the signal strength indication is weak, without interfering with the evaluation of signals (degree of angle, transmission point and hop counts) for effectiveness (Zhang *et al.* 2017; Singh and Khilar 2017).

Computing time: Is the period appropriated for the algorithm to perform calculations and to produce output for the localization processes. DV-Hop, WH, CC, WCL, DEEC-GAUSS localization was computed within the specific timeframe to perform the simulated operation in MATLAB (Zhao *et al.* 2021).

Average localization miscalculation: This is the localization error during the calculation and estimation of the true location of the unknown sensor node (Chen *et al.* 2015; Gao *et al.* 2019).

Localization inaccuracy variance: Defined to be the measurement of an individual unit that is set for calculating the mean error (Chen *et al.* 2015).

Network Traffic: General network traffic is a characteristic of the movement of packets between clusters of nodes in a WSN. There can be many traffic sources from the local sensor node to the BS. It is determined by the performance requirements such as accuracy of node localisation and quality of service (QoS) (Shakshuki *et al.* 2019).

6.4 Chapter Summary

This research work for node localization using the DEEC-GAUSS Gradient Distance Elimination algorithm (DGGDEA) has proven that it performs better than the other algorithms when considering the comparative analysis from the simulation performance for 200 to 450 sensor nodes. We further note that there was an optimal statistic from the simulation analysis scenarios.

The node localization advantage for the DGGDEA is that it enhances aggregation of sensor node data locations that are unknown with limited energy and minimizes localization error within a specific time frame, when compared to other modern algorithms. The range-based and range-free localization of sensor nodes are now localized according to their current location with the use of the DGGDEA algorithm. The PoE for DGGDEA outperforms the other classical algorithms with respect to performances and high accuracy, as displayed in Table 6-3. Chapter Seven of this research work will present the summary, conclusion and contributions for this research work.

CHAPTER SEVEN: SUMMARY, CONCLUSIONS, AND SIGNIFICANT CONTRIBUTIONS

7.1 Introduction

In this chapter, the summary of the research work is presented. The conclusions of the study are reached by reflecting on the aim and objectives of the research project. The extent to which the aim and objectives were achieved are elucidated. This chapter provides insight into the summary, conclusions and significant contributions made by this study to the body of knowledge. The challenges experienced in this research study are discussed succinctly in this chapter. The chapter concludes with a section on plans for future research. The chapter ends this project thesis with a short conclusion. Table 7-1 shows an alignment of the aims and objectives and provides a concise recap of the research study.

7.2 Summary of Research

In this research study, a novel algorithm was proposed from the traditional algorithms for solving the problems of hyper-heuristic approaches for maximizing energy efficiency and node localization in WSNs. The overarching aim of this research study was to develop effective hyper-heuristic optimization algorithms to efficiently optimize energy efficiency and node localization in WSNs.

Chapter One introduced the scope of the study. The overview of WSNs, the problem statement, aim, objectives of the research, and the gaps identified were introduced. Furthermore, a chapter by chapter breakdown was provided. Chapter Two presented a comprehensive background and literature review on WSNs from Web of Science, IEEE database, Google Scholar, Inderscience, Scopus, and other globally recognised journal article databases. The gaps identified were the node localization and energy efficiency issues and these were discussed with an in-depth review of relevant journal articles using the PRISMA methodology.

Chapter Three presented the theoretical framework and conceptual models used in the study. The theoretical framework, namely, DR comprised six phases to guide the research study, namely, *Identify the problem, Describe the objectives, Design and develop the artefact, Test the artefact, Evaluate testing results and Communicate the testing results*. The Theory of modelling and simulation was also discussed at length. Justification for use of the theoretical frameworks were discussed in Chapter Three. An emergent conceptual model for this research using a combination of DR and simulation was presented as a hyper-heuristic model discussed in Chapter Three, Section 3.5 and Section 3.9.

Chapter Four unpacked the research methodology, a scientific approach using hyper-heuristic models for energy efficiency and node localization for WSNs. The DEEC-GAUSS method (Chapter Four, Section 4.3) was developed for energy efficiency and the DGGDEA method (Chapter Four, Section 4.7) was developed for node localization optimization. These methods are unprecedented for use in energy efficiency and node localization and largely represent the contribution of this study. These novel hyper-heuristic algorithms were presented in Chapter Four showing detailed steps with mathematical equations, pseudocode and flow charts.

Chapter Five presented an analysis of results and discussion of novel DEEC-GAUSS Algorithm for energy efficiency. DEEC-GAUSS was implemented in MATLAB R2020a; the results of the simulation experiments were analysed in this chapter. The second [RO 2] and fourth [RO 4] objectives for this study were achieved in this chapter. The results of the hyper-heuristic energy efficiency with a maximum of 100 sensor nodes and the energy optimization of hyper-heuristics approach for larger networks having 1 000 sensor nodes to 1 500 sensor nodes were presented and discussed. Results showed that the novel DEEC-GAUSS outperformed other state-of-the-art algorithms for energy efficiency in WSNs.

Chapter Six presented the analysis and discussion of novel DEEC-Gradient Distance Elimination Algorithm (DGGDEA) for node localization to achieve research objective three [RO 3] and research objective four [RO 4] of the research study for 200 to 450 sensor nodes. The metrics probability of error (PoE) and accuracy of the node localization were compared to other modern algorithms. The DGGDEA algorithm outclassed other algorithms in terms of performance.

Chapter Seven presented the summary, alignment of research, conclusions, significant contributions of the study, challenges of the research’s proposed model and plans for future research work.

7.3 Conclusions of the Study

In this section, how each of the objectives were satisfied in this research is discussed with each objective itemized and a detailed explanation of how the objective was achieved is provided. The four objectives set at the beginning of this research work (Chapter One) are discussed below:

- **Research Objective One [RO 1]**: *Develop novel hyper-heuristic optimisation algorithms for energy efficiency and maximization of node localization for WSNs*.

  To achieve research objective one, an extensive literature review (Chapter Two) on WSNs for energy efficiency optimization and node localization was conducted. The hyper-heuristic analysis of pieces of literature from a vast number of research articles that were centred on meta-heuristics, hybrid heuristics and hyper-heuristic approaches were considered. The in-depth research undertaken was necessary to uncover gaps. Various problems related to node localisation and energy efficiency as well as their corresponding algorithms (solutions) were reviewed from the extant literature.

  Consequently, a meta-analysis was used to statistically analyse the heuristic approaches, namely, the meta-heuristic approach, hybrid-heuristic approach, and hyper-heuristic approach. The meta-analysis report informed the decision on adopting the hyper-heuristic approach to solve the research problem on energy efficiency and node localization. DEEC-GAUSS model for energy efficiency and DGGDEA model for node localisation were developed. Details of these algorithms are presented in Chapter Four, Section 4.3 and Section 4.7. The DR theoretical framework and the hyper-heuristic conceptual models discussed in Chapter Three guided the development of the hyper-heuristic optimization algorithms for energy efficiency and node localization in WSNs.

- **Research Objective Two [RO 2]**: *Implement the novel hyper-heuristic optimization algorithm for energy efficiency in smaller and larger WSNs in a simulation environment.*

  To achieve the optimization of energy in WSNs, a theoretical framework (Chapter Three, Figure 3-2) and conceptual models (Chapter Three, Figure 3-3 and Figure 3-5) were used to underpin this research study in WSNs. This research work developed a hyper-heuristic algorithm for energy efficiency in smaller and larger networks using a scientific approach. The hyper-heuristic algorithm combines DEEC and Gaussian Elimination method to form DEEC-GAUSS to optimize energy efficiency in WSNs. The algorithm described in detail in Chapter Four, Section 4.3 was implemented and explicit results of the DEEC-GAUSS for energy efficiency in smaller and larger networks were presented in Chapter Five.

- **Research Objective Three [RO 3]**: *Simulate the novel hyper-heuristic optimization algorithm for node localisation in WSNs.*

  To achieve this objective, a scientific approach using the DEEC-Gaussian Gradient Distance Algorithm (DGGDEA) was developed. This algorithm was described in detail in Chapter Four. The novel hyper-heuristic algorithm utilized three meta-heuristic algorithms, namely, Distributed Energy Efficiency Clustering algorithm (DEEC), Gaussian Elimination Algorithm (GAUSS) and Gradient Distance Elimination Algorithms to develop the hyper-heuristic optimization model for node localization in WSNs. The implementation of the novel hyper-heuristic DGGDEA for node localization showed the best performance in comparison to other state-of-the-art algorithms. During the simulation analysis using 200 to 450 sensor nodes with 20 static anchors the optimization node localization error and the probability of error (PoE) were determined, with the mean estimation for the locations of sensor nodes in WSNs. The comparative analysis was completed with the state-of-the-art clustering algorithms to determine the performance evaluations using the number of data packets sent to the BS as well as reduction of node localization error and the probability of error. It is evidenced that the performance of the range-free approach of the novel DGGDEA in contrast to traditional state-of-the-art algorithms such as WC, WCL, CC, WH and DV-Hop in the application showed a reduction in the node localisation error for 20 to 80 sensor nodes and a reduction in node localisation error for 200 to 450 sensor nodes (Chapter Six, Table 6-1, Table 6-2).

- **Research Objective Four [RO 4]**. *Analyse the performance of the hyper-heuristic optimisation algorithms with other state-of-the art algorithms using simulations.*

The novel DEEC-GAUSS algorithm was compared to other classical methods. The novel DEEC-GAUSS model outclassed other methods, by optimizing energy efficiency for 100 sensor nodes, 1 000 to 1 500 sensor nodes. The performance metrics used were first node dead (FND), tenth node dead (TND), last node dead, number of packets sent to BS, overall execution time for initial energy between 0.5 J to 0.8 J. The simulation aggregation performances and the number of static rounds used in the simulation for the energy efficiency optimization was 5 000 all through the simulation (Chapter Five).

The novel hyper-heuristic optimization algorithm, namely, DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA) which comprises of Distributed Energy Efficiency Clustering algorithm (DEEC), Gaussian Elimination Algorithm (GAUSS), and Gradient Distance Algorithm (GDA) outperformed other classical approaches for node localization in WSNs. The optimization of the novel DGGDEA algorithm enhanced node localization error within the specific time frame compared to other modern algorithms with distinct results and error probability. The results were discussed in detail in Chapter Six.

Table 7-1 presents the alignment of research objectives, theoretical framework and conceptual models, data collection methods and data analysis. The table thus provides a concise summary of the research.

Table 7-1: Alignment of the Research Aim and Objectives

AIM: The aim of this research study was to develop effective hyper-heuristic optimization algorithms to efficiently optimize energy efficiency and node localization in WSNs.

Research Objectives	Theoretical Framework and Conceptual Models	Data Collection Methods/Data Sources	Data Analysis/Results
[RO1]: Develop novel hyper-heuristic optimisation algorithms for energy efficiency and maximization of node localization for WSNs.	PRISMA, Design Research, hyper-heuristic model, and scientific approach	The systematic review for meta heuristic, hybrid heuristic and hyper-heuristic approaches	The hyper-heuristic algorithm is the best approach from the meta-analysis result in optimizing energy efficiency and node localization in WSNs. The design of the hyper-heuristic model is discussed (Chapter Two, Chapter Three, and Chapter Four)
[RO 2]: Implement the novel hyper-heuristic optimization algorithm for energy efficiency in smaller and larger WSNs in a simulation environment.	Design Research, Theory of Modelling and Simulation, hyper-heuristic conceptual models	The simulation of the novel hyper-heuristic model using DEEC-GAUSS) implemented in MATLAB R2020a using a static 5,000 number of rounds with the initial energy ranging from 0.5J to 0.8J.	The DEEC-GAUSS algorithm for energy efficiency was tested in a simulation environment to validate the optimization of energy efficiency in WSNs for the results of 100, 1000 to 1500 sensor nodes. (Chapter Three, Chapter Four and Chapter Five).
[RO 3]: Simulate the novel hyper-heuristic optimization algorithm for node localisation in WSNs.	Design Research, Theory of Modelling and Simulation, hyper-heuristic conceptual models	The simulation of the novel hyper-heuristic DEEC-Gaussian Gradient Distance Algorithm (DGGDEA) was simulated in the MATLAB R2020a environment.	The DGGDEA algorithm for node localization was implemented in a simulated environment to test the node localization error for 200 to 450 sensor nodes with a static number of 20 anchor nodes in order to optimize node localization accuracy (Chapter Three, Four and Chapter Six).
[RO 4]: Analyse the performance of the hyper-heuristic optimisation algorithms with other state-of-the art algorithms using simulations.	Design research, theory of modelling and simulation, hyper-heuristic conceptual models	The performance evaluation of DEEC-GAUSS for optimizing energy efficiency and DGGDEA for node localization errors outclassed traditional algorithms.	The result presented shows that the DEEC-GAUSS algorithm based on the performance evaluation metrics used, outperformed the other modern algorithms for the smaller and larger networks in optimizing energy efficiency. The DGGDEA algorithm outclass other classical algorithms for optimizing node localization errors based on the evaluation performance metrics in terms of the number of data packets sent to the BS, probability of error, localization error and data packet to BS. (Chapter Three, Chapter Five, Chapter Six and Chapter Seven).

7.4 Challenges of the Study

This section discusses the challenges experienced in this research study on energy efficiency and node localization maximization.

- Developing the framework to ascertain the energy optimization efficiency and node localization error from the literature was a tedious process. Previous researchers focused on the following algorithms: density-based clustering algorithm and density-based spatial clustering algorithm with noise (DBSCAN). K-Means Algorithm, ACO, fuzzy flustering, LEACH, stable selection protocols, traffic bases clustering (TBC) protocols, energy and distance-based clustering (EDBC), and Euclidean-distance. Consequently, a novel approach was developed and adopted to achieve the desired results for this research work using DEEC-GAUSS and DGGDEA.
- Amalgamating distributed energy efficiency clustering (DEEC) with Gaussian elimination and determining the initial energy to be used with a model comparison was another challenge.
- The challenge of the proposed model for the Gaussian elimination fails when any of the pivots in the element series become zero. The procedure was re-ordered to avoid partial pivoting when the piece becomes zero. The result can be accurate for the calculations in WSNs.

7.5 Significant Contribution

Node localization and energy efficiency are real life challenges in WSNs that have become an increasingly important research area in academia. Despite various models and approaches that have been proposed, ranging from bio-inspired and non-bio-inspired algorithms the solutions to these problems have not been long lasting (Kumar, Dadheech and Chaudhary 2020; Sneha and Nagarajan 2020; Kim *et al.* 2021).

These problems in WSNs necessitated the need to contribute to the body of knowledge in this research focus. This study made the following contributions in alleviating the energy efficiency optimization and node localization error and probability of error problem.

The following are the significant contributions:

1. The combining of the Distribute Energy Efficiency Clustering algorithm and Gaussian Elimination algorithms were adopted to optimize energy efficiency in wireless sensor networks. DEEC-GAUSS was developed as the hyper-heuristic solution. The algorithm and pseudocode were presented in Section 4.3 and the MATLAB code is presented in Annexure A. The presented approach significantly reduces the constraints of energy efficiency by optimizing the first node dead (FND), last node dead (LND), tenth node dead (TND) and improving the energy lifespan of the sensor nodes.

2. This study further presented a hyper-heuristic approach that combines the distributed energy efficiency clustering algorithm, gaussian elimination algorithm and gradient distance algorithm to optimize node localization in WSNs. DGGDEA was developed as the hyper-heuristic solution. The algorithm and pseudocode were presented in detail in Section 4.7 and the MATLAB code is presented in Annexure B. The presented approach improved on the accuracy of location estimation, sensor node positioning, localization error and the reduction of the probability of error of sensor nodes.

3. This research study produced three journal publications in peer-reviewed scientific journals. The details of the publications are outlined in the introductory sections of this thesis. These publications will contribute to the body of knowledge.

The performance of the presented models was evaluated and analysed through simulation. The presented results show an overwhelming improvement in energy efficiency and node localization optimization problems.

7.6 Plans for Future Work

Future experiments are required on other clustering algorithms to improve performance in terms of optimizing node localization and energy efficiency harvesting technologies in the enhancement of the operation of WSNs. In the future, the scope of this work will broaden to incorporate simulations of the enhanced proposed method on bigger numbers of sensor nodes.

Furthermore, node localization utilization in WSN needs more exploration. It is essential to explore other clustering algorithms for modifying and improving the network stability period for more larger WSNs.

7.7 Conclusion

This research study investigated the significant challenges of WSNs, which are energy maximization and node localization, necessary to assist the vibrant organization in minimizing the overall energy consumption as well as localising sensor nodes with a greater accuracy within the WSN.

DEEC-GUASS outperformed traditional algorithms for energy optimisation using standard performance metrics such as first node dead, all dead nodes, packets sent to BS (network throughput) and execution time for 100 sensor nodes and 1 000 to 1 500 sensor nodes. Energy was set from 0.5J to 0.8J in the simulation environment.

DGGDEA outperformed traditional algorithms for node localization error. The mean node localisation error for the novel DGGDEA with 20 to 80 sensor nodes was 11% (Chapter Six, Table 6-1). This represents a drastic reduction when compared to other state-of-the-art algorithms. The novel DGGDEA also showed a drastic reduction in node localization error for 200 to 450 sensor nodes when benchmarked against other state-of-the art algorithms (Chapter Six, Table 6-2). The number hop size, the distance of the average hop size, the error model, and the increase in the number of packets sent to the BS within a minimum time frame were used to determine the node localization accuracy. The networks throughput rate was stabilized with minimal energy efficiency usage.

REFERENCES

Abar, S., Theodoropoulos, G. K., Lemarinier, P. and O'Hare, G. M. 2017. Agent based modelling and simulation tools: A review of the state-of-art software. *Computer Science Review,* 24: 13-33. Available: https://doi.org/10.1016/j.cosrev.2017.03.001 (Accessed 18 May 2021).

Abdulkarem, M., Samsudin, K., Rokhani, F. Z. and A Rasid, M. F. 2020. Wireless sensor network for structural health monitoring: A contemporary review of technologies, challenges, and future direction. *Structural Health Monitoring,* 19(3): 693-735. Available: https://doi.org/10.1177/1475921719854528 (Accessed 05 May 2020).

Abdurohman, M., Supriadi, Y. and Fahmi, F. Z. 2020. A modified E-LEACH routing protocol for improving the lifetime of a wireless sensor network. *Journal of Information Processing Systems,* 16(4): 845-858. Available: https://www.koreascience.or.kr/article/JAKO202026964745233.page (Accessed 6 December 2021).

Abella, C. S., Bonina, S., Cucuccio, A., D'Angelo, S., Giustolisi, G., Grasso, A. D., Imbruglia, A., Mauro, G. S., Nastasi, G. A. and Palumbo, G. 2019. Autonomous energy-efficient wireless sensor network platform for home/office automation. *IEEE Sensors Journal,* 19(9): 3501-3512. Available: https://10.1109/JSEN.2019.2892604 (Accessed 05 March 2020).

Aderohunmu, F. A., Deng, J. D. and Purvis, M. 2011. Enhancing clustering in wireless sensor networks with energy heterogeneity. *International Journal of Business Data Communications and Networking (IJBDCN),* 7(4): 18-31. Available: https://10.4018/jbdcn.2011100102 (Accessed 5 September 2021).

Adom, D., Hussein, E. K. and Agyem, J. A. 2018. Theoretical and conceptual framework: Mandatory ingredients of a quality research. *International Journal of Scientific Research,* 7(1): 438-441. Available: https://www.researchgate.net/publication/322204158 (Accessed 16 March 2021).

Adu-Manu, K. S., Adam, N., Tapparello, C., Ayatollahi, H. and Heinzelman, W. 2018. Energy-harvesting wireless sensor networks (EH-WSNs) A Review. *ACM transactions on Ssensor Nnetworks (TOSN),* 14(2): 1-50. Available: https://dl.acm.org/doi/abs/10.1145/3183338 (Accessed 4 March 2021).

Agbehadji, I. E., Millham, R., Fong, S. J. and Yang, H. 2018. Kestrel-based Search Algorithm (KSA) for parameter tuning unto long short term memory (lstm) network for feature selection in classification of high-dimensional bioinformatics datasets. *In 2018 Federated Conference on Computer Science and Information Systems (FedCSIS) IEEE.*: 15-20. Available: https://10.15439/2018F52 (Accessed 20- August 2021).

Agbehadji, I. E., Millham, R. C., Fong, S. J. and Yang, H. 2019. Integration of kestrel-based search algorithm with artificial neural network for feature subset selection. *International Journal Bio-Inspired Computing*, 13: 222–233.

Ahmad, M., Ikram, A. A., Wahid, I., Inam, M., Ayub, N. and Ali, S. 2018. A bio-inspired clustering scheme in wireless sensor networks: Bee WSNs. *Procedia Computer Science,* 130: 206-213. Available: https://doi.org/10.1016/j.procs.2018.04.031 (Accessed 07 August 2021).

Al-Hayani, B. and Ilhan, H. 2020. Efficient cooperative image transmission in one-way multi-hop sensor network. *The International Journal of Electrical Engineering & Education,* 57(4): 321-339. Available: https://doi.org/10.1177/0020720918816009 (Accessed 7 March 2020).

Al-Janabi., T. A. and Al-Raweshidy, H. S. 2017. Optimised clustering algorithm-based centralised architecture for load balancing in IoT network. *In 2017 International Symposium on Wireless Communication Systems (ISWCS) IEEE*: 269-274. Available: https://ieeexplore.ieee.org/abstract/document/8108123 (Accessed 08- August 2021).

Al-Sodairi, S. and Ouni, R. 2018. Reliable and energy-efficient multi-hop LEACH-based clustering protocol for wireless sensor networks. Sustainable Computing. *Informatics and Systems*, 1–13. Available: https://doi.org/10.1016/j.suscom.2018.08.007 (Accessed 09 August 2021).

Alarifi, A. and Tolba, A. 2019. Optimizing the network energy of cloud assisted internet of things by using the adaptive neural learning approach in wireless sensor networks. *Computers in Industry,* 106: 133-141. Available: https://doi.org/10.1016/j.compind.2019.01.004 (Accessed 15 March 2021).

Alghamdi, T. A. 2020. Energy efficient protocol in wireless sensor network: Optimized cluster head selection model. *Telecommunication System,* 74: 331–345. Available: https://doi.org/10.1007/s11235-020-00659-9 (Accessed 09 August 2021).

Alquhayz, H. and Jemmali, M. 2021. Fixed urgent window pass for a wireless network with user preferences. *Wireless Personal Communications,* (120): 1-27. Available: https://doi.org/10.1007/s11277-021-08524-x (Accessed 02 September 2021).

Anand, J. 2020. Trust-value based wireless sensor network using compressed sensing. *Journal of Electronics,* 2(02): 88-95. Available: https://doi.org/10.36548/jei.2020.2.003 (Accessed 12 December 2020).

Anandh, S. J. and Baburaj, E. 2020. Energy efficient routing technique for wireless sensor networks using ant-colony optimization. *Wireless Personal Communications,* 114(4): 3419-3433. Available: https://doi.org/10.1007/s11277-020-07539-0 (Accessed 13 July 2020).

Anuradha, D. and Srivatsa, S. K. 2019. Energy effectual reconfigurable routing protocol (E2R2P) for cluster based underwater wireless sensor networks. *Journal Ambient Intelligence Human Computing*. Available: https ://doi.org/10.1007/s1265 2-019-01413 -z (Accessed 03 June 2021).

Arjunan, S. and Sujatha, P. 2018. Lifetime maximization of wireless sensor network using fuzzy based unequal clustering and ACO based routing hybrid protocol. *Applied Intelligence,* 48(8): 2229-2246. Available: https://doi.org/10.1007/s10489-017-1077-y (Accessed 03 March 2020).

Aroba, O. J., Naicker, N. and Adeliyi, T. 2021a. A hyper-heuristic heterogeneous multisensor node scheme for energy efficiency in larger wireless sensor networks using DEEC-Gaussian algorithm. *Mobile Information Systems,* 2021(6658840). Available: https://doi.org/10.1155/2021/6658840 (Accessed 15th February 2021).

Aroba, O. J., Naicker, N. and Adeliyi, T. 2021b. An innovative gaussian clustering hyper-heuristic scheme for energy-efficientoptimization in wireless sensor networks. *Journal of Sensors*, 2021. Available: https://doi.org/10.1155/2021/6666742 (Accessed 11th February 2021).

Aroba, O. J., Naicker, N., Adeliyi, T. and Ogunsakin, E. O. 2020. Meta-analysis of heuristic approaches for optimizing node localization and energy efficiency in wireless sensor networks. *International Journal of Engineering and Advanced Technology (IJEAT),* 10(1): 73-87. Available: https://10.35940/ijeat.A1717.1010120 (Accessed 01 November 2020).

Arora, S. and Singh, S. 2017. Node localization in wireless sensor networks using a butterfly optimization algorithm. *Arabian Journal for Science and Engineering*, 42(8): 3325-3335. Available: https://10.1007/s13369-017-2471-9 (Accessed 20 September 2021).

Arya, R. and Sharma, S. C. 2018. Optimization approach for energy minimization and bandwidth estimation of WSN for data centric protocols. *International Journal of System Assurance Engineering and Management*, 9(1): 2-11. Available: https://doi.org/10.1007/s13198-015-0397-8 (Accessed 11 June 2020).

Ashween, R., Ramakrishnan, B. and Joe, M. M. 2020. Energy efficient data gathering technique based on optimal mobile sink node selection for improved network life time in wireless sensor network (WSN). *Wireless Personal Communications,* 113(4): 2107-2126. Available: https://doi.org/10.1007/s11277-020-07309-y (Accessed 4 February 2021).

Aslam, M., Munir, E. U., Rafique, M. M. and Hu, X. 2016. Adaptive energy-efficient clustering path planning routing protocols for heterogeneous wireless sensor networks. *Sustainable Computing: Informatics and Systems,* 12: 57-71. Available: https://doi.org/10.1016/j.suscom.2016.09.001 (Accessed 13 July 2021).

Audrito, G., Damian.i, F., Viroli, M. and Bin., E. 2018. Distributed real-time shortest-paths computations with the field calculus. *2018 IEEE Real-Time Systems Symposium (RTSS)*: 23-34. Available: https://10.1109/RTSS.2018.00013 (Accessed 6 August 2020).

Ayadi, H., Zouinkhi, A., Boussaid, B., Abdelkrim, M. N. and Val, T. 2016. Energy efficiency in wireless sensor networks. *2016 17th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA)*: 766-771. Available: https://10.1109/STA.2016.7952060 (Accessed 14 July 2021).

Babayo, A., Anisi, M. H. and Ali, I. 2017. A review on energy management schemes in energy harvesting wireless sensor networks. *Renewable and Sustainable Energy Reviews,* 76: 1176-1184. Available: https://doi.org/10.1016/j.rser.2017.03.124 (Accessed 04 June 2021).

Bammer, G., O'Rourke, M., O'Connell, D., Neuhauser, L., Midgley, G., Klein, J. T., Grigg, N. J., Gadlin, H., Elsum, I. R. and Bursztyn, M. 2020. Expertise in research integration and implementation for tackling complex problems: when is it needed, where can it be found and how can it be strengthened? *Palgrave Communications*, 6(1): 1-16. Available: https://doi.org/10.1057/s41599-019-0380-0 (Accessed 02 June 2021).

Banerjee, S., Chowdhury, C., Chattopadhyay, S. and Aslam, N. 2017. Two phased routing protocol incorporating distributed genetic algorithm and gradient based heuristic in clustered WSN. *Wireless Personal Communications,* 97(4): 5401-5425. Available: https://doi.org/10.1007/s11277-017-4786-y (Accessed 12 October 2020).

Barakabitze, A. A., William-Andey Lazaro, A., Ainea, N., Mkwizu, M. H., Maziku, H., Matofali, A. X., Iddi, A. and Sanga, C. 2019. Transforming African education systems in science, technology, engineering, and mathematics (STEM) using ICTs: Challenges and opportunities. *Education Research International*, 2019. Available: https://doi.org/10.1155/2019/6946809 (Accessed 12 August 2020).

Barcelo-Ordinas, J. M., Ferrer-Cid, P., Garcia-Vidal, J., Ripoll, A. and Viana, M. 2019. Distributed multi-scale calibration of low-cost ozone sensors in wireless sensor networks. *Sensors*, 19(11): 2503. Available: https://doi.org/10.3390/s19112503 (Accessed 20 May 2021).

Basturk, B. 2016. An artificial bee colony (ABC) algorithm for numeric function optimization. *In Proceedings of the IEEE Swarm Intelligence Symposium, Indianapolis, in, USA, 12–14 May 2006*: 789–798. Available: https://ci.nii.ac.jp/naid/20001441290/ (Accessed 7 June 2021).

Behera, T. M., Mohapatra, S. K., Samal, U. C., Khan, M. S., Daneshmand, M. and Gandomi, A. H. 2019. Residual energy-based cluster-head selection in WSNs for IoT application. *IEEE Internet of Things Journal,* 6(3): 5132-5139. Available: https://10.1109/JIOT.2019.2897119 (Accessed 6 May 2020).

Bhagat, A. and Kushwaha, A. S. 2021. NHAP-RZLEACH-based hybrid framework to enhance network lifetime in wireless sensor networks. *Proceeding of first doctoral symposium on natural computing research: DSNCR 2020* 169: 413. Available: https://doi.org/10.1007/978-981-33-4073-2_38 (Accessed 9 June 2020).

Bhat, S. J. and Santhosh, K. 2020. Is localization of wireless sensor networks in irregular fields a challenge? *Wireless Personal Communications,* 114: 2017-2042. Available: https://doi.org/10.1007/s11277-020-07460-6 (Accessed 10 October 2020).

Bhola, J., Soni, S. and Cheema, G. K. 2019. Genetic algorithm based optimized leach protocol for energy efficient wireless sensor networks. *Journal Ambient Intelligence Human Computing*. Available: https://doi.org/10.1007/s12652-019-01382-3 (Accessed 7 June 2021).

Biswas, M., Islam, R., Shom, G. K., Shopon, M., Mohammed, N., Momen, S. and Abedin, A. 2017. Banglalekha-isolated: A multi-purpose comprehensive dataset of handwritten bangla isolated characters. *Data in Brief- Elsevier,* 12: 103-107. Available: https://doi.org/10.1016/j.dib.2017.03.035 (Accessed 12 April 2021).

Bongale, A. M., Nirmala, C. R. and Bongale, A. M. 2019. Hybrid cluster head election for WSN based on firefly and harmony search algorithms. *Wireless Personal Communications,* 106(2): 275-306. Available: https://doi.org/10.1007/s11277-018-5780-8 (Accessed 8 June 2021).

Bozorgi, S. M. and Bidgoli, A. M. 2019. HEEC: a hybrid unequal energy-efficient clustering for wireless sensor networks. *Wireless Networks,* 1-22. Available: https://10.1007/s11276-018-1744-x (Accessed 9 June 2021).

Bui, K. H. N., Agbehadji, I. E., Millham, R. C., Camacho, D. and Jung, J. J. 2020. Distributed artificial bee colony approach for connected appliances in smart home energy management system. *Expert System,* 37(e): 12521. Available: https://doi.org/10.1111/exsy.12521 (Accessed 11 June 2021).

Burke, E. K., Hyde, M. R., Kendall and Woodward, G. 2010. A genetic programming Hyper-heuristic approach for evolving two-dimensional strip packing heuristics. *IEEE Transactions on Evolutionary Computation*. Available: https://www.researchgate.net/profile/Graham-Kendall/publication/224148094 (Accessed 12 June 2021).

Burke, E. K. and Qu, R. 2019. Hybridisations within a graph-based hyper-heuristic framework for university timetabling problems. *Journal of the Operational Research Society,* 60 (9): 1273–1285. Available: https://doi.org/10.1057/jors.2008.102 (Accessed 13 June 2021).

Burnap, A., Ren, Y., Gerth, R., Papazoglou, G., Gonzalez, R. and Papalambros, P. Y. 2015. When crowdsourcing fails: A study of expertise on crowdsourced design evaluation. *Journal of Mechanical Design,* 137(3). Available: https://doi.org/10.1115/1.4029065 (Accessed 13 June 2021).

Cai, X., Wang, P., Du, L., Cui, Z., Zhang, W. and Chen, J. 2019. Multi-objective three-dimensional DV-hop localization algorithm with NSGA-II. *IEEE Access,* 19: 10003-10015. Available: https://10.1109/JSEN.2019.2927733 (Accessed 14 June 2021).

Cao, Y., Liu, J. and Xu, Z. 2021. A hybrid particle swarm optimization algorithm for RFID network planning. *Soft Computing,* 25: 5747–5761. Available: https://doi.org/10.1007/s00500-020-05569-1 (Accessed 4 August 2021).

Carlos-Mancilla, M., López-Mellado, E. and Siller, M. 2016. Wireless sensor networks formation: approaches and techniques. *Journal of Sensors,* 2016. Available: https://doi.org/10.1155/2016/2081902 (Accessed 16 June 2021).

Cespedes-Mota, A., Castanon, G., Martinez-Herrera, A. F., Cardenas-Barron, L. E. and Sarmiento, A. M. 2018. Differential evolution algorithm applied to wireless sensor distribution on different geometric shapes with area and energy optimization. *Journal Network Computing, 119*: 14–23. Available: https://doi.org/10.1016/j.jnca.2018.06.006 (Accessed 16 June 2021).

Chamanian, S., Baghaee, S., Uluşan, H., Zorlu, Ö., Uysal-Biyikoglu, E. and Külah, H. 2019. Implementation of energy-neutral operation on vibration energy harvesting WSN. *IEEE Sensors Journal,* 19(8): 3092-3099. Available: https://10.1109/JSEN.2019.2890902 (Accessed 12 June 2021).

Chandrakanth, H. G., Anand, D. G. and Peter, T. J. 2017. Research challenges and characteristic features in wireless sensor networks. *International Journal of Advanced Networking and Applications,* 9(1): 3321. Available: https://www.proquest.com/openview/5981a9361f2bfcb50c91418e2c1342c6/1?pq-origsite=gscholar&cbl=886380 (Accessed 17 June 2021).

Chandren, M. R., Hasan, M. K., Hammoodi, M. R. and Maroosi, A. 2021. An improved harmony search algorithm for proactive routing protocol in VANET. *Journal of Advanced Transportation,* 2021. Available: https://doi.org/10.1155/2021/6641857 (Accessed 13 June 2020).

Chang, J. and Liu, F. 2021. A byzantine sensing network based on majority-consensus data aggregation mechanism. *Sensors,* 21: 248. Available: https://doi.org/10.3390/s21010248 (Accessed 18 June 2021).

Chawra, V. K. and Gupta, G. P. 2020. Salp: metaheuristic-based clustering for wireless sensor networks. in nature-inspired computing applications in advanced communication networks. *IGI Global*: 41-56. Available: 10.4018/978-1-7998-1626-3. Ch 003 (Accessed 19 June 2021).

Cheikhrouhou, O. and Koubâa, A. 2019. Blockloc: secure localization in the internet of things using blockchain. *15th International Wireless Communications & Mobile Computing Conference (IWCMC), IEEE* 2021: 629–634. Available: https://10.1109/IWCMC.2019.8766440 (Accessed 28th August 2020).

Chen, Y., Li, X., Ding, Y., Xu, J. and Liu, Z. 2018. An improved DV-Hop localization algorithm for wireless sensor networks. In: Proceedings of *2018 13th IEEE conference on industrial electronics and applications (ICIEA).* IEEE, 1831-1836. Available: https://ieeexplore.ieee.org/abstract/document/8398006/ (Accessed 10 May 2020).

Chou, J.-S. and Nguyen, T.-K. 2018. Forward forecast of stock price using sliding-window metaheuristic-optimized machine-learning regression. *IEEE Transactions on Industrial Informatics*, 14(7): 3132-3142. Available: https://doi.org/10.1016/j.asoc.2018.03.036 (Accessed 21 June 2021).

Corchado, J. M. and Juan, M. 2021. DeepTech–AI-IoT in smart cities. *Kharazmi University* 01(20): 411. Available: http://hdl.handle.net/10366/144490 (Accessed 20 June 2021).

Coveney, P. V., Swadling, J. B., Wattis, J. A. and Greenwell, H. C. 2012. Theory, modelling and simulation in origins of life studies. *Chemical Society Reviews*, 41(16): 5430-5446. Available: https://pubs.rsc.org/en/content/articlelanding/2012/cs/c2cs35018a/unauth (Accessed 6th December 2021).

Cowling, P., Kendall, G. and Soubeiga, E. 2002. A hyperheuristic approach for scheduling a sales summit. In: Selected papers of the Third International Conference on the Practice And Theory of Automated Timetabling, PATAT 2000, *Lecture Notes in Computer Science, Springer, Berlin*: 176–190. Available: https://doi.org/10.1007/3-540-44629-X_11 (Accessed 20 June 2021).

Cravero, A., Lagos, D. and Espinosa, R. 2018. Big data/IoT use in wine production: A systematic mapping study. *IEEE Latin America Transactions*, 16(5): 1476-1484. Available: https://10.1109/TLA.2018.8408444 (Accessed 21 June 2021).

Cui, L., Xu, C., Li, G., Ming, Z., Feng, Y. and Lu, N. 2018. A high accurate localization algorithm with DV-Hop and differential evolution for wireless sensor network. *Applied Soft Computing*, 68: 39–52. Available: https://doi.org/10.1016/j.asoc.2018.03.036 (Accessed 22 June 2021).

Daneshvar, S. M., Mohajer, P. A. and Mazinani, S. M. 2019. Energy-efficient routing in WSN: A centralized cluster-based approach via grey wolf optimizer. *IEEE Access*, 7: 170019-170031. Available: https://10.1109/ACCESS.2019. 2955993 (Accessed 3 June 2020).

Darji, H. and Shah, H. B. 2016. Genetic algorithm for energy harvesting wireless sensor networks. *In Proceedings of the 2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)* , 1398-1402: 20–21.

Available: https://ieeexplore.ieee.org/abstract/document/7808061 2955993 (Accessed 7 December 2021).

Dattatraya, K. N. and Rao, K. R. 2019. Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN. *Journal of King Saud University-Computer and Information Sciences*. *IEEE Access,* 1319-1578 Available: https://doi.org/10.1016/j.jksuci.2019.04.003 (Accessed 22 June 2021).

de León, A. D., Lalla-Ruiz, E., Melián-Batista, B. and Moreno-Vega, J. M. 2017. Meta-learning-based system for solving logistic optimization problems. *International Conference on Computer Aided Systems Theory*: 339-346. Available: https://link.springer.com/chapter/10.1007/978-3-319-74718-7_41 (Accessed 13 March 2021).

Derakhshan, F. and Yousefi, S. 2019. A review on the applications of multiagent systems in wireless sensor networks. *International Journal of Distributed Sensor Networks,* 15(5): 1550147719850767. Available: https://doi.org/10.1177/1550147719850767 (Accessed 12 August 2020).

Devika, G. and Karegowda, A. 2015. Performance enhancement of LEACH, V-LEACH and MOD-LEACH clustering routing protocols for wireless sensor networks. *International Conference on Research in Business Management & Information Technology*: 29-30. Available: https://www.elkjournals.com/microadmin/UploadFolder/7449IT-16.pdf (Accessed 22 June 2021).

Devika, G., Ramesh, D. and Karegowda, A. G. 2021. Energy optimized hybrid PSO and wolf search based LEACH. *International Journal of Information Technology,* 13: 721–732. Available: https://doi.org/10.1007/s41870-020-00597-4 (Accessed 22 June 2021).

Dey, N. 2020. Applications of cuckoo search algorithm and its variants. *Springer Nature,* 324. Available: https://books.google.co.za/books?id=Nf7sDwAAQBAJ&dq=Cuckoo+Search+and+Its+Variants+in+Digital+Image+Processing:+A+Comprehensive&lr=&source=gbs_navlinks_s (Accessed 12 August 2021).

Dhanalakshmi, B., Sai-Ramesh, L. and Selvakumar, K. 2021. Intelligent energy-aware and secured QoS routing protocol with dynamic mobility estimation for wireless sensor networks. *Wireless Networks,* 27(2): 1503-1514. Available: https://link.springer.com/article/10.1007/s11276-020-02532-8 (Accessed 04 June 2021).

Dhiman, V., Kumar, M. and Sharma, A. 2020. A radical study of energy efficient hierarchical cluster-based routing protocols for WSN. *International Journal on Electrical Engineering and Informatics,* 12: 445-469. Available: https://10.15676/ijeei.2020.12.3.4 (Accessed 23 June 2021).

Dodig-Crnkovic, G. 2002. Scientific methods in computer science. Proceedings of the Conference for the Promotion of Research in IT at New Universities and at University Colleges in Sweden, Skövde, Suecia: 126-130. Available: http://poincare.math.rs/~vladaf/Courses/Matf%20MNSR/Literatura/Scientific%20Methods%20in%20Computer%20Science.pdf (Accessed 28 November 2021).

Dou, H., Chen, Y., Yang, Y. and Long, Y. 2021. A secure and efficient privacy-preserving data aggregation algorithm. *Journal of Ambient Intelligence and Humanized Computing*: 1-9. Available: https://doi.org/10.1007/s12652-020-02801-6 (Accessed 24 June 2021).

Downton, P. 2003. Design research. Available: https://books.google.co.za/books?hl=en&lr=&id=QeTQlylyJTYC&oi=fnd&pg=PA1&dq=Design+research+by+Downton,+Peter&ots=i5CmSE9Ytv&sig=7cx_izvtdRlkjljZbJk8jASCVX0&redir_esc=y#v=onepage&q=Design%20research%20by%20Downton%2C%20Peter&f=false (Accessed 24 June 2021).

Dwivedi, A. K. and Sharma, A. 2020. FEECA: Fuzzy based energy efficient clustering approach in wireless sensor network. *EAI Endorsed Transactions on Scalable Information Systems* 7. Available: https://eudl.eu/doi/10.4108/eai.13-7-2018.163688 (Accessed 25 June 2021).

Edla, D. R., Kongara, M. C. and Cheruku, R. 2019. A PSO based routing with novel fitness function for improving lifetime of WSNs. *Wireless Personal Communications*, 104(1): 73-89. Available: https://doi.org/10.1007/s11277-018-6009-6 (Accessed 15 June 2020).

Eekels, J. and Roozenburg, N. F. M. 1991. A methodological comparison of the structures of scientific research and engineering design: their similarities and differences. *Design Studies*, 12(4): 197-203. Available: https://doi.org/10.1016/0142-694X(91)90031-Q (Accessed 26 June 2021).

Elbhiri, B., Saadane, R., El Fkihi, S. and Aboutajdine, D. 2010. Developed Distributed Energy-Efficient Clustering (DDEEC) for heterogeneous wireless sensor networks. *In: 5th International Symposium on I/V Communications and Mobile Network (ISVC)*. Available: https://10.1109/ISVC.2010.5656252 (Accessed 27 June 2021).

Elhabyan, R., Shi, W. and St-Hilaire, M. 2019. Coverage protocols for wireless sensor networks: Review and future directions. *Journal of Communications and Networks*, 21(1): 45-60. Available: https://ieeexplore.ieee.org/abstract/document/8680729 (Accessed 12 July 2020).

Elhoseny, M. and Hassanien, A. E. 2019. Optimizing cluster head selection in WSN to prolong its existence. *Dynamic Wireless Sensor Networks*: 93-111. Available: https://doi.org/10.1007/978-3-319-92807-4_5 (Accessed 9 June 2020).

Ellis, T. J. and Levy, Y. 2010. A guide for novice researchers: Design and development research methods. Proceedings of Informing Science & IT Education Conference (InSITE) 10: 107-118.
Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.170.2962&rep=rep1&type=pdf (Accessed 29 November 2021).

Elisha, T. 2016. The application of Information and Communication Technology (I.C.T.) in Nigerian academic libraries prospects and problems *Kashim Ibrahim Library Ahmadu Bello University, Zaria* 6(1). Available: https://10.4314/tim.v6i1.27194 (Accessed 17 June 2021).

Elshrkawey, M., Elsherif, S. M. and Wahed, M. E. 2018. An enhancement approach for reducing the energy consumption in wireless sensor networks. *Journal of King Saud University-Computer and Information Sciences,* 30(2): 259-267. Available: https://doi.org/10.1016/j.jksuci.2017.04.002 (Accessed 21 February 2021).

Engmann, F., Katsriku, F. A., Abdulai, J.-D., Adu-Manu, K. S. and Banaseka, F. K. 2018. Prolonging the lifetime of wireless sensor networks: a review of current techniques. *Wireless Communications and Mobile Computing,* Article ID 8035065: 1-24. Available: https://doi.org/10.1155/2018/8035065 (Accessed 3 January 2021).

Essiet, I. O., Sun, Y. and Wang, Z. 2019. Optimized energy consumption model for smart home using improved differential evolution algorithm. *Energy,* 172(1): 354–365. Available: https://doi.org/10.1016/j.energy.2019.01.137 (Accessed 28 June 2021).

Estrada-López, J. J., Castillo-Atoche, A. A., Vázquez-Castillo, J. and Sánchez-Sinencio, E. 2018. Smart soil parameters estimation system using an autonomous wireless sensor network with dynamic power management strategy. *IEEE Sensors Journal,* 18(21): 8913-8923. Available: https://10.1109/JSEN.2018.2867432 (Accessed 20 June 2020).

Faheem, M., Butt, R. A., Raza, B., Ashraf, M. W., Ngadi, M. A. and Gungor, V. C. 2019. Energy efficient and reliable data gathering using internet of software-defined mobile sinks for WSNs-based smart grid applications. *Computer Standards & Interfaces,* 66: 103341. Available: https://doi.org/10.1016/j.csi.2019.03.009 (Accessed 18 July 2020).

Fahmy, H. M. A. 2021. Simulators and emulators for WSNs. *Concepts, Applications, Experimentation and Analysis of Wireless Sensor Networks*: 469-585. Available: https://doi.org/10.1007/978-3-030-58015-5_7 (Accessed 01 August 2021).

Faris, H., Aljarah, I., Al-Betar, M. A. and Mirjalili, S. 2018. Grey wolf optimizer: a review of recent variants and applications. *Neural Computing and Applications,* 30(2): 413-435. Available: https://doi.org/10.1007/s00521-017-3272-5 (Accessed 24 May 2021).

Farmer, E., Van Rooij, J., Riemersma, J. and Jorna, P. 2017. *Handbook of simulator-based training*. Available:
https://books.google.co.za/books?hl=en&lr=&id=FnFBDgAAQBAJ&oi=fnd&pg=PT9&dq=HANDBOOK+OF+SIMULATOR-

BASED+TRAINING&ots=m5PJ6Lxm76&sig=cDO7OV-IFsstcuu6kI73tX7AM3k&redir_esc=y#v=onepage&q=HANDBOOK%20OF%20SIMULATOR-BASED%20TRAINING&f=false (Accessed 18 May 2021).

Farooq, U. 2019. Wireless Sensor Network Challenges and Solutions. *Virtual University of Pakistan* 1: 2-6. Available: https://10.13140/RG.2.2.22191.59043 (Accessed 1 May 2021).

Fawzy, A. E., Amer, A., Shokair, M. and Saad, W. 2016. Four-layer routing protocol with Location based Topology Control of active nodes in WSN. *In Proceedings of the 2016 11th International Conference on Computer Engineering & Systems (ICCES), Cairo, Egypt*: 66–72. Available: 10.1109/ICCES.2016.7821977 (Accessed 02 August 2021).

Ferreiro, A. I., Rabaçal, M. and Costa, M. 2016. A combined genetic algorithm and least squares fitting procedure for the estimation of the kinetic parameters of the pyrolysis of agricultural residues. *Energy Conversion and Management*, 125: 290–300. Available: https://10.1016/J.ENCONMAN.2016.04.104 (Accessed 04 August 2021).

Fetters, M., D and Molina-Azorin, J. F. 2017. The Journal of Mixed Methods Research starts a new decade: The mixed methods research integration trilogy and its dimensions. *Journal of Mixed Methods Research*. Available: https://doi.org/10.1177/1558689817714066 (Accessed 30 May 2021).

Fotohi, R. and Firoozi, B.,S. 2020. A novel countermeasure technique to protect WSN against denial-of-sleep attacks using firefly and Hopfield neural network (HNN) algorithms. *The Journal of Supercomputing*, 76: 6860–6886. Available: https://doi.org/10.1007/s11227-019-03131-x (Accessed 18 April 2021).

Frimpong, S. O., Agbehadji, I. E., Millham, R. and Jung, J. J. 2020. Nature-Inspired Search Method for Cost Optimization of Hybrid Renewable Energy Generation at the Edge. *In 2020 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD) IEEE*: 1-6. Available: https://10.1109/icABCD49160.2020.9183811 (Accessed 03 September 2021).

Fu, Y., Wang, C., Liu, R., Liang, G., Zhang, H. and Ur Rehman, S. 2018. Moving object localization based on UHF RFID phase and laser clustering. *Sensors*, 18(3): 825. Available: https://www.mdpi.com/1424-8220/18/3/825 (Accessed 1 June 2021).

Gajalakshmi, G. and Srikanth, G. U. 2016. A survey on the utilization of Ant Colony Optimization (ACO) algorithm in WSN. *In 2016 International Conference on Information Communication and Embedded Systems (ICICES) IEEE*: 1-4. Available: https://10.1109/ICICES.2016.7518949 (Accessed 22 June 2020).

Gao, D., Zhang, S., Zhang, F., Fan, X. and Zhang, J. 2019. Maximum data generation rate routing protocol based on data flow controlling technology for rechargeable wireless sensor networks. *CMC-Computer Material Continuation*, 59(2): 649-667. Available: https://doi:10.32604/cmc.2019.05195 (Accessed 4 August 2021).

Garcia, G. T., Sanchez, V. M., Marin, C. N. L., Cortez, J. I., Acevedo, C. A. R., Gonzalez, G. S. A., Ameca, J. L. H. and Garcia, M. D. C. M. 2018. Wireless sensor network for monitoring physical variables applied to green technology (IoT green technology). *European Journal of Electrical Engineering and Computer Science,* 2: 2. Available: https://10.24018/ejece.2018.2.2.15 (Accessed 5 August 2021).

García, J., Moraga, P., Valenzuela, M. and Pinto, H. 2020. A db-scan hybrid algorithm: an application to the multidimensional knapsack problem. *Mathematics,* 8(4): 507-515. Available: https://doi.org/10.3390/math8040507 (Accessed 15 March 2021).

Garimella, R. M., Edla, D. R. and Kuppili, V. 2018. Energy efficient design of wireless sensor network: clustering. *Centre for Communications International Institute of Information Technology Hyderabad* 500(32). Available: https://10.14419/IJET.V7I4.5.20046 (Accessed 3 January 2021).

Gautam, P. R., Kumar, S. and Kumar, A. 2021. Sensor localization in WSNs using rotating directional-antenna at the base station. *In Advances in VLSI, Communication, and Signal Processing.* Singapore: Springer, 705-718. Available: https://doi.org/10.1007/978-981-15-6840-4_58 (Accessed 21 June 2021).

Gayen, S., Smarandache, F., Jha, S., Singh, M. K., Broumi, S. and Kumar, R. 2020. Introduction to plithogenic hypersoft subgroup. *Neutrosophic Sets and Systems,* 33. Available: https://www.researchgate.net/publication/343862910_Introduction_to_Plithogenic_Hypersoft_Subgroup (Accessed 5 August 2021).

Geerts, L. G. 2011. A design science research methodology and its application to accounting information systems research. *International Journal of Accounting Information Systems,* 12(2): 142-151. Available: https://doi.org/10.1016/j.accinf.2011.02.004 (Accessed 7 August 2021).

Georgioudakis, M. and Plevris, V. 2020. A comparative study of differential evolution variants in constrained structural optimization. *Frontiers in Built Environment,* 4: Article 102. Available: https://doi.org/10.3389/fbuil.2020.00102 (Accessed 7 August 2021).

Gharghan, S. K., Nordin, R., Jawad, A. M., Jawad, H. M. and Ismail, M. 2018. Adaptive neural fuzzy inference system for accurate localization of wireless sensor network in outdoor and indoor cycling applications. *IEEE Access,* 6: 38475-38489. Available: https://10.1109/ACCESS.2018.2853996 (Accessed 13 March 2020).

Gharib, S., Ali, S. R., Khan, R. and Munir, N. 2015. System of linear equations, gaussian elimination. *Global Journal of Computer Science and Technology,* 15(5). Available: https://computerresearch.org/index.php/computer/article/view/1253 (Accessed 7 August 2021).

Ghate, V. V. and Vijayakumar, V. 2018. Machine learning for data aggregation in WSN: A survey. *International Journal of Pure and Applied Mathematics*, 118(24): 1-12. Available: https://acadpubl.eu/hub/2018-118-24/3/529.pdf (Accessed 7 July 2020).

Giri, P., Ng, K. and Phillips, W. 2018. Wireless sensor network system for landslide monitoring and warning. *IEEE Transactions on Instrumentation and Measurement*, 68(4): 1210-1220. Available: https://10.1109/TIM.2018.2861999 (Accessed 10 March 2020).

Gouda, O., Nassif, A. B., AbuTalib, M. and Nasir, Q. 2021. A systematic literature review on metaheuristic optimization techniques in WSNs. *Open Research and Development Group* 2021. Available: https://www.researchgate.net/profile/Ali-Nassif/publication/348433130_A_Systematic_Literature_Review_on_Metaheuristic_Optimization_Techniques_in_WSNs/links/5ffee3d092851c13fe0a3c66/A-Systematic-Literature-Review-on-Metaheuristic-Optimization-Techniques-in-WSNs.pdf (Accessed 5 January 2021).

Goyal, D. 2016. Power management in wireless sensor network. In*: 2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom) IEEE*: 598-601. Available: https://ieeexplore.ieee.org/abstract/document/7724333 (Accessed 21 June 2020).

Grcar, J. 2011. Mathematicians of Gaussian elimination. *Notices of the AMS*, 58(6): 782-792. Available: https://www.ams.org/notices/201106/rtx110600782p.pdf (Accessed 8 August 2021).

Gu, Z., Wang, Y., Shen, T. and Lau, F. C. 2020. On Heterogeneous sensing capability for distributed rendezvous in cognitive radio networks. *IEEE Transactions On Mobile Computing*, 1: 1. Available: https://10.1109/TMC.2020.2997077 (Accessed 9 August 2021).

Guimaraes, R. R., Passos, L. A., Holanda Filho, R., de Albuquerque, V. H. C., Rodrigues, J. J., Komarov, M. M. and Papa, J. P. 2018. Intelligent network security monitoring based on optimum-path forest clustering. *IEEE Network*, 33(2): 126-131. Available: https://10.1109/MNET.2018.1800151 (Accessed 25 May 2021).

Guleria, K. and Verma, A. K. 2019. Comprehensive review for energy efficient hierarchical routing protocols on wireless sensor networks. *Wireless Networks*, 25(3): 1159-1183. Available: https://doi.org/10.1007/s11276-018-1696-1 (Accessed 22 March 2021).

Guntupalli, L., Martinez-Bauset, J. and Li, F. Y. 2018. Performance of frame transmissions and event-triggered sleeping in duty-cycled WSNs with error-prone wireless links. *Computer Networks*, 134: 215-227. Available: https://doi.org/10.1016/j.comnet.2018.01.047 (Accessed 9 August 2020).

Gupta, H. P., Rao, S. V. and Venkatesh, T. 2016. Analysis of stochastic coverage and connectivity in three-dimensional heterogeneous directional wireless sensor networks.

Pervasive and Mobile Computing, 29: 38-56. Available: https://doi.org/10.1016/j.pmcj.2015.08.004 (Accessed 10 August 2021).

Gupta, P. and Sharma, A. K. 2019. Designing of energy efficient stable clustering protocols based on BFOA for WSNS. *Journal of Ambient Intelligence and Humanized Computing*, 10(2): 681–700. Available: https://doi.org/10.1007/s12652-018-0719-1 (Accessed 11 August 2021).

Hamidouche, R., Aliouat, Z. and Gueroui, A. M. 2018. Genetic algorithm for improving the lifetime and QoS of wireless sensor networks. *Wireless Personal Communications*, 101(4): 2313–2348. Available: https://doi.org/10.1007/s11277-018-5817-z (Accessed 18 August 2021).

Han, G. and Zhang, L. 2018. WPO-EECRP: energy-efficient clustering routing protocol based on weighting and parameter optimization in WSN. *Wireless Personal Communications,* 98(1): 1171-1205. Available: https://doi.org/10.1007/s11277-017-4914-8 (Accessed 21 May 2021).

Han, Y., Zhang, J. and Sun, D. 2018. Error control and adjustment method for underwater wireless sensor network localization. *Applied Acoustics,* 130: 293-299. Available: https://doi.org/10.1016/j.apacoust.2017.08.007 (Accessed 8 March 2020).

Hancock, D. R. and Algozzine, B. 2017. *Doing case study research: A practical guide for beginning researchers*. Available: https://books.google.co.za/books?hl=en&lr=&id=9DfwDQAAQBAJ&oi=fnd&pg=PP1&dq=Case+Study+Method+for+Design+Research:+A+Justification&ots=n4BvlJgAJR&sig=HToEwgg3oOdrcdE8aZs4qoD313o&redir_esc=y#v=onepage&q&f=false (Accessed 03 April 2021).

Hao, Z., Dang., J., Yan., Y. and Wang., X. 2021. A node localization algorithm based on Voronoi diagram and support vector machine for wireless sensor networks. *International Journal of Distributed Sensor Networks,* 17(2): 1550147721993410. Available: https://doi.org/10.1177/1550147721993410 (Accessed 18 August 2021).

Hardin, B. 2017. Implementing the heston option pricing model in object-oriented cython. *All Graduate Plan B and other Reports* 1146. Available: https://digitalcommons.usu.edu/gradreports/1146/ (Accessed 10 May 2021).

Haseeb, K., Almustafa, K. M., Jan, Z., Saba, T. and Tariq, U. 2020. Secure and energy-aware heuristic routing protocol for wireless sensor network. *IEEE Access,* 8: 163962-163974. Available: https://10.1109/ACCESS.2020.3022285 (Accessed 3 August 2020).

Haseeb, K., Islam, N., Almogren, A., Din, I. U., Almajed, H. N. and Guizani, N. 2019. Secret sharing-based energy-aware and multi-hop routing protocol for IoT based WSNs. *IEEE*

Access, 7: 79980-79988. Available: https://ieeexplore.ieee.org/abstract/document/8736739 (Accessed 13 May 2020).

Hasnat, M. A., Akbar, Z., Iqbal, Z. A., Khan, U., Qasim, N. and Javaid.N. 2015. Bio inspired distributed energy efficient clustering for Wireless Sensor Networks, in: Information Technology: Towards New Smart World. *IEEE Access*: 1–7. Available: https://10.1109/NSITNSW.2015.7176429 (Accessed 15 August 2021).

Hassan, A. A., Shah, W., Husein, A. M., Talib, M. S., Mohammed, A. A. J. and Iskandar, M. 2019. Clustering approach in wireless sensor networks based on k-means: Limitations and recommendations. *IJRTE-Blue Eyes Intelligence Engineering,* 7(65): 119-126. Available: https://F10200476S519/19 (Accessed 19 August 2021).

Heinzelman, W. B., Chandrakasan, A. P. and Balakrishnan, H. 2002. An application-specific protocol architecture for wireless microsensor networks. *IEEE Transactions on Wireless Communications,* 1(4): 660-670. Available: https://10.1109/TWC.2002.804190 (Accessed 19 August 2021).

Heinzelman, W. R., Chandrakasan, A. and Balakrishnan, H. 2010. Energy-efficient communication protocol for wireless microsensor networks. *IEEE Access- Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*: 1–10 Available: https://10.1109/HICSS.2000.926982 (Accessed 19 August 2021).

Hevner, A. R., March, S. T., Park, J. and Ram, S. 2004. Design science in information systems research. *MIS Quarterly,* 28: 75-105. Available: https://doi.org/10.2307/25148625 (Accessed 22 August 2021).

Hijazi, H., Kandil, N., Zaarour, N. and Hakem, N. 2019. Gradient descent localization algorithm based on received signal strength technique in a noisy wireless sensor network. In: Proceedings of *2019 Fourth International Conference on Advances in Computational Tools for Engineering Applications (ACTEA)*. IEEE, 1-5. Available: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8851085 (Accessed 5 April 2021).

Hoang, D., Yadav, P., Kumar, R. and Panda, S. K. 2010. A robust harmony search algorithm-based clustering protocol for wireless sensor networks. *IEEE International Conference on Communications Workshops*: 1–5 Available: https://10.1109/ICCW.2010.5503895 (Accessed 17 June 2021).

Hu, F. and Cao, X. 2010. *Wireless sensor networks: principles and practice*. Boca Raton, Fla,: CRC Press. Available: https://doi.org/10.1201/9781439882665 (Accessed 23 August 2021).

Huang, H., Guo, S., Gui, G., Yang, Z., Zhang, J., Sari, H. and Adachi, F. 2019. Deep learning for physical-layer 5G wireless techniques: Opportunities, challenges and solutions. *IEEE*

Wireless Communications, 27(1): 214-222. Available: https://ieeexplore.ieee.org/abstract/document/8786074 (Accessed 4 May 2020).

Hudson, J., Denzinger, J., Kasinger, H. and Bauer, B. 2011. Dependable risk-aware efficiency improvement for self-organizing emergent systems. *2011 IEEE Fifth International Conference on Self-Adaptive and Self-Organizing Systems*: 11-20. Available: https://10.1109/SASO.2011.12 (Accessed 24 August 2021).

Ilyas, M., Arif, M., Khurshid, H., Siddiqui, S. U., Jatoi, S. A., Jan, S. A., Khan, S. A., Khan, A., Ibrahim, M. I., Saleem, N. and Ghafoor, A. 2015. Estimating spatial population structure through quantification of Oil content and phenotypic diversity in Pakistani Castor Bean (Ricinus communis L.). *Science Technology Development,* 34: 147-154. Available: https://10.3923/std.2015.147.154 (Accessed 25 August 2021).

Iwendi, C., Zhang, Z. and Du, X. 2018. ACO based key management routing mechanism for WSN security and data collection. *In 2018 IEEE International Conference on Industrial Technology,* 1935-1939. Available: https://10.1109/ICIT.2018.8352482 (Accessed 21 June 2020).

Jabeur, N., Yasar, A. U. H., Shakshuki, E. and Haddad, H. 2020. Toward a bio-inspired adaptive spatial clustering approach for IoT applications. *Future Generation Computer Systems,* 107: 736-744. Available: https://https://doi.org/10.1016/j.future.2017.05.013 (Accessed 7 May 2021).

Janakiraman, S. 2018. A hybrid ant colony and artificial bee colony optimization algorithm-based cluster head selection for IoT. *Procedia Computer Science,* 143: 360-366. Available: https://doi.org/10.1016/j.procs.2018.10.407 (Accessed 12 October 2020).

Janarthanan, A. and Kumar, D. 2019. Localization based evolutionary routing (LOBER) for efficient aggregation in wireless multimedia sensor networks. *Computers, Materials & Continua,* 60(3): 895-912. Available: https://10.32604/cmc.2019.06805 (Accessed 26 August 2021).

Jari, A. and Avokh, A. 2021a. PSO-based sink placement and load-balanced anycast routing in multi-sink WSNs considering compressive sensing theory. *Engineering Applications of Artificial Intelligence,* 100, 0952-197. Available: https://doi.org/10.1016/j.engappai.2021.104164 (Accessed 27 August 2021).

Javadpour, A., Adelpour, N., Wang, G. and Peng, T. 2018. Combing fuzzy clustering and PSO algorithms to optimize energy consumption in WSN networks. *2018 IEEE Smart World, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing*: 1371-1377. Available: https://ieeexplore.ieee.org/abstract/document/8560216/ (Accessed 02 July 2020).

Javaid, L. and Bansal, K. 2021. Improving the packet delivery rate in wireless sensor networks. *Dogo Rangsang Research Journal,* 11(1): 82-85. Available: https://www.journal-dogorangsang.in/no_1_Online_21/12.pdf

Jayanthi, N. and Valluvan, K. R. 2018. Bio-inspired optimization routing technique using DNA sequencing algorithm for wireless sensor networks. *Wireless Personal Communications,* 101(4): 2365-2381. Available: https://doi.org/10.1007/s11277-018-5821-3 (Accessed 26 August 2021).

Jayekumar, M. and Nagarajan, V. 2018. Route failure recovery algorithm for dense wireless sensor networks. In: Proceedings of *2018 IEEE International Conference on System, Computation, Automation and Networking (ICSCA).* IEEE, 1-6. Available: https://ieeexplore.ieee.org/abstract/document/8541157 (Accessed 12 May 2020).

Jiang, A. and Zheng, L. 2018. An effective hybrid routing algorithm in WSN: Ant colony optimization in combination with hop count minimization. *Sensors,* 18(4): 1020. Available: https://doi.org/10.3390/s18041020 (Accessed 2 June 2020).

Jibreel, F. 2019. Improved Enhanced Distributed scheme for heterogeneous wireless sensor network. *International Journal of Engineering Research and Advanced Technology (IJERAT),* 5(1): 6-11. Available: https://10.31695/IJERAT.2019.3359 (Accessed 25 August 2021).

Jibreel, F., Daabo, M. I. and Gbolagade, K. A. 2020. Gateway-stable Election Protocol for Heterogeneous Wireless Sensor Network. *Asian Journal of Research in Computer Science*: 40-48. Available: https://10.9734/ajrcos/2020/v5i130127 (Accessed 28 August 2021).

Jin, R., Zhou, X. and Wang, Y. 2020. An Efficient Energy Routing Protocol Based on Gradient Descent Method in WSNs. *Journal of Information Hiding and Privacy Protection,* 2(3): 115-123. Available: https://10.32604/jihpp.2020.010180 (Accessed 1 November 2020).

Joshi, J., Awasthi, P., Mukherjee, S., Kumar, R., Kurian, D. S. and Deka, M. J. 2016. SEED: Secure and energy efficient data transmission in Wireless Sensor Networks. *IEEE Access,* 25–27: 1–6. Available: https://10.1109/ICoICT.2016.7571961 (Accessed 29 August 2021).

Jozkowski, A. C. 2017. Reason & rigor: how conceptual frameworks guide research. *Occupational Therapy in Health Care,* 31(4): 378-379. Available: https://doi.org/10.1080/07380577.2017.1360538 (Accessed 12 April 2021).

Kadir, E. A., Rosa, S. L. and Yulianti, A. 2018. Application of WSNs for detection land and forest fire in Riau Province Indonesia. In: Proceedings of *2018 International Conference on Electrical Engineering and Computer Science (ICECOS).* IEEE, 25-28. Available: https://ieeexplore.ieee.org/abstract/document/8605197/ (Accessed 17 May 2020).

Kanwar, V. and Kumar, A. 2021. DV-Hop-based range-free localization algorithm for wireless sensor network using runner-root optimization. *The Journal of Supercomputing*, 77(3): 3044-3061. Available: https://doi.org/10.1007/s11227-020-03385-w (Accessed 1 September 2021).

Karabiyik, U. and Akkaya, K. 2019. Digital forensics for IoT and WSNS. In: *Mission-oriented sensor networks and systems: Art and science*. Springer, 171-207. Available: https://link.springer.com/chapter/10.1007/978-3-319-92384-0_6 (Accessed 03 June 2021).

Kassabalidis, I., El-Sharkawi, M. A., Marks, R. J., Arabshahi, P. and Gray, A. A. 2019. Swarm intelligence for routing in communication networks. *Global Telecommunication*, 6: 3613–3617. Available: https://10.1109/GLOCOM.2001.966355 (Accessed 3 September 2021).

Kaswan, A., Singh, V. and Jana, P. K. 2018. A multi-objective and PSO based energy efficient path design for mobile sink in wireless sensor networks. *Pervasive and Mobile Computing*, 46: 122-136. Available: https://doi.org/10.1016/j.pmcj.2018.02.003 (Accessed 7 June 2020).

Kaur, A., Aggrawal, N. and Lal, S. 2020. An Accurate Localization in Wireless Sensor Networks. *In 2020 6th International Conference on Signal Processing and Communication (ICSC) IEEE*: 18-22. Available: https://10.1109/ICSC48311.2020.918 (Accessed 4 September 2021).

Kaur, K., Garg, S., Kaddoum, G., Ahmed, S. H. and Jayakody, D. N. K. 2019. En-osco: energy-aware osmotic computing framework using hyper-heuristics. *Proceedings of the ACM MobiHoc Workshop on Pervasive Systems in the IoT Era*: 19-24. Available: https://doi.org/10.1145/3331052.3332473 (Accessed 4 September 2021).

Kaur, K. and Sharma, E. S. 2020. Analysis grid based DEEC protocol with priority queue for increasing lifetime of WSN. *International Journal of Research and Analytical Reviews (IJRAR)*, 7(2): 699-703. Available: http://www.ijrar.org/papers/IJRAR2004238 (Accessed 4 September 2021).

Kaur, S. and Mahajan, R. 2018. Hybrid meta-heuristic optimization based energy efficient protocol for wireless sensor networks. *Egyptian Informatics Journal*, 19(3): 145-150. Available: https://doi.org/10.1016/j.eij.2018.01.002 (Accessed 5 September 2021).

Kaur, T. and Kumar, D. 2018. Particle swarm optimization-based unequal and fault-tolerant clustering protocol for wireless sensor networks. *IEEE Sensors Journal*, 18(11): 4614–4622. Available: https://10.1109/JSEN.2018.2828099 (Accessed 6 September 2021).

Kaushik, A., Indu, S. and Gupta, D. 2019. A grey wolf optimization approach for improving the performance of wireless sensor networks. *Wireless Personal Communications*, 106(3):

1429-1449. Available: https://doi.org/10.1007/s11277-019-06223-2 (Accessed 26 May 2021).

Kennedy, J. and Eberhart, R. C. 2019. Particle swarm optimization. In*: Proceedings of IEEE International Conference on Neural Networks,* Piscataway 27: 1942–1948. Available: https://10.1109/ICNN.1995.488968 (Accessed 7 September 2021).

Khalaf, O. I. and Abdulsahib, G. M. 2019. Frequency estimation by the method of minimum mean squared error and P-value distributed in the wireless sensor network. *Journal Information Science Engineering,* 35(5): 1099-1112. Available: https://10.6688/JISE.201909_35(5).0010 (Accessed 7 April 2020).

Khalid, A. D., Noor, J. A.-M., Iyad, F. J. and Ala, F. K. 2017. Energy efficient clustering algorithm for wireless sensor networks. In*: IEEE WiSPNET*. Available: https://10.1109/WiSPNET.2017.8299826 (Accessed 9 September 2021).

Khalid, R., Javaid, N., Rahim, M. H., Aslam, S. and Sher, A. 2019. Fuzzy energy management controller and scheduler for smart homes. *Computer Information System,* 21: 103–118. Available: https://doi.org/10.1016/j.suscom.2018.11.010 (Accessed 10 September 2021).

Khan, A., Gupta, S. and Gupta, S. K. 2020. Multi-hazard disaster studies: Monitoring, detection, recovery, and management, based on emerging technologies and optimal techniques. *International Journal of Disaster Risk Reduction,* 47. Available: https://doi.org/10.1016/j.ijdrr.2020.101642 (Accessed 1 June 2020).

Kiani, F. and Seyyedabbasi, A. 2018. Wireless sensor network and internet of things in precision agriculture. *International Journal of Advanced Computer Science and Applications,* 9: 6. Available: http://dx.doi.org/10.14569/IJACSA.2018.090614 (Accessed 10 September 2021).

Kivunja, C. 2018. Distinguishing between theory, theoretical framework, and conceptual framework: A systematic review of lessons from the field. *International Journal of Higher Education,* 7(6): 44-53. Available: https://eric.ed.gov/?id=EJ1198682 (Accessed 31 May 2021).

Koteswara, R. S. and Nanda, K. J., K. 2018. Performance Evaluation of Routing Protocols in Wireless Sensor Networks. *3rd International Conference On Internet of Things: Smart Innovation and Usages, 2018 IoT-SIU,* 120(6): 201–209. Available: https://doi.org/10.1109/IoT-SIU.2018.8519933 (Accessed 11 September 2021).

Krishna, K. H., Babu, Y. S. and Kumar, T. 2016. Wireless network topological routing in wireless sensor networks. *Procedia Computer Science,* 79: 817-826. Available: https://doi.org/10.1016/j.procs.2016.03.111 (Accessed 12 September 2021).

Krishnamurthi, R., Kumar, A., Gopinathan, D., Nayyar, A. and Qureshi, B. 2020. An overview of iot sensor data processing, fusion, and analysis techniques. *Sensors,* 20(21): 6076. Available: https://www.mdpi.com/869554 (Accessed 12 September 2021).

Krishnan, M., Yun, S. and Jung, Y. M. 2019. Enhanced clustering and ACO-based multiple mobile sinks for efficiency improvement of wireless sensor networks. *Computer Networks,* 160: 33-40. Available: https://www.sciencedirect.com/science/article/pii/S1389128619300234 (Accessed 4 March 2021).

Kuechler, W. L. and Vaishnavi, V. 2006. So, talk to me: The effect of explicit goals on the comprehension of business process narratives. *MIS Quarterly,* 1: 961-979. Available: https://10.2307/25148761 (Accessed 12 September 2021).

Kulkarni, V. R., Desai, V. and Kulkarni, R. V. 2019. A comparative investigation of deterministic and metaheuristic algorithms for node localization in wireless sensor networks. *Wireless Networks,* 25(5): 2789-2803. Available: https://doi.org/10.1007/s11276-019-01994-9 (Accessed 13 September 2021).

Kumar, L. and Patle, D. 2020. Lifetime enhancement in wireless sensor networks using adaptive clustering and thresholding. *International Journal of Innovative Research in Technology and Management,* 4(1). Available: http://ijirtm.com/UploadContaint/finalPaper/IJIRTM-0401202007.pdf (Accessed 14 September 2021).

Kumar, R., Edalatpanah, S. A., Jha, S. and Singh, R. 2019. A novel approach to solve gaussian valued neutrosophic shortest path problems. *International Journal of Engineering and Advanced Technology,* 8. Available: https://books.google.co.za/books?hl=en&lr=&id=GGWdDwAAQBAJ&oi=fnd&pg=PA352&dq=A+novel+approach+to+solve+gaussian+valued+neutrosophic+shortest+path+problems&ots=YkMe-S4EeQ&sig=5Ye2AtMJ9r0Rt01dMX81HGJtJJQ&redir_esc=y#v=onepage&q=A%20novel%20approach%20to%20solve%20gaussian%20valued%20neutrosophic%20shortest%20path%20problems&f=false (Accessed 13 September 2021).

Kumar, R., Edalatpanah, S. A. and Mohapatra, H. 2020. A note on optimal path selection approach for fuzzy reliable shortest path problem. *Journal of Intelligent & Fuzzy Systems,* 1: 1-4. Available: https://content.iospress.com/articles/journal-of-intelligent-and-fuzzy-systems/ifs200923 (Accessed 14 September 2021).

Kumar, R., Jha, S. and Singh, S. 2020. A different approach for solving the shortest path problem under mixed fuzzy environment. *International Journal of Fuzzy System Applications*, 9: 132-161. Available: https://www.igi-global.com/article/a-different-approach-for-solving-the-shortest-path-problem-under-mixed-fuzzy-environment/250823 (Accessed 15 September 2021).

Kumar, R., Tripathi, S. and Agrawal, R. 2020. A review on security in wireless sensor network. *2020 International Conference on Emerging Smart Computing and Informatics (ESCI)*: 304-308. Available: https://10.1109/ESCI48226.2020.9167610 (Accessed 16 September 2021).

Kumar, S., Kumar, S. and Batra, N. 2020. Optimized distance range free localization algorithm for WSN. *Wireless Personal Communications*, 117: 1-29. Available: https://doi.org/10.1007/s11277-020-07950-7 (Accessed 16 September 2021).

Kumaresan, K. and Kalyani, S. N. 2021. Energy efficient cluster based multilevel hierarchical routing for multi-hop wireless sensor network. *Journal of Ambient Intelligence and Humanized Computing*, 12(3): 3821-3830. Available: https://link.springer.com/article/10.1007/s12652-020-01700-0 (Accessed 13 February 2021).

Lan, K. C. and Wei, M. Z. 2017. A compressibility-based clustering algorithm for hierarchical compressive data gathering. *IEEE Sensors Journal*, 17(8): 2550-2562. Available: https://10.1109/JSEN.2017.2669081 (Accessed 17 September 2021).

Langner, I., Riedel, O., Czwikla, J., Heinze, F., Rothgang. H., Zeeb, H. and Haug, U. 2020. Linkage of routine data to other data sources in germany: a practical example illustrating challenges and solutions *Das Gesundheitswesen*, 82(2): S117-S121. Available: https://10.1055/a-0999-5509 (Accessed 17 September 2021).

Lee, J.-Y. and Lee, D. 2021. K-means clustering-based WSN protocol for energy efficiency improvement. *International Journal of Electrical & Computer Engineering*, 11(3). Available: https://10.11591/ijece.v11i3.pp2371-2377 (Accessed 18 September 2021).

Li, J. G., X.; , Guo, L., Ji, S., Han, M. and Cai, Z. 2015. Optimal routing with scheduling and channel assignment in multi-power multi-radio wireless sensor networks. *Ad Hoc Networks*, 31: 45–62. Available: https://doi.org/10.1016/j.adhoc.2015.03.006 (Accessed 18 September 2021).

Li, X., Keegan, B. and Mtenzi, F. 2018a. Energy efficient hybrid routing protocol based on the artificial fish swarm algorithm and ant colony optimisation for WSNs. *MDPI Sensors*, 18 (10): 3351-3368. Available: https://doi.org/10.3390/s18103351 (Accessed 23 September 2021).

Lipare, A., Edla, D. R. and Kuppili, V. 2019. Energy efficient load balancing approach for avoiding energy hole problem in WSN using Grey Wolf Optimizer with novel fitness function. *Applied Soft Computing*, 84: 105706. Available: https://doi.org/10.1016/j.asoc.2019.105706 (Accessed 4 June 2020).

Liu, H., Nayak, A., and Stojmenovic, I. 2010. Applications, models, problems, and solution strategies. *Wireless Sensor and Actuator Networks*: 1. Available: https://10.1002/9780470570517 (Accessed 20 September 2021).

Lu, C., Li, X., Yu, W., Zeng, Z., Yan, M. and Li, X. 2021. Sensor network sensing coverage optimization with improved artificial bee colony algorithm using teaching strategy. *Computing,* 103: 1439–1460. Available: https://doi.org/10.1007/s00607-021-00906-0 (Accessed 5 August 2021).

Lv, Y., Liu, W., Wang, Z. and Zhang, Z. 2020. WSN localization technology based on hybrid GA-PSO-BP algorithm for indoor three-dimensional space. *Wireless Personal Communications*, 114(1): 167-184. Available: https://link.springer.com/article/10.1007/s11277-020-07357-4 (Accessed 1 November 2020).

Mahapatra, C., Payal, A. and Chopra, M. 2020. Review of WSN and its quality-of-service parameters using nature-inspired algorithm. In: Proceedings of *International Conference on Innovative Computing and Communications*. Springer, 451-461. Available: https://link.springer.com/chapter/10.1007/978-981-15-0324-5_39 (Accessed 30 August 2020).

Manikandan, S. and Chinnadurai, M. 2021. Effective energy adaptive and consumption in wireless sensor network using distributed source coding and sampling techniques. *Wireless Personal Communications,* 118(2): 1393-1404. Available: https://link.springer.com/article/10.1007/s11277-021-08081-3 (Accessed 16 February 2021).

Mazumdar, N., Nag, A. and Nandi, S. 2021. HDDS: Hierarchical data dissemination strategy for energy optimization in dynamic wireless sensor network under harsh environments. *Ad Hoc Networks,* 111: 102348. Available: https://www.sciencedirect.com/science/article/pii/S157087052030696X (Accessed 14 February 2021).

McKenney, S. and Reeves, T. C. 2021. Educational design research: Portraying, conducting, and enhancing productive scholarship. *Medical Education,* 55(1): 82-92. Available: https://doi.org/10.1111/medu.14280 (Accessed 01 July 2021).

McKinsey, G. 2018. Big data too big to ignore, data crunchers, Forrester research. *Hadoop Apache,* 1: 3-10. Available: https://Too-Big-Ignore-Business-Wiley/dp/1119217849 (Accessed 2 July 2021).

Mehrani, M., Shanbehzadeh, J., Sarrafzadeh, A., Mirabedini, S. J. and Manford, C. 2010. Feed: fault tolerant, energy efficient, distributed clustering for WSN. *The 12th International Conference on Advanced Communication Technology (ICACT).* Available: https://ieeexplore.ieee.org/abstract/document/5440395 (Accessed 3 July 2021).

Mejia, J., Ochoa-Zezzatti, A., Cruz-Mejía, O. and Mederos, B. 2020. Prediction of time series using wavelet Gaussian process for wireless sensor networks. *Wireless Networks*: 1-8. Available: https://doi.org/10.1007/s11276-020-02250-1(0123456789().,-volV)(0123456789(). ,- volV) (Accessed 3 July 2021).

Meng, Y., Zhan, Y., Gu, J., Zhang, L. and Chang, Y. 2020. 3-D Localization in WSNs Using UAVs. World Scientific Research Journal, 6(10): 321-332.Available : https://10.6911/WSRJ.202010_6(10).0040 (Accessed 09 December 2021)

Messous, S. and Liouane, H. 2020. Online Sequential DV-Hop Localization Algorithm for Wireless Sensor Networks. *Mobile Information Systems*, 2020(8195309): 14. Available: https://doi.org/10.1155/2020/8195309 (Accessed 5 July 2021).

Mhatre, M., Kumar, A. and Jha, C. K. 2019. Energy-efficient wireless sensor's routing using balanced unequal clustering technique. *Pervasive Computing: A Networking Perspective and Future Directions*: 81–91. Available: https://doi.org/10.1007/978-981-13-3462-7_8 (Accessed 6 July 2021).

Micheli, P., Wilner, S. J., Bhatti, S. H., Mura, M. and Beverland, M. B. 2019. Doing design thinking: Conceptual review, synthesis, and research agenda. *Journal of Product Innovation Management*, 36(2): 124-148. Available: https://onlinelibrary.wiley.com/doi/full/10.1111/jpim.12466 (Accessed 2 June 2021).

Mirjalili, S. and Lewis, A. 2016. The whale optimization algorithm. *Advances in Engineering Software*, 95: 51-67. Available: http://dx.doi.org/10.1016/j.advengsoft.2016.01.008 (Accessed 06 September 2021).

Mishra, D., Vijayakumar, P., Sureshkumar, V., Amin, R., Islam, S. H. and Gope, P. 2018. Efficient authentication protocol for secure multimedia communications in IoT-enabled wireless sensor networks. *Multimedia Tools and Applications*, 77(14): 18295-18325. Available: https://link.springer.com/article/10.1007/s11042-017-5376-4 (Accessed 17 August 2020).

Mohajerani, A. and Gharavian, D. 2016. An ant colony optimization based routing algorithm for extending network lifetime in wireless sensor networks. *Wireless Networks*, 22: 2637–2647. Available: https://doi.org/10.1007/s11276-015-1061-6 (Accessed 7 July 2021).

Mohamed, A. W. and Suganthan, P. N. 2018. Real-parameter unconstrained optimization based on enhanced fitness-adaptive differential evolution algorithm with novel mutation. *Soft Computing*, 22(10): 3215-3235. Available: https://doi.org/10.1007/s00500-017-2777-2 (Accessed 7 July 2021).

Mohapatra, H., Panda, S., Rath, S., Edalatpanah, S. A. and Kumar, S. 2020a. A tutorial on powershell pipeline and its loopholes. *International Journal of Emerging Trends in Engineering Research*, 8: 975-982. Available: http://www.warse.org/IJETER/static/pdf/file/ijeter05852020.pdf (Accessed 9 July 2021).

Mohapatra, H., Rath, A. K., Landge, P. B. and Bhise, D. 2020a. A comparative analysis of clustering protocols of wireless sensor network. *International Journal of Mechanical and Production Engineering Research and Development (IJMPERD),* 10(3): 8371-8386. Available: http://www.tjprc.org/publishpapers/2-67-1598435348-IJMPERDJUN2020795.pdf (Accessed 8 July 2021).

Mohapatra, H., Rath, S., Panda, S. and Kumar, R. 2020c. Handling of man-in-the-middle attack in wsn through intrusion detection system. *International Journal of Emerging Trends in Engineering Research,* 8: 1503-1510. Available: https://doi.org/10.30534/ijeter/2020/05852020 (Accessed 8 July 2021).

Moorthi, R. and Thiagarajan, R. 2020. Energy consumption and network connectivity based on Novel-LEACH-POS protocol networks. *Computer Communications,* 149: 90-98. Available: https://doi.org/10.1016/j.comcom.2019.10.006 (Accessed 30 August 2021).

Mosavvar, I. and Ghaffari, A. 2019. Data aggregation in wireless sensor networks using firefly algorithm. *Wireless Personal Communications* 104(1): 307-324. Available: https://link.springer.com/content/pdf/10.1007/s11277-018-6021-x.pdf (Accessed 6 March 2020).

Mostafaei, H., Chowdhury, M. U., Islam, R. and Gholizadeh, H. 2015. Connected P-Percent coverage in wireless sensor networks based on degree constraint dominating set approach. *Proceedings of the 18th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems*: 157-160. Available: https://doi.org/10.1145/2811587.2811625 (Accessed 9 July 2021).

Mostafaei, H. and Obaidat, M. S. 2018. A distributed efficient algorithm for self-protection of wireless sensor networks. *2018 IEEE International Conference on Communications (ICC)*: 1-6. Available: https://10.1109/ICC.2018.8422400 (Accessed 10 July 2021).

Mozamir, M. S., Bakar., R. B. A., Din., W. I. S. W. and Musa, Z. 2020. GbLN-PSO Algorithm for Indoor Localization in Wireless Sensor Network. *IOP Conference Series: Materials Science and Engineering,* 769(1): 012033. Available: https://iopscience.iop.org/article/10.1088/1757-899X/769/1/012033/meta (Accessed 11 July 2021).

Mukherjee, A., Goswami, P., Yan, Z., Yang, L., Routray, S. and Palai, G. 2020. Distributed gradient descent based cluster head identification in MIMO sensor networks. *Optik* 204: 164185. Available: https://doi.org/10.1016/j.ijleo.2020.164185 (Accessed 15 June 2020).

Naeimi, S., Hamidreza, G., Chee-Onn, C. and Hiroshi, I. 2017. A survey on the taxonomy of cluster-based routing protocols for homogeneous wireless sensor networks. *Sensors,* 12(6): 7350–7409. Available: https://doi.org/10.3390/s120607350 (Accessed 12 July 2021).

Naghashzadeh, M., Haghshenas, A., Sami, A. and Lo, D. 2021. How do users answer MATLAB questions on Q&A sites? A case study on stack overflow and mathworks. In: Proceedings of *2021 IEEE International Conference on Software Analysis, Evolution and Reengineering (SANER)*. IEEE, 526-530. Available: https://ieeexplore.ieee.org/abstract/document/9426047 (Accessed 1 May 2021).

Najeh, T., Sassi, H. and Liouane, N. 2018. A novel range free localization algorithm in wireless sensor networks based on connectivity and genetic algorithms. *International Journal of Wireless Information Networks,* 25(1): 88-97. Available: https://link.springer.com/article/10.1007/s10776-017-0375-y (Accessed 4 September 2020).

Nam, S. M. and Kim, H.-J. 2021. WSN-SES/MB: System entity structure and model base framework for large-scale wireless sensor networks. *Sensors,* 21(2): 430. Available: https://doi.org/10.3390/s21020430 (Accessed 13 July 2021).

Naranjo, P. G. V., Shojafar, M. M., ostafaei, H., Pooranian, Z. and Baccarelli, E. P. 2017. SEP: A prolong stable election routing algorithm for energy-limited heterogeneous fog-supported wireless sensor networks. *Journal of Supercomputing,* 73: 733–755. Available: https://10.1007/s11227-016-1785-9 (Accessed 14 July 2021).

Nayak, P., Swetha, G. K., Gupta, S. and Madhavi, K. 2021. Routing in wireless sensor networks using machine learning techniques: challenges and opportunities. *Measurement*: 108974. Available: https://doi.org/10.1016/j.measurement.2021.108974 (Accessed 14 July 2021).

Nayyar, A. and Singh, R. 2019. IEEMARP-a novel energy efficient multipath routing protocol based on Ant Colony Optimization (ACO) for dynamic sensor networks. *Multimedia Tools and Applications*: 1-32. Available: https://link.springer.com/content/pdf/10.1007/s11042-019-7627-z.pdf (Accessed 2 June 2020).

Naz, A., Javaid, N., Iqbal, M. M., Ali, M., Imran, M. and Khan, Z. A. 2018. TBEENISH: threshold balanced energy efficient network integrated super heterogeneous protocol for WSNs. In: Proceedings of *2018 32nd International Conference on Advanced Information Networking and Applications Workshops (WAINA)*. IEEE, 104-111. Available: https://ieeexplore.ieee.org/abstract/document/8418056 (Accessed 4 June 2020).

Nehra, V., Sharma, A. K. and Tripathi, R. K. 2020. I-deec: improved deec for blanket coverage in heterogeneous wireless sensor networks. *Journal of Ambient Intelligence and Humanized Computing,* 11(9): 3687-3698. Available: https://doi.org/10.1007/s12652-019-01552-3 (Accessed 14 July 2021).

Nemer, I., Sheltami, T., Shakshuki, E., Elkhail, A. A. and Adam, M. 2021. Performance evaluation of range-free localization algorithms for wireless sensor networks. *Personal and Ubiquitous Computing,* 25: 177-203. Available:

https://link.springer.com/content/pdf/10.1007/s00779-020-01370-x.pdf (Accessed 18 February 2021).

Ng, C. K. 2018. Design and optimization of RFID-enabled wireless sensor network (WSN) monitoring system for biological and pharmaceutical products storage. *Department of Industrial and Systems Engineering*. Available: https://theses.lib.polyu.edu.hk/handle/200/9748 (Accessed 1 March 2021).

Nguyen, T. T. and Pan, J. S. and Dao, T.K. 2019. An improved flower pollination algorithm for optimizing layouts of nodes in wireless sensor network. *IEEE Access* 7: 75985-75998. Available: https://10.1109/ACCESS.2019.2921721 (Accessed 15 July 2021).

Nord, J. H., Koohang, A. and Paliszkiewicz, J. 2019. The Internet of Things: Review and theoretical framework. *Expert Systems with Applications*, 133: 97-108. Available: https://www.sciencedirect.com/science/article/pii/S0957417419303331 (Accessed 13 March 2021).

Norouzi, A., Babamir, F. S. and Orman, Z. 2018. A tree based data aggregation scheme for wireless sensor networks using GA. *Wireless Sensor Network*, 4(8): 191. Available: https://10.4236/wsn.2012.48028 (Accessed 16 July 2021).

Nunoo-Mensah, H., Boateng, K. O. and Gadze, J. D. 2018. The adoption of socio-and bio-inspired algorithms for trust models in wireless sensor networks: A survey. *International Journal of Communication Systems*, 31(7): 3444. Available: https://doi.org/10.1002/dac.3444 (Accessed 17 July 2021).

O'Mahony, G. D., Harris, P. J. and Murphy, C. C. 2020. Detecting interference in wireless sensor network received samples: a machine learning approach. *In 2020 IEEE 6th World Forum on Internet of Things (WF-IoT)*: 1-6. Available: https://10.1109/WF-IoT48130.2020.9221332 (Accessed 19 July 2021).

Oktaviani, F. 2021. Managing piety, respectability and professionalism within women's bodies. In: *Reimagining Faith and Management: The Impact of Faith in the Workplace* 1: 47-52. Available: https://www.taylorfrancis.com/chapters/edit/10.4324/9781003041733-5/managing-piety-respectability-professionalism-within-women-bodies-fitri-oktaviani (Accessed 20 July 2021).

Oliveira, D., Miranda, L. and Miranda, L. B. B. 2020. Lohans' magic squares and the Gaussian elimination method. *Journal of Nepal Mathematical Society*, 3(1): 31-36. Available: https://www.nepjol.info/index.php/jnms/article/download/33001/25970 (Accessed 21 July 2021).

Osamy, W., Salim, A. and Khedr, A. M. 2020. An information entropy based-clustering algorithm for heterogeneous wireless sensor networks. . *Wireless Networks*, 26(3): 1869–1886. Available: https://doi.org/10.1007/s11276-018-1877-y (Accessed 21 July 2021).

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T., Mulrow, C. D., Shamseer, L. and Moher, D. 2020. Mapping of reporting guidelines for systematic reviews and meta-analyses generated a comprehensive item bank for future reporting guidelines. *Journal of Clinical Epidemiology,* 118: 60-68. Available: https://doi.org/10.1016/j.jclinepi.2019.11.010 (Accessed 12 June 2021).

Pakdel, H. and Fotohi, R. 2021. A firefly algorithm for power management in wireless sensor networks (WSNs). *Journal of Supercomputing*: 1-22. Available: https://doi.org/10.1007/s11227-021-03639-1 (Accessed 12 January 2021).

Pal, R., Yadav, S. and Karnwal, R. 2020. EEWC: energy-efficient weighted clustering method based on genetic algorithm for HWSNs. *Complex & Intelligent Systems*: 1-10. Available: https://link.springer.com/content/pdf/10.1007/s40747-020-00137-4.pdf (Accessed 20 June 2020).

Pallapothu, S. K. and Mehta, N. B. 2018. Energy-efficient detection using ordered transmissions in energy harvesting WSNs. In: Proceedings of *2018 IEEE International Conference on Communications (ICC).* IEEE, 1-6. Available: https://ieeexplore.ieee.org/abstract/document/8422271?casa_token=NpSO6WOaO8YAAAA A:TJSQTo5x9bhyYdcfjeQCfjjp6rg9IwzSXKoYFCKG3OJf8rrNPbpdvG4t3x54gznzrNTOAJ UNAzk (Accessed 9 July 2020).

Pan, J. S., Dao, T. K., Pan, T. S., Nguyen, T. T., Chu, S. C. and Roddick, J. F. 2017. An improvement of the flower pollination algorithm for node localization optimization in WSN. *Journal of Information Hiding and Multimedia Signal Processing,* 8(2): 486-499. Available: http://bit.kuas.edu.tw/~jihmsp/2017/vol8/JIH-MSP-2017-02-022.pdf (Accessed 13 June 2021).

Panag, T. S. and Dhillon, J. S. 2018. A novel random transition based PSO algorithm to maximize the lifetime of wireless sensor networks. *Wireless Personal Communications,* 98: 2261–2290. Available: https://doi.org/10.1007/s11277-017-4973-x (Accessed 8 May 2021).

Pang, S., Wang, F., Zhen, Z., Li, K., Ren, H., Shafie-Khah, M. and Catalão, J. P. 2018. Pattern classification and PSO optimal weights based sky images cloud motion speed calculation method for solar PV power forecasting. *In 2018 IEEE Industry Applications Society Annual Meeting (IAS)* 1-9. Available: https://10.1109/IAS.2018.8544468 (Accessed 9 May 2021).

Panneerselvam, J., Ali, H., Tariq, U. U., Hussain, M., Lu, L. and Zhai, X. 2020. ARSH-FATI a novel metaheuristic for cluster head selection in wireless sensor networks. *IEEE Systems Journal,* 15(2): 2386-2397. Available: https://10.1109/JSYST.2020.2986811 (Accessed 10 May 2021).

Patil, B. and Kadam, R. 2018. A novel approach to secure routing protocols in WSN. *2018 2nd International Conference on Inventive Systems and Control (ICISC)*: 1094-1097. Available: https://ieeexplore.ieee.org/abstract/document/8398973 (Accessed 4 May 2020).

Paul, A. K. and Sato, T. 2017. Localization in wireless sensor networks: A survey on algorithms, measurement techniques, applications and challenges. *Journal of Sensor and Actuator Networks,* 6(4): 24. Available: https://doi.org/10.3390/jsan6040024 (Accessed 11 May 2021).

Pawar, M. S. and Khandelwal, A. 2021. Performance of LEACH, MOD-LEACH, PEGASIS FOR WSN. *International Research Journal of Modernization in Engineering Technology and Science,* 2: 1-8. Available: https://10.1109/ICPCSI.2017.8392168 (Accessed 13 May 2021).

Pfeffers, K., Tuunanen, T., Gengler, C. E., Rossi, M., Hui, W., Virtanen, V. and Bragge, J. 2006. The design science research process: A model for producing and presenting information systems research. Proceedings of the First International Conference on Design Science Research in Information Systems and Technology (DESRIST 2006), Claremont, CA, USA: 83-106. Available: https://www.tandfonline.com/doi/abs/10.2753/MIS0742-1222240302 (Accessed 9 December 2021).

Plomp, T. and Nienke, N. 2013. Educational design research: An introduction. In: *Educational design research*: 11-50. Available: https://d1wqtxts1xzle7.cloudfront.net/48472657/educational-design-research-part-a-with-cover-page-v2.pdf 12 (Accessed 14 May 2021).

Poluru, R. K., Reddy, M., Basha, S. M., Patan, R. and Kallam, S. 2020. Enhanced Adaptive Distributed Energy-Efficient Clustering (EADEEC) for wireless sensor networks. *Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science,)* 13(2): 168-172. Available: https://doi.org/10.2174/2213275912666190404162447 (Accessed 14 May 2021).

Poonguzhali, P. K. and Ananthamoorthy, N. P. 2020. Design of mutated harmony search algorithm for data dissemination in wireless sensor network. *Wireless Personal Communications,* 111(2): 729-751. Available: https://doi.org/10.1007/s11277-019-06882-1 (Accessed 14 May 2021).

Prabowo, S., Abdurohman, M. and Erfianto, B. 2015. (EDsHEED) Enhanced Simplified Hybrid, Energy-efficient, Distributed clustering for wireless sensor network. In*: 2015 3rd International Conference on Information and Communication Technology (ICoICT) IEEE* 1: 97-101. Available: https://ieeexplore.ieee.org/abstract/document/7231404 (Accessed 11 September 2021).

Pradeep, S., Muthurajkumar, S., Ganapathy, S. and Kannan, A. 2021. A matrix translation and elliptic curve based cryptosystem for secured data communications in WSNs. *Wireless*

Personal Communications: 1-20. Available: https://link.springer.com/article/10.1007/s11277-021-08221-9 (Accessed 11 May 2021).

Prakash, A., Mishra, R. and Kushwaha, A. S. 2020. Exterior Bound Allotted Advanced Node Distribution for Energy Efficient Clustering (EBAN DEEC) Protocol in WSN. *International Journal of Research and Development in Applied Science and Engineering (IJRDASE),* 20(2). Available: http://ijrdase.com/ijrdase/wp-content/uploads/2020/06/Exterior-Bound-Allotted-Advanced-Node-Distribution-for-Energy-Efficient-Clustering-EBAN-DEEC-Protocol-in-WSN-Ashish-Ramesh-Astha.pdf (Accessed 2 August 2021).

Prashar, D. and Jha, N. 2021. Review of secure distributed range-free hop-based localization algorithms in the wireless sensor networks. In: *Multimedia Security,* 66(2): 283-302. Available: https://doi.org/10.1007/978-981-15-8711-5_15 (Accessed 16 May 2021).

Prashar, D., Joshi, G. P., Jha, S., Yang, E. and Son, K. C. 2021. Three-dimensional distance-error-correction-based hop localization algorithm for IoT devices. *CMC-Computers Materials & Contiua*, 66(2): 1529-1549. Available: https://doi.org/10.1007/978-981-15-8711-5_15 (Accessed 16 May 2021).

Prithi, S. and Sumathi, S. 2020. LD2FA-PSO: A novel learning dynamic deterministic finite automata with PSO algorithm for secured energy efficient routing in wireless sensor network. *Ad Hoc Networks,* 97: 102024. Available: https://www.sciencedirect.com/science/article/pii/S1570870519304585 (Accessed 5 March 2020).

Priyadarshini, R. R. and Sivakumar, N. 2019. Enhancing coverage and connectivity using energy prediction method in underwater acoustic WSN. *Journal Ambient Intelligence Human Computer* 11(7): 2751-2760. Available: https://doi.org/10.1007/s12652-019-01334-x (Accessed 17 May 2021).

Pule, M., Yahya, A. and Chuma, J. 2017. Wireless sensor networks: A survey on monitoring water quality. *Journal of Applied Research and Technology,* 15(6): 562-570. Available: https://doi.org/10.1016/j.jart.2017.07.004 (Accessed 17 May 2021).

Puri, D. and Bhushan, B. 2019. Enhancement of security and energy efficiency in WSNs: Machine Learning to the rescue. In: Proceedings of *2019 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS).* IEEE, 120-125. Available: https://ieeexplore.ieee.org/abstract/document/8974465 (Accessed 24 May 2021).

Qiao, D. and Pang, G. K. 2011. Localization in wireless sensor networks with gradient descent. *Proceedings of 2011 IEEE Pacific Rim Conference on Communications, Computers and Signal Processing*: 91-96. Available: https://10.1109/PACRIM.2011.6032873 (Accessed 19 May 2021).

Qu, R. and Burke, E. K. 2019. Hybridisations within a graph-based hyper-heuristic framework for university timetabling problems. *Journal of the Operational Research Society,* 60: 1273–1285. Available: https://doi.org/10.1057/jors.2008.102 (Accessed 20 May 2021).

Qureshi, T., Javaid, N., Malik, M., Qasim, U. and Khan, Z. A. 2012. On performance evaluation of variants of DEEC in WSNs. *2012 Seventh International Conference on Broadband, Wireless Computing, Communication and Applications*: 162-169. Available: https://10.1109/BWCCA.2012.35 (Accessed 19 May 2021).

Rahiminasab, A., Tirandazi, P., Ebadi, M. J., Ahmadian, A. and Salimi, M. 2020. An energy-aware method for selecting cluster heads in wireless sensor networks. *Applied Sciences,* 10(21): 7886. Available: https://doi.org/10.3390/app10217886 (Accessed 20 May 2021).

Rai, A., Deswal, S. and Singh, P. 2016. An energy-efficient E-LEACH protocol for wireless sensor networks. *International Journal of Engineering Science and Computing,* 6(7): 1654-1660. Available: https://doi.org/10.1016/j.eij.2021.01.003 (Accessed 21 May 2021).

Rajakumar, R., Amudhavel, J., Dhavachelvan, P. and Vengattaraman, T. 2017. GWO-LPWSN: Grey wolf optimization algorithm for node localization problem in wireless sensor networks. Journal of *Computer Networks and Communications*. 2017, 7348141, 1-10 Available: https://doi.org/10.1155/2017/7348141 (Accessed 04 June 2021).

Rajput, M., Sharma, S. K. and Khatri, P. 2017. Performance analysis of leach based approaches for large area coverage in wireless sensor network. *In Proceedings of the 2017 International Conference on Information, Communication, Instrumentation and Control (ICICIC), Indore, India,* 1-5. Available: https://10.1109/ICOMICON.2017.8279162 (Accessed 22 May 2021).

Rao, P. C. S., Jana, P. K. and Banka, H. 2016. A particle swarm optimization-based energy-efficient cluster head selection algorithm for wireless sensor networks. *Wireless Networks,* 23(7): 2005–2020. Available: https://doi.org/10.1007/s11276-016-1270-7 (Accessed 22 May 2021).

Rathore, R. S., Sangwan, S., Prakash, S., Adhikari, K., Kharel, R. and Cao, Y. 2020. Hybrid WGWO: whale grey wolf optimization-based novel energy-efficient clustering for EH-WSNs. *EURASIP. Journal on Wireless Communications and Networking,* 2020: 1-28. Available: https://link.springer.com/content/pdf/10.1186/s13638-020-01721-5.pdf (Accessed 6 June 2020).

Rault, T., Bouabdallah, A. and Challal, Y. 2019. Energy efficiency in wireless sensor networks: A top-down survey. *Computer Networks,* 67: 104-122. Available: https://doi.org/10.1016/j.comnet.2014.03.027 (Accessed 22 May 2021).

Ravitch, S. M. and Riggan, M. 2017. *Reason & rigor: how theoretical frameworks guide research*. 1-264. Available: https://us.sagepub.com/en-us/nam/reason-rigor/book241777 (Accessed 22 May 2021).

Rawat, P., Chauhan, S. and Priyadarshi, R. 2020. Energy-efficient cluster head selection scheme in heterogeneous wireless sensor network. *Journal of Circuits, Systems, and Computers.* 29 (13). 2050204. Available: https://doi.org/10.1142/s0218126620502047 (Accessed 22 May 2021).

Ray, A. and De, D. 2016. Energy efficient clustering protocol based on K-means (EECPK-means)-midpoint algorithm for enhanced network lifetime in wireless sensor network. *IET Wireless Sensor Systems,* 6(6): 181–191. Available: https://digital-library.theiet.org/content/journals/10.1049/iet-wss.2015.0087 (Accessed 14 June 2020).

Raychaudhuri, A. and De, D. 2020. Bio-inspired Algorithm for Multi-objective Optimization in Wireless Sensor Network. In: *Nature Inspired Computing for Wireless Sensor Networks*. Springer, 279-301. Available: https://link.springer.com/chapter/10.1007/978-981-15-2125-6_12 (Accessed 14 July 2020).

Reddy, D. L., Puttamadappa, C. and Suresh, H. 2021. Merged glowworm swarm with ant colony optimization for energy efficient clustering and routing in Wireless Sensor Network. *Pervasive and Mobile Computing,* 71: 101338. Available: https://doi.org/10.1016/j.pmcj.2021.101338 (Accessed 24 May 2021).

Reddy, M. P. and Rajan, S. V. 2017. DEEC protocol for WSNs. *India Advances in Wireless and Mobile Communications,* 10(1): 0973-6972. Available: http://www.ripublication.com/awmc17/awmcv10n1_05.pdf (Accessed 23 May 2021).

Renu, S., Yen, L., Belay, A., Lin, H. P. and Jeng, S. S. 2017. Hybrid Beam Forming with Data Logging Scheduling (DLS) for wireless sensor network (WSN). *In 2017 International Conference on Applied System Innovation (ICASI)*: 1603-1606. Available: https://10.1109/ICASI.2017.7988238 (Accessed 25 May 2021).

Risteska Stojkoska, B. 2017. Nodes localization in 3D wireless sensor networks based on multidimensional scaling algorithm. *International scholarly research notices* 2014. Available: https://doi.org/10.1155/2014/845027 (Accessed 27 May 2021).

Robinson, S., 2008. Conceptual modelling for simulation Part II: a framework for conceptual modelling. *Journal of the Operational Research Society,* 59(3): 291-304.

Rodriguez-Zurrunero, R., Utrilla, R., Romero, E. and Araujo, A. 2018. An adaptive scheduler for real-time Operating Systems to extend WSN nodes lifetime. *Wireless Communications and Mobile Computing,* 2018, 1-10. Available: ttps://doi.org/10.1155/2018/4185650 (Accessed 27 May 2021).

Roselin, J., Latha, P. and Benitta, S. 2017. Maximizing the wireless sensor networks lifetime through energy-efficient connected coverage. *Ad Hoc Networks,* 62: 1–10. Available: https://doi.org/10.1016/j.adhoc.2017.04.001 (Accessed 28 May 2021).

Roslin, S. E. and Daniel, A. 2021. Data validation and integrity verification for trust based data aggregation protocol in WSN. *Microprocessors and Microsystems,* 80: 103354. Available: https://doi.org/10.1016/j.micpro.2020.103354 (Accessed 29 June 2021).

Sahoo, B. M., Amar, D. G., Suman, A. Y. and Shubhi, G. 2019. ESRA: Enhanced Stable Routing Algorithm for Heterogeneous Wireless Sensor Networks. *In 2019 International Conference on Automation, Computational and Technology Management (ICACTM),:* 148-152. Available: https://10.1109/ICACTM.2019.8776740 (Accessed 29 May 2021).

Saini, A., Kansal, A. and Randhawa, N. S. 2019. Minimization of energy consumption in WSN using hybrid WECRA approach. *Procedia Computer Science,* 155: 803-808. Available: https://www.sciencedirect.com/science/article/pii/S1877050919310361 (Accessed 1 September 2020).

Saini, P. and Sharma, A. K. 2010. E-DEEC-enhanced distributed energy efficient clustering scheme for heterogeneous WSN. *First International Conference on Parallel, Distributed And Grid Computing (PDGC 2010) IEEE*: 205-210. Available: https://10.1109/PDGC.2010.5679898 (Accessed 30 May 2021).

Samorani, M., Wang, Y., Lv, Z. and Glover, F. 2019. Clustering-driven evolutionary algorithms: an application of path relinking to the quadratic unconstrained binary optimization problem. *Journal of Heuristics,* 25(4): 629-642. Available: https://link.springer.com/article/10.1007/s10732-018-9403-z (Accessed 3 February 2021).

Sangaiah, A. K., Sadeghilalimi, M., Hosseinabadi, A. A. R. and Zhang, W. 2019. Energy consumption in point-coverage wireless sensor networks via bat algorithm. *IEEE Access,* 7: 180258-180269. Available: https://ieeexplore.ieee.org/abstract/document/8895809 (Accessed 20 April 2021).

Sasaki, T. and Murao, H. 1982. Efficient Gaussian elimination method for symbolic determinants and linear systems. *ACM Transactions on Mathematical Software (TOMS),* 8(3): 277-289. Available: https://dl.acm.org/doi/pdf/10.1145/356004.356007 (Accessed 17 May 2021).

Schotsch, B., Schepker, H. and Vary, P. 2011. The performance of short random linear fountain codes under maximum likelihood decoding. *2011 IEEE International Conference on Communications (ICC)*: 1-5. Available: https://10.1109/icc.2011.5962476 (Accessed 2 June 2021).

Sefati, S., Abdi, M. and Ghaffari, A. 2021. Cluster-based data transmission scheme in wireless sensor networks using black hole and ant colony algorithms. *International Journal* *of Communication Systems*, 34(9): e4768. Available: https://onlinelibrary.wiley.com/doi/full/10.1002/dac.4768 (Accessed 29 April 2021).

Sein, M. K., Henfridsson, O., Purao, S., Rossi, M. and Lindgren, R. 2011. Action design research. *MIS Quarterly,* 35(1): 37-56. Available: https://www.jstor.org/stable/23043488?seq=1#metadata_info_tab_contents (Accessed 3 June 2021).

Shah-Hosseini, H. 2011. Principal components analysis by the galaxy-based search algorithm: a novel metaheuristic for continuous optimisation. *International Journal of Computational Science and Engineering,* 6(1-2): 132-140. Available: https://doi.org/10.1504/IJCSE.2011.041221 (Accessed 4 June 2021).

Shahbaz, A. N., Barati, H. and Barati, A. 2021. Multipath routing through the firefly algorithm and fuzzy logic in wireless sensor networks. *Peer-to-Peer Networking and Applications,* 14(2): 541-558. Available: https://link.springer.com/article/10.1007/s11227-021-03639-1 (Accessed 13 January 2021).

Shahbazian, R. and Ghorashi, S. A. 2017. Distributed cooperative target detection and localization in decentralized wireless sensor networks. *Journal of Supercomputing,* 73(4): 1715-1732. Available: https://10.1007/s11227-016-1877-6 (Accessed 4 June 2021).

Shahina, K. and Vaidehi, V. 2018. Clustering and data aggregation in wireless sensor networks using machine learning algorithms. In: Proceedings of *2018 International Conference on Recent Trends in Advanced Computing (ICRTAC).* IEEE, 109-115. Available: https://ieeexplore.ieee.org/abstract/document/8679318?casa_token=Er5XNQjaQDcAAAAA:6HSNv3dXQEFTJjoD7pwDZX6SSvSm2Ov-QumwSelJU2Hv6ifO7nNsVpUNBJ8Vh19WHcUkEYFaP3s (Accessed 23 June 2020).

Shakshuki, E., Elkhail, A. A., Nemer, I., Adam, M. and Sheltami, T. 2019 Comparative Study on Range-Free Localization Algorithms. *Procedia Computer Science,* 151: 501-510. Available: https://doi.org/10.1016/j.procs.2019.04.068 (Accessed 5 June 2021).

Shankar, A., Sivakumar, N. R., Sivaram, M., Ambikapathy, A., Nguyen, T. K. and Dhasarathan, V. 2021. Increasing fault tolerance ability and network lifetime with clustered pollination in wireless sensor networks. *Journal of Ambient Intelligence and Humanized Computing*, 12(2): 2285-2298. Available: https://doi.org/10.1007/s12652-020-02325-z (Accessed 5 June 2021).

Sharma, N. and Gupta, V. 2020. Meta-heuristic based optimization of WSNs energy and lifetime-A Survey. *In 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence) IEEE*: 369-374. Available: https://ieeexplore.ieee.org/abstract/document/9058294 (Accessed 02 September 2020).

Shen, S., Sun, L., Dang, Y., Zou, Z. and Wang, R. 2018. Node localization based on improved PSO and mobile nodes for environmental monitoring WSNs. *International Journal of Wireless Information Networks,* 25(4): 470-479. Available: https://link.springer.com/article/10.1007/s10776-018-0414-3 (Accessed 14 June 2020).

Shivapur, S., Kanakaraddi, S. G. and Chikaraddi, A. K. 2015. Load balancing techniques in wireless sensor networks: a comparative study. *International Journal Emerging Technology Computer Science Electronics* 14(2): 1–6. Available: https://www.ijetcse.com/admin/uploads/Load%20Balancing%20Techniques%20in%20Wireless%20Sensor%20Networks:%20A%20Comparative%20Study_1605526207.pdf (Accessed 8 June 2021).

Singh, A., Sharma, S. and Singh, J. 2021. Nature-inspired algorithms for wireless sensor networks: A comprehensive survey. *Computer Science Review,* 39: 100342. Available: https://doi.org/10.1016/j.cosrev.2020.100342 (Accessed 8 June 2021).

Singh, M. and Soni, S. K. 2017. A comprehensive review of fuzzy-based clustering techniques in wireless sensor networks. . *Sensor Review,* 37(3): 289-304. Available: https://doi.org/10.1108/SR-11-2016-0254 (Accessed 9 June 2021).

Singh, P. and Mittal, N. 2021. An efficient localization approach to locate sensor nodes in 3D wireless sensor networks using adaptive flower pollination algorithm. *Wireless Networks,* 27: 1-16. Available: https://doi.org/10.1007/s11276-021-02557-7 (Accessed 9 June 2021).

Singh, S., Chand, S., Kumar, R., Malik., A. and Kumar, B. 2016. NEECP: Novel energy-efficient clustering protocol for prolonging lifetime of WSNs. *IET Wireless Sensor Systems,* 5(6): 151-157. Available: https://ieeexplore.ieee.org/document/7574974/ (Accessed 11 June 2021).

Singh, S., Malik, A. and Kumar, R. 2017. Energy efficient heterogeneous DEEC protocol for enhancing lifetime in WSNs. *Engineering Science and Technology, an International Journal,* 20(1): 345-353. Available: https://doi.org/10.1016/j.jestch.2016.08.009 (Accessed 12 June 2021).

Singh, S. K., Kumar, P. and Singh, J. P. 2017. A survey on successors of LEACH protocol. *IEEE Access,* 5: 4298–4328. Available: https://10.1109/ACCESS.2017.2666082 (Accessed 12 June 2021).

Singh, S. P. and Sharma, S. C. 2019. Implementation of a PSO based improved localization algorithm for wireless sensor networks. *IETE Journal of Research,* 65: 502–514. Available: https://doi.org/10.1080/03772063.2018.1436472 (Accessed 13 June 2021).

Solangi, S. A., Hakro, D. N., Memon, M., Khoumbati, K. U. R. and Jalbani, A. H. 2019. Optimization by genetic algorithm in wireless sensor networks utilizing multiple sinks.

Mehran University Research Journal of Engineering & Technology, 38(4): 923-934. Available: https://search.informit.org/doi/abs/10.3316/INFORMIT.729803289620844 (Accessed 22 June 2020).

Sorensen, K., Sevaux, M. and Glover, F. 2017. A history of metaheuristics. In: *Handbook of Heuristics.* Springer 23: 1-8. Available: https://arxiv.org/pdf/1704.00853.pdf (Accessed 02 February 2021).

Srikanth, N. and Prasad, M. G. 2018. Efficient clustering protocol using fuzzy K-means and midpoint algorithm for lifetime improvement in WSNs. *International Journal of Intelligent Engineering and Systems,* 11(4): 61-71. Available: http://www.inass.org/2018/2018083107.pdf (Accessed 16 June 2021).

Srivastava, V., Tripathi, S. and Singh, K. 2019. Energy efficient optimized rate-based congestion control routing in wireless sensor network. *Journal of Ambient Intelligence Human Computer* . 11(3),1325-1338. Available: https://doi.org/10.1007/ (Accessed 17 June 2021).

Sruthi, P. and Sahadevaiah, K. 2021. A novel efficient heuristic based localization paradigm in wireless sensor network. *Wireless Personal Communications*: 2021. 1-21. Available: https://doi.org/10.1007/s11277-021-08091-1 (Accessed 14 June 2021).

Strumberger, I., Beko, M., Minovic, M. and Bacanin, N. 2018a. Elephant herding optimization algorithm for wireless sensor network localization problem In Doctoral Conference on Computing, Electrical and Industrial Systems *Springer,* vol 2, 175-184. Available: https://doi.org/10.1007/978-3-319-78574-5_17 (Accessed 15 June 2021).

Strumberger I., Beko M., Tuba M., Minovic M., Bacanin N. 2018b. Elephant herding optimization algorithm for wireless sensor network localization problem. In: Camarinha-Matos L., Adu-Kankam K., Julashokri M. eds. *Technological Innovation for Resilient Systems. DoCEIS 2018. IFIP Advances in Information and Communication Technology*, vol 521. Springer, Cham. https://doi.org/10.1007/978-3-319-78574-5_17 (Accessed 7 December 2021).

Strumberger, I., Minovic, M., Tuba, M. and Bacanin, N. 2019. Performance of elephant herding optimization and tree growth algorithm adapted for node localization in wireless sensor networks. *Sensors,* 19 (11): 2515.

Stueben, M. 2018. Beware of OOP. *Good Habits for Great Coding*: 197-201. Available: https://link.springer.com/chapter/10.1007/978-1-4842-3459-4_16 (Accessed 9 May 2021).

Sujatha, S. R. and Siddappa, M. 2017. Node localization method for wireless sensor networks based on hybrid optimization of particle swarm optimization and differential evolution. .

IOSR J Computer Engineering, 19(2): 07-12. Available: https://10.2174/1874444301406010621 (Accessed 17 June 2021).

Sujatha, S. R. and Siddappa, M. 2018. Self-adaptive differential evolution-based localization of sensors in the wireless sensor network. *International Journal of Applied Engineering Research*, 13: 86–90. Available: https://www.ripublication.com/ijaer18/ijaerv13n1_13.pdf (Accessed 14 June 2021).

Sun, Y., Dong, W. and Chen. 2017. An Improved routing algorithm based on Ant Colony Optimization in wireless sensor networks. *IEEE communications Letters*, 21(6): 1317-1320. Available: https://10.1109/LCOMM.2017.2672959 (Accessed 15 June 2021).

Sun, Y., Yu, J. and Wang, Y. 2019. Heuristic localization algorithm with a novel error control mechanism for wireless sensor networks with few anchor nodes. *Journal of Sensors*, 2018. 1-14. Available: https://doi.org/10.1155/2018/5190543 (Accessed 16 June 2021).

Sun, Z., Zhang, Z., Xiao, C. and Qu, G. 2018. DS evidence theory based trust ant colony routing in WSN. *China Communications*, 15(3): 27-41. Available: https://ieeexplore.ieee.org/abstract/document/8331989 (Accessed 20 February 2021).

Tamandani, Y. K., Bokhari, M. U. and Kord, M. Z. 2017. Computing geometric median to locate the sink node with the aim of extending the lifetime of wireless sensor networks. *Egyptian Informatics Journal*, 18(1): 21-27. Available: https://doi.org/10.1016/j.eij.2016.06.003 (Accessed 16 June 2021).

Tan, F. 2020. The algorithms of distributed learning and distributed estimation about Intelligent wireless sensor network. *Sensors*, 20(5): 1302. Available: https://doi.org/10.3390/s20051302 (Accessed 01 August 2021).

Tao, F., Laili, Y. and Zhang, L. 2015. Brief history and overview of intelligent optimization algorithms. In: *Configurable intelligent optimization algorithm.* New York: Springer, 3–33. Available: https://doi.org/10.1007/978-3-319-08840-2_1 (Accessed 15 June 2021).

Tay, M. and Senturk, A. 2021. A new energy-aware cluster head selection algorithm for wireless sensor networks. *Wireless Personal Communications*: 1-17. Available: https://doi.org/10.1007/s11277-021-08990-3 (Accessed 29 October 2021).

Teegavarapu, S., Summers, J. D. and Mocko, G. M. 2008. Case study method for design research: A justification. In: Proceedings of *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. 495-503. Available: https://asmedigitalcollection.asme.org/IDETC-CIE/proceedings-abstract/IDETC-CIE2008/495/329310 (Accessed 20 May 2021).

Tian, J., Gao, M. and Ge, G. 2016. Wireless sensor network node optimal coverage based on improved genetic algorithm and binary ant colony algorithm. *EURASIP Journal on Wireless Communications and Networking,* 104. Available: https://doi.org/10.1186/s13638-016-0605-5 (Accessed 18 June 2021).

Tiwari, P., Saxena, V. P., Mishra, R. G. and Bhavsar, D. 2015. Wireless sensor networks: Introduction, advantages, applications and research challenges. *HCTL Open International Journal of Technology Innovations and Research (IJTIR),* 14: 1-11. Available: *https://www.researchgate.net/publication/296802403* (Accessed 19 June 2021).

Tiwari, S. 2019. Survey paper of wireless sensor network. *International Journal of Scientific Research and Engineering Trends,* 5(6): 1-5. Available: https://ijsret.com/wp-content/uploads/2019/11/IJSRET_V5_issue6_521.pdf (Accessed 2 March 2021).

Tobi, H. and Kampen, J. K. 2018. Research design: the methodology for interdisciplinary research framework. *Quality & Quantity,* 52(3): 1209-1225. Available: https://doi.org/10.1007/s11135-017-0513-8 (Accessed 19 June 2021).

Tomic, S. and Mezei, I. 2016. Improvements of DV-Hop localization algorithm for wireless sensor networks. Telecommunication Systems 61(1): 93-106. Available: https://10.1007/s11235-015-0014-9 (Accessed 3 December 2021).

Tsai, C. W., Liu, S. J. and Wang, Y. C. 2018. A parallel metaheuristic data clustering framework for cloud. *Journal of Parallel and Distributed Computing,* 116: 39-49. Available: https://doi.org/10.1016/j.jpdc.2017.10.020 (Accessed 21 June 2021).

Tuba, E., Tuba, M. and Beko, M. 2018. Two stage wireless sensor node localization using firefly algorithm. In: *Smart trends in systems, security and sustainability*. Springer, 113-120. Available: https://link.springer.com/chapter/10.1007/978-981-10-6916-1_10 (Accessed 26 April 2021).

Uhl-Bien, M. and Arena, M. 2018. Leadership for organizational adaptability: A theoretical synthesis and integrative framework. *The Leadership Quarterly,* 29(1): 89-104. Available: https://www.sciencedirect.com/science/article/pii/S104898431730111X (Accessed 16 March 2021).

Ullah, I. and Youn, H. Y. 2020. Efficient data aggregation with node clustering and extreme learning machine for WSN. *Journal of Supercomputing*: 1-27. Available: https://link.springer.com/content/pdf/10.1007/s11227-020-03236-8.pdf (Accessed 5 July 2020).

Umamaheswari, S. 2021. Hybrid Optimization Model for Energy Efficient Cloud Assisted Wireless Sensor Network. *Wireless Personal Communications,* 118: 873–885. Available: https://doi.org/10.1007/s11277-020-08048-w (Accessed 7 August 2021).

Upadhyay, V. 2021. *Distributed energy-efficient clustering algorithm - DEEC, MATLAB Central File Exchange*. Available : https://www.mathworks.com/matlabcentral/fileexchange/49025-distributed-energy-efficient-clustering-algorithm-deec) (Accessed 6 December 2021).

Vangheluwe, H., De Lara, J. and Mosterman, P. J. 2002. An introduction to multi-paradigm modelling and simulation. Proceedings of the AIS'2002 Conference (AI, Simulation and Planning in High Autonomy Systems), Lisboa, Portugal: 9-20. Available: *https://biblio.ugent.be/publication/158059* (Accessed 2nd December 2021).

Vançin, S. and Erdem, E. 2018. Threshold balanced sampled DEEC model for heterogeneous wireless sensor networks. *Wireless Communications and Mobile Computing,* 2018. 1-15. Available: https://doi.org/10.1155/2018/4618056 (Accessed 21 June 2021).

Vera-Amaro, R., Rivero-Ángeles, M. E. and Luviano-Juárez, A. 2020. Data collection schemes for animal monitoring using WSNS-assisted by UAVS: WSNs-oriented or UAV-oriented. *Sensors,* 20(1): 262. Available: https://www.mdpi.com/1424-8220/20/1/262 (Accessed 02 January 2021).

Verma, N. and Singh, D. 2018. Data redundancy implications in wireless sensor networks. *Procedia Computer Science*, 132: 1210-1217. Available: https://doi.org/10.1016/j.procs.2018.05.036 (Accessed 22 June 2021).

Vidyasagar, P., Atif, S. and Elizabeth, C. 2009. Wireless sensor networks: A survey. *2009 International Conference on Advanced Information Networking and Applications Workshops* 641. Available: https://www.computer.org/csdl/proceedings/waina/2009/12OmNA0dMMG (Accessed 24 June 2021).

Vishal, P. and Ramesh Babu, A. 2019. Firefly algorithm for intelligent context-aware sensor deployment problem in wireless sensor network. *Journal of Circuits, Systems and Computers,* 28(06): 1950094. Available: https://www.worldscientific.com/doi/abs/10.1142/S0218126619500944 (Accessed 13 June 2020).

Vojdani, M. and Dehghan, M. 2011. Localization in anchor less wireless sensor network. *In Proceedings of the International Conference on Computer Engineering and Applications* 2: 671. Available: https://www.researchgate.net/publication/259307418_Localization_in_Anchor_Less_Wireless_Sensor_Network (Accessed 25 June 2021).

Wan, Q., Weng, M. J. and Liu, S. 2019. Optimization of wireless sensor networks based on differential evolution algorithm. *International Journal of Online & Biomedical Engineering,* 15(1): 183–195. Available: *https://biblio.ugent.be/publication/158059* (Accessed 25 June 2021).

Wang, C., Suo, L., Bian, D., Lv, J. and Tian, S. 2019a. Performance analysis and design of LT codes under the Gaussian elimination algorithm in wireless sensor networks. *IEEE Access*, 7: 55797-55806. Available: https://10.1109/ACCESS.2019.2913171 (Accessed 25 June 2021).

Wang, J., Cao, J., Li, B., Lee, S. and Sherratt, R. S. 2015. Bio-inspired ant colony optimization based clustering algorithm with mobile sinks for applications in consumer home automation networks. *IEEE Transactions on Consumer Electronics*, 61(4): 438–444. Available: https://10.1109/TCE.2015.7389797 (Accessed 06 September 2021).

Wang, J., Gao, Y., Liu, W., Sangaiah, A. K. and Kim, H. J. 2019b. An improved routing schema with special clustering using PSO algorithm for heterogeneous wireless sensor network. *Sensors,* 19(3): 671. Available: https://doi.org/10.3390/s19030671 (Accessed 1 May 2021).

Wang, J., Gao, Y., Yin, X., Li, F. and Kim, H. J. 2018. An enhanced PEGASIS algorithm with mobile sink support for wireless sensor networks. *Wireless Communications and Mobile Computing.* 2018.1-13. Available: https://doi.org/10.1155/2018/9472075 (Accessed 23 June 2021).

Wang, J., Gao, Y., Zhou, C., Sherratt, S. and Wang, L. 2020. Optimal coverage multi-path scheduling scheme with multiple mobile sinks for WSNs. *Computers, Materials & Continua*, 62(2): 695-711. Available: http://centaur.reading.ac.uk/89031/ (Accessed 21 June 2020).

Wang, P. and Tu, G. 2020. Localization algorithm of wireless sensor network based on matrix reconstruction. *Computer Communications,* 154: 216-222. Available: https://doi.org/10.1016/j.comcom.2020.01.051 (Accessed 2 May 2021).

Wang, W. and Tong, G. 2020. Multi-path unequal clustering protocol based on ant colony algorithm in wireless sensor networks. *IET Networks,* 9(2): 56-63. Available: https://ietresearch.onlinelibrary.wiley.com/doi/full/10.1049/iet-net.2019.0096 (Accessed 1 July 2020).

Wang, Z. J., Zhan, Z. H. and Zhang, J. 2018. Solving the energy-efficient coverage problem in wireless sensor networks: A distributed genetic algorithm approach with a hierarchical fitness evaluation. *Energies,* 11(12): 3526. Available: https://doi.org/10.3390/en11123526 (Accessed 3 May 2021).

Wei, W., Song, H., Li, W., Shen, P. and Vasilakos, A. 2017. Gradient-driven parking navigation using a continuous information potential field based on wireless sensor network. *Information Sciences,* 408: 100-114. Available: https://www.sciencedirect.com/science/article/pii/S0020025517306928 (Accessed 16 June 2020).

Wieringa, R. J. 2014. *Design science methodology for information systems and software engineering.* Springer. Available:

https://books.google.co.za/books?hl=en&lr=&id=xLKLBQAAQBAJ&oi=fnd&pg=PR5&dq=Design+science+methodology+for+information+systems+and+software+engineering&ots=bWEsaqWrNx&sig=QmPX661bd4IHptXK9M_i6D12ESg&redir_esc=y#v=onepage&q=Design%20science%20methodology%20for%20information%20systems%20and%20software%20engineering&f=false (Accessed 7 September 2021).

Williams, R. 2016. Diffusion of appropriate educational technology in open and distance e-learning in developing commonwealth countries. *Final project report. Internet learning Trust, United Kingdom* 1. Available: http://hdl.handle.net/11599/182 (Accessed 4 May 2021).

Wohwe Sambo, D., Yenke, B. O., Förster, A. and Dayang, P. 2019. Optimized clustering algorithms for large wireless sensor networks: A review. *Sensors,* 19(2): 322. Available: https://www.mdpi.com/1424-8220/19/2/322 (Accessed 13 September 2020).

Wu, C., Gunatilaka, D., Saifullah, A., Sha, M., Tiwari, P. B., Lu, C. and Chen, Y. 2016. Maximizing Network Lifetime of WirelessHART Networks under Graph Routing. *In Proceedings of the 2016 IEEE First International Conference on Internet-of-Things Design and Implementation (IoTDI), Berlin, Germany* 4–8 176–186. Available: https://10.1109/IoTDI.2015.43 (Accessed 5 May 2021).

Xia, B., Liu, T., Ding, T. and Wang, Z. 2020. An Improved PSO Localization Algorithm for UWB Sensor Networks. *Wireless Personal Communications,* 117: 1-17. Available: https://doi.org/10.1007/s11277-020-07968-x (Accessed 6 May 2021).

Xie, G. and Pan, F. 2016. Cluster-based routing for the mobile sink in wireless sensor networks with obstacles. *IEEE Access,* 4: 2019-2028. Available: https://ieeexplore.ieee.org/abstract/document/7458804 (Accessed 21 June 2020).

Xu, M. and Zhou, J. 2020. Elite immune ant colony optimization-based task allocation for maximizing task execution efficiency in agricultural wireless sensor networks. *Journal of Sensors,* .14(10): 4712-4721. Available: https://doi.org/10.1155/2020/3231864 (Accessed 7 June 2020).

Yadav, A., Kumar, S. and Vijendra, S. 2018. Network life time analysis of WSNs using particle swarm optimization. *Procedia Computer Science,* 132: 805-815. Available: https://www.sciencedirect.com/science/article/pii/S187705091830824X (Accessed 14 April 2021).

Yadav, R. K. and Mishra, R. 2021. Analysis of DEEC Deviations in Heterogeneous WSNs: A Survey. *Computer Communication, Networking and IoT*: 229. Available: https://link.springer.com/content/pdf/10.1007/978-981-16-0980-0.pdf#page=241 (Accessed 22 June 2021).

Yang, T. and Wu, X., 2015. Accurate location estimation of sensor node using received signal strength measurements. *AEU-International Journal of Electronics and*

Communications, 69(4): 765-770. Available: https://doi.org/10.1016/j.aeue.2014.12.007 (Accessed 9 May 2021).

Yang, X. S. and Zhao, Y. X. 2020. Firefly algorithm and flower pollination algorithm In Nature-Inspired Computation and Swarm Intelligence. *Academic Press* 1: 35-48. Available: https://doi.org/10.1016/B978-0-12-819714-1.00012-9 (Accessed 8 May 2021).

Yang, Y., Li, B. and Ye, B. 2016. Wireless sensor network localization based on PSO algorithm in NLOS environment. *8th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC) Hangzhou* 15: 292–295. Available: https://10.1109/IHMSC.2016.87 (Accessed 9 May 2021).

Yick, J. B., Mukherjee and Ghosal, D. 2018. Wireless sensor network survey. *Computer Networks*, 52(12): 2292 – 2330. Available: https://doi.org/10.1016/j.comnet.2008.04.002 (Accessed 10 May 2021).

Yin, K. R. 2014. Case study research: Design and methods (applied social research methods). *Canadian Journal of Program Evaluation* 5: 282. Available: https://10.3138/cjpe.30.1.108 (Accessed 11 May 2021).

Yin, L., Luo, J. and Luo., H. 2018. Tasks scheduling and resource allocation in fog computing based on containers for smart manufacturing. *IEEE Transactions on Industrial Inform* 14(10): 4712–4721. Available: https://10.1109/TII.2018.2851241 (Accessed 12 May 2021).

Yogarajan, G. and Revathi, T. 2018. Nature inspired discrete firefly algorithm for optimal mobile data gathering in wireless sensor networks. *Wireless Networks*, 24(8): 2993-3007. Available: https://link.springer.com/article/10.1007/s11276-017-1517-y (Accessed 13 March 2021).

Yong-jun, C. and Yuan, S. 2012. Minimum energy consumption topology control for wireless sensor networks. *电子科技大学学报* 41(4): 568-573. Available: https://en.cnki.com.cn/Article_en/CJFDTotal-DKDX201204019.htm (Accessed 14 May 2021).

Yuan, X., Elhoseny, M., El-Minir, H. K. and Riad, A. M. 2017. A genetic algorithm-based, dynamic clustering method towards improved WSN Longevity. *Journal Network System Management*, 25: 21–46. Available: https://link.springer.com/content/pdf/10.1007/s10922-016-9379-7.pdf (Accessed 12 June 2020).

Yue, Y., Cao, L. and Luo, Z. 2019. Hybrid artificial bee colony algorithm for improving the coverage and connectivity of wireless sensor networks. *Wireless Personal Communications*, 108(3): 1719-1732. Available: https://link.springer.com/article/10.1007/s11277-019-06492-x (Accessed 26 May 2021).

Zehra, S. S., Qureshi, R., Dev, K., Shahid, S. and Bhatti, N. A. 2021. Comparative analysis of bio-inspired algorithms for underwater wireless sensor networks. *Wireless Personal Communications,* 116(2): 1311-1323. Available: https://link.springer.com/content/pdf/10.1007/s11277-020-07418-8.pdf (Accessed 1 April 2021).

Zeigler, B. P., Muzy, A. and Kofman, E. 2018. Theory of modeling and simulation: discrete event & iterative system computational foundations. Available: https://books.google.co.za/books?hl=en&lr=&id=VBhpDwAAQBAJ&oi=fnd&pg=PP1&dq=Theory+of+Modeling+and+Simulation:+Integrating+Discrete+Event+and+Continuous+Complex+Dynamic+Systems&ots=SuC5HKvEAq&sig=JExSe0E7f3J1PgGTPmQ6ODyzzFw&redir_esc=y#v=onepage&q=Theory%20of%20Modeling%20and%20Simulation%3A%20Integrating%20Discrete%20Event%20and%20Continuous%20Complex%20Dynamic%20Systems&f=false (Accessed 17 May 2021).

Zhang, J. and Dong, D. 2019. A general intelligent optimization algorithm combination framework with application in economic load dispatch problems. *Energies,* 12(11): 2175. Available: https://doi.org/10.3390/en12112175 (Accessed 14 May 2021).

Zhang, J., Yin, J., Xu, T., Gao, Z., Qi, H. and Yin, H. 2018a. The optimal game model of energy consumption for nodes cooperation in WSN. *Journal of Ambient Intelligence Humanization Computing* 11: 589–599. Available: https://doi.org/10.1007/s12652-018-1128-1 (Accessed 15 May 2021).

Zhang, W., Wei, X., Han, G. and Tan, X. 2018b. An energy-efficient ring cross-layer optimization algorithm for wireless sensor networks. *IEEE Access,* 6: 16588-16598. Available: https://10.1109/ACCESS.2018.2809663 (Accessed 18 June 2020).

Zhang, K., Zhang, G., Yu, X. and Hu, S. 2021. Boundary-based anchor selection method for WSNs node localization. *Arabian Journal for Science and Engineering,* 46: 1-14. Available: https://doi.org/10.1007/s13369-020-05286-9 (Accessed 16 May 2021).

Zhang, Y., Xing, S., Zhu, Y., Yan, F. and Shen, L. 2017. RSS-based localization in WSNs using Gaussian mixture model via semidefinite relaxation. *IEEE communications Letters,* 21(6): 1329-1332. Available: https://10.1109/LCOMM.2017.2666157 (Accessed 17 May 2021).

Zhao, Q., Cheng, Y. and Zhou, T. 2021. Research on node localization algorithm in WSN Based on TDOA. *Journal of Physics,* 1757(1): 012142. Available: https://iopscience.iop.org/article/10.1088/1742-6596/1757/1/012142/meta (Accessed 18 May 2021).

Zhao, X., Xiong, X., Sun, Z., Zhang, X. and Sun, Z. 2019. An immune clone selection-based power control strategy for alleviating energy hole problems in wireless sensor networks. Journal of *Ambient Intelligence Human Computing Chemical Engineering* 11: 2505-2518. Available: https://doi.org/10.1007/s12652-019-01300-7 (Accessed 20 May 2021).

Zhenhua, C. 2016. Research on Wireless Sensor Network Location Algorithm Based on Matrix Reconstruction. *Signal Processing,* 134: 100-112. Available: https://doi.org/10.1016/j.sigpro.2016.11.014 (Accessed 21 May 2021).

Zhou, Y., Wang, N. and Xiang, W. 2017. Clustering hierarchy protocol in wireless sensor networks using an improved PSO algorithm. *IEEE Access,* 5: 2241–2253. Available: https://10.1109/ACCESS.2016.2633826 (Accessed 22 May 2021).

Zhu, J., Zou, Y. and Zheng, B. 2017. Physical-layer security and reliability challenges for industrial wireless sensor networks. *IEEE Access,* 5: 5313–5320. Available: https://ieeexplore.ieee.org/abstract/document/7892930 (Accessed 12 March 2021).

Zlobinsky, N. and Cheng, L. 2018. SAM: A Meta-Heuristic Algorithm for Singlemachine Scheduling Problems. *SAIEE Africa Research Journal,* 109(1): 58-68. Available: https://10.23919/SAIEE.2018.8531800 (Accessed 22 May 2021).

ANNEXURE A: TURN IT IN REPORT - COVER PAGE

Thesis 9 December 2021

ORIGINALITY REPORT

14%	12%	8%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.hindawi.com Internet Source	4%
2	njavaid.com Internet Source	2%
3	Oluwasegun Julius Aroba, Nalindren Naicker, Timothy Adeliyi. "A Hyper-Heuristic Heterogeneous Multisensor Node Scheme for Energy Efficiency in Larger Wireless Sensor Networks Using DEEC-Gaussian Algorithm", Mobile Information Systems, 2021 Publication	1%
4	Oluwasegun Julius Aroba, Nalindren Naicker, Timothy Adeliyi. "An Innovative Hyperheuristic, Gaussian Clustering Scheme for Energy-Efficient Optimization in Wireless Sensor Networks", Journal of Sensors, 2021 Publication	1%
5	Submitted to Durban University of Technology Student Paper	<1%
	link.springer.com	

ANNEXURE B: CERTIFICATE OF LANGUAGE EDITING

Geraldine Coertze

Independent Communications Consultant

Language Practitioner –

English Language Academic Text Editor

Certificate of English Language Academic Editing

Author: Oluwasegun Julius Aroba (22064647) **Date:** 08 December 2021

Document type: Doctoral thesis

Discipline: Information and Technology

Academic supervisors: Dr N. Naicker, Dr T. Adeliyi

Higher Education Institution: Durban University of Technology

Thesis title: Improving Node Localization and Energy Efficiency for Wireless Sensor Networks using Hyper-Heuristic Optimization Algorithms

This serves to certify that the above thesis was language edited and that assistance was provided with checking the citations and the format of the reference list.

The document was returned to the author with tracked changes, comments and a comprehensive academic editing report to facilitate the multi-stage correction process. It was the responsibility of the author to accept or reject changes and to attend to all issues raised in the comments and in the report. The final, corrected version of the document was not proofread.

Ms Geraldine Coertze

Communications Consultant and Language Practitioner

Address: Pelham, Pietermaritzburg Email: gericoe@gmail.com Cell: +2782 620 2266

Individual member: South African Translators' Association

Associate member: Professional Editors' Guild (SA)

Entry-level member: Chartered Institute of Editing and Proofreading (UK)

Full member: South African Communication Association

Highest qualification: MSocSc (CCMS), UKZN